# The Transaction Network in Japan's Interbank Money Markets

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*Interbank payment and settlement flows have changed substantially in the last decade. This paper applies social network analysis to settlement data from the Bank of Japan Financial Network System (BOJ-NET) to examine the structure of transactions in the interbank money market. We find that interbank payment flows have changed from a star-shaped network with money brokers mediating at the hub to a decentralized network with numerous other channels. We note that this decentralized network includes a core network composed of several financial subsectors, in which these core nodes serve as hubs for nodes in the peripheral sub-networks. This structure connects all nodes in the network within two to three steps of links. The network has a variegated structure, with some clusters of institutions on the periphery, and some institutions having strong links with the core and others having weak links. The structure of the network is a critical determinant of systemic risk, because the mechanism in which liquidity shocks are propagated to the entire interbank market, or likewise absorbed in the process of propagation, depends greatly on network topology. Shock simulation examines the propagation process using the settlement data.*

Keywords: Interbank market; Real-time gross settlement; Network; Small world; Core and periphery; Systemic risk

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## I. Introduction

The payment and settlement flows of Japan's interbank money market have changed substantially, in step with the introduction in January 2001 of real-time gross settlement (RTGS), the implementation of the quantitative easing policy, the emergence of asset management trusts, the increase in direct-dealing transactions, and the abolishment of settlements through money brokers' accounts. We extract data on interbank transactions from the settlement data of the Bank of Japan Financial Network System (BOJ-NET), and then use network theory, which has increasingly been applied to the social sciences in recent years, to measure, using a variety of network statistics, the characteristics of the interbank market's complex fund flows, viewed as a transaction network.

We also examine the structural changes in interbank transactions that have occurred as a result of the above-noted factors, comparing data for December 1997, which was prior to the introduction of RTGS and implementation of the zero interest rate policy (ZIRP), with data for December 2005, which was under RTGS and while the quantitative easing policy after ZIRP was in force. Much of these structural changes reflected changes in settlement practices that will be discussed in Section III.C.

We find that interbank payment flows have changed from a star-shaped network with money brokers mediating at the hub to a decentralized network with numerous other channels. Whereas in December 1997 the linkages were concentrated on money brokers, in December 2005 there were more financial institutions with multiple transaction partners, and this resulted in a further decentralization of the network. We also found that those institutions that originally had a small number of links saw an even further decrease in the number of their links, and that this tendency was stronger for incoming network in which links were measured only for firms' funding.

A close examination of the decentralized network structure in 2005 (December, here and below) shows that the core of the overall network comprises a sub-network. This core network includes money brokers, major banks, asset management trusts, trust banks, major securities firms, affiliated financial institutions, and some large regional banks, among which there are very close links, almost to the point of a complete network, that is, every node linked to every other node. The components of this core network serve as a hub for financial institutions on the network's periphery, and should thereby play a critical role in the flow of funds through the network.

Financial institutions participating in the transaction network are closely linked through the core network, and a connection to a broad range of financial institutions can be achieved through only two or three legs. The network's structure on the periphery is not uniform, but rather quite varied, with clusters forming based on mutual ties with specific members on the periphery. These include such financial institutions as those with either strong or weak ties to a portion of the core, but relatively weak ties with other peripheral financial institutions, those that are linked to the core virtually independently, those with a variety of links to the core, and those with almost no link to the core at all.

The structure of the network is a critical determinant of systemic risk. The process by which a liquidity shock triggered by a financial institution within the network, such as a delayed settlement or failure to execute a payment caused by a shortage of funds, propagates to the overall interbank market, or likewise is absorbed on the way of propagation, depends greatly on network topology. We analyze the network's structure to see what that implies regarding the stability, and robustness to shocks, of interbank transactions. We find that knowledge of network structure can provide valuable input to a central bank's process of designing systems to supply liquidity to the market.

It is very difficult to measure a network's dynamic reaction to shocks using a qualitative approach based on static structural information. Simulation analysis provides a valuable tool for studying financial contagion, and has proven to be an important analytical approach in the recent literature. How a liquidity shock as described above propagates across the network under RTGS depends greatly on information about settlement value (which equates to the "thickness" of linkages) and about the sequence and timing of payments. In Appendix 1, we run a simulation based on actual data as a first approximation, albeit under several strong assumptions on the reaction of participants against the propagation caused by an initial shock.

This paper is organized as follows. In Section II, we introduce the literature that uses network analysis to investigate interbank payment structures and the structure of payment flows over settlement systems.[1] During this process, we provide commentary on the statistics used in network analysis, while also examining the significance of the statistics from the perspective of systemic risk. In Section III, we introduce the data used in our analysis and provide an overview of the structure of interbank transactions as well as of structural changes between two points in time. In Section IV, we examine the structural characteristics of the interbank market using both statistics and visual analysis with a network graph, and see what that implies regarding the interbank market's stability and robustness to shocks. In Section V, we summarize our conclusions. Appendix 1 shows the results from a simulation of payment delay/default contagion across the network caused by a liquidity shock. Appendix 2 provides a commentary on the characteristics of the "power law distribution" often observed in many different social networks, and shows that the same characteristics are seen in the interbank transaction network.

## II. Recent Literature and Network Statistics

Interbank transactions lead to a complex web of credits and debits among financial institutions. The interbank money markets, one of which is a market for the monetary policy, have become increasingly diverse in both market participants and products traded as a result of globalization and financial market advancements, and this has made it considerably more complex. The world's central banks have analyzed in various ways, from the perspective of examining systemic risk, what changes have occurred in interbank money markets and how these changes have impacted the market's stability and robustness to shocks.

In this section, we introduce literature focused on analyzing the structure of interbank transaction networks. While doing so, we provide commentary on the network

1. It is noted that literature survey does not cover recent studies after 2006, when this work was prepared for the 2006 *Financial System Report* (Bank of Japan [2006]).

statistics used in this research, and consider their significance in the context of systemic risk.[2] Only a portion of this literature uses static analyses of network structure, while much of it focuses on interbank market contagion and a dynamic analysis of its probability as well as depth and stretch. Nearly all of the literature uses simulation as an analytical tool.

This is probably an anomaly caused by data constraints. Because of the difficulty in obtaining data on individual interbank transactions, direct analysis of network structure is rare. Consequently, the literature has largely had to use the debit/credit data of individual financial institutions to approximate, one way or another, matrices on the debit/credit relationships among financial institutions, and then use this as a basis for studying contagion instead of primary work to examine real transaction data. Because the debit/credit data on $N$ financial institutions is used to infer an $N \times N$ matrix, the result of this approximation is crucially affected by the assumed network structure. In addition, as we show in the next section, actual networks have heterogeneous structures that make it extremely difficult to deduce the matrices.[3] Accordingly, a network analysis applied to such estimated data elicits nothing more than information on model assumptions, rendering it virtually meaningless. Because of the limit of data and methodology, the literature has focused on dynamic analysis to obtain generalized knowledge of the transmission of shocks, which provides valuable information for studying systemic risk.

As the usefulness of such analysis became recognized, the regulatory authorities started empirically analyzing contagion using actual data they have on debits/credits among financial institutions, as well as actual transaction data from the payment system provided by central banks. There is also considerable literature, primarily from central banks, regarding the stability and efficiency of the settlement system, which is inseparable from the payment of interbank transactions. Some of these literatures perform simulations and stress tests on actual settlement data.[4]

2. Network analysis has become a popular tool in the economics and finance fields, largely owing to the recent rapid development of social network analysis. Sociology has devoted more time to the study of real social networks, including personal connections and regional communities. The main thrust of this research is on human behavior and the composition of society and organizations, however, and there has been almost no quantitative analysis of network structures. In the graph theory area of mathematics, meanwhile, analysis, academic in nature, has been focused on networks that have rules and can be dealt with analytically. However, recently proposed models to express complex network structures that actually exist have enabled an understanding of networks using statistics, which in turn has led to greater use of social network analysis through a synthesis with the two preceding approaches. This approach has attracted attention in a wide variety of social sciences, and appeared in a substantial body of literature, particularly since the concepts of a small-world network and scale-free network were introduced in the 1990s. Interest in social networks is also rising in the field of economics, and the lead paper selected for the Ninth Econometric Society World Congress (held every five years) was Jackson (2007), which presented several ways to apply social network analysis in economics.

3. In addition, even if accurate $N \times N$ matrix data were obtainable, it would be nothing more than an aggregation of credit with different payment dates and maturities, and estimating the individual transaction data needed to analyze contagion would be impossible from such matrix data.

4. The representative literature includes the following. Sheldon and Maurer (1998) present pioneering empirical research using the maximum entropy method to estimate a matrix of bilateral credit based on aggregate credit data; Furfine (2003) proposes a simulation algorithm to describe the mechanism of a contagion through bank failures; Upper and Worms (2004) and Elsinger, Lehar, and Summer (2006) examine the effectiveness of safety nets and central bank-supplied liquidity in controlling contagion, endogenizing the loss rate at default; Cifuentes, Ferrucci, and Shin (2005) add the impact of declining asset prices caused by distress selling; Müller (2006) examines how the presence of credit lines magnifies the contagion due to sudden loss of the credit line at the default of the credit supplier; Blåvarg and Nimander (2002) and Mistrulli (2005) use data on bilateral credit exposure obtained from bank regulators; Amundsen and Arnt (2005) use transaction data from the settlement

We introduce below literature that uses network analysis to examine the structure of interbank transactions. Studies can be broken down into three types, depending on the data used: that using data on bilateral bank exposures, that extracting data on individual transactions from the settlement system, and that using transaction data received from interbank market operators.

**A. Pioneering Research Using Data on Bilateral Bank Exposures**

Research using data on bilateral bank exposures includes Müller (2003) and Müller (2006), both of which use internal data from the Swiss National Bank on large-value interbank exposures.[5] First we introduce Müller (2003), while also explaining the network statistics used in the analysis.

Müller (2003) notes that Swiss banks are obligated to report to the Swiss National Bank their credit lines and value of exposure in the interbank market, including off-balance-sheet transactions, to the top 10 (top 20 for large banks) counterparties in terms of that exposure. Using a graph to visualize the debit/credit structure of approximately 300 banks (including foreign bank[6] and credit cooperatives), it finds the following. (1) Two large banks serve as hubs for the interbank market, and transactions between other banks are few and far between, making the network's linkage density (number of existing bilateral banking transaction pairs divided by the total potential number of pairs) extremely sparse, and the network structure therefore very centralized. However, (2) grouping separately the 24 cantonal banks and more than 80 regional banks, each group forms its own sub-network with its own characteristics. (3) Specifically, the cantonal banks in the former group tend to transact with each other, with the members forming homogenous links, resulting in a less sparse network density. (4) The regional banks in the latter group have a strong tendency to focus their transactions on a single counterparty, resulting in a centralized network.

Müller (2003) uses various statistics for its network analysis in an attempt to quantify the network structure. The network is made up of nodes (members) and their links, as well as the quantity of information contained in these nodes and links. The nodes are also referred to as vortexes, and the links between them are also referred to as ties.[7] The most basic statistic is the number of links held by each node, termed degree. The number of links whereby the bank provides funding or credit is termed out-degrees, and number of links aimed at procuring funding is termed in-degrees. The strength of the links held by each mode is also expressed as valued degree. When looking at the network in terms of exposure as in Müller (2003), out-strength (valued out-degree) equates to each bank's gross credits, and in-strength (valued in-degree) equates to their gross liabilities.

system provided by the central bank in a similar manner of Furfine (2003); Elsinger, Lehar, and Summer (2006) and Boss *et al.* (2006) consider a macro shock as an upsurge of credit and market risks damaging the banking sector, which causes a bank failure and triggers default contagion under weakened bank portfolios. There are also many empirical studies such as Degryse and Nguyen (2007), Wells (2004), and Van Lelyveld and Liedorp (2006).

5. Müller (2006) develops Müller (2003) with a focus on analyzing contagion, using reported data on credit lines to run simulations, including of the possibility of a solvent bank defaulting owing to difficulty in getting funding. Müller (2006) omits that portion of the network analysis using statistics shown in Müller (2003).

6. Domestic banks in Switzerland have exposure to foreign banks in their domestic interbank market, and must report data on this exposure if it ranks within the top 10 or 20.

7. We use the everyday term "link" in this paper, although the academic terms for link are arc in a directed graph and edge in an undirected graph.

In contrast, research using transaction data relies on two types of quantitative data, the volume (number) of transactions, and the value (amount) of transactions, within a finite period. Müller (2003) considers banks with higher degree and strength to be closer to the center of the debit/credit network, and therefore more important players within the financial system. In this respect, degree and strength are the most easily understood statistics for measuring the centrality of a node within a network.

Considerable information can also be obtained based on the relationship between degree and strength. Müller (2003) showed that because of the strong positive correlation between credits and debits (out-degree and in-degree), banks with a large number of credit counterparties also had a large number of debit counterparties, and also showed that the positive correlation between out-strength and out-degree was weaker than that between in-strength and in-degree, which implies that banks with a large value of credits did not necessarily have these credits with a large number of banks, suggesting the possibility that their credits were concentrated with certain banks. It also shows a high correlation between in-degree and out-strength, suggesting a tendency for banks that have liabilities with a large number of counterparties to also have a large value of credits. The contagion effects on the overall network are likely to be larger in the case of a default of such a bank, even when compared with other banks high in both degree and strength.

Such contagion effects cannot be measured if the only information is on the degree and strength of each node. In addition, the network density described above is nothing more than an indication of connectivity, in other words, the average probability that a link exists between two random nodes, making it impossible to know the contagion effects from a network's heterogeneous structure. To address this, Müller (2003) measures both distance (the minimum number of steps to link nodes $i$ and $j$) and average distance (the average distance between node $i$ and *all other* nodes $j$),[8] and treats nodes with a shorter average distance as more centrally positioned in the network. The maximum reach of each node via linkages is called the influence domain, and measured either as the number of reachable nodes or the percentage of them to all nodes. This is a valuable statistic for knowing a contagion's maximum reachable area. With these statistics related to distance and domain, like those related to degree and strength, it is possible to measure separately based on the direction of credit (whether it is a receivable or payable).

Although the network density measured by Müller (2003) was a very sparse 3 percent, all nodes had a 97 percent influence domain, meaning that no matter where a contagion starts, it could reach nearly all banks. The average distance of each node ranged from 1.4 at the shortest (one of the two large banks) to six at the longest, with the overall average of all nodes very short at 2.5, suggesting that nearly all banks can be reached in very few steps.[9]

In addition to the average distance statistic, Müller (2003) used betweenness centrality. While the former measures centrality (closeness) to other nodes, the latter expresses the contribution that a third node can make as a waypoint along the shortest

8. This is also referred to as path length and average path length.
9. The maximum distance for each node is called eccentricity. The greatest eccentricity among all nodes is referred to as the network diameter.

route between two other nodes.[10] Betweenness centrality for node $k$ uses the number of paths with the shortest distance between nodes $i$ and $j$ as the denominator, and the number of the shortest paths that go through node $k$ as the numerator, and an aggregate total for every $i$-$j$ pair is calculated for every node $k$. Of two banks A and B with the same degree, if bank A has a higher betweenness centrality, it means that, relative to bank B, it is located on a more important paths in the network, is more likely to be involved in the transmission of a liquidity shock and, if it becomes unable to pay a transaction, is more likely to have a larger impact on the network. Müller (2003) found that in addition to the two large banks, three cantonal banks, one regional bank, and three foreign banks had high betweenness centrality and were a potential channel for contagion. The more important a bank is as a debtor, the greater is its tendency to have a high betweenness centrality and occupy an important position within the network, in contrast with banks that are important as a creditor, where no such tendency exists.

### B. Research Using Settlement Data

Inaoka *et al.* (2004) use BOJ-NET settlement data, from roughly the same period studied by Müller (2003), to analyze payment networks. A primary funds settlement with large value done by financial institutions is the settlement through the BOJ's current account, where interbank and other transactions are settled via transfers.[11] Interbank transactions comprise the bulk of these transfer settlements excluding the receipt or payment of funds for Japanese government bonds (JGBs).[12]

In contrast with using stock data as in Müller (2003), observing the network structure using transaction data requires accumulating data over a defined period. Inaoka *et al.* (2004) use one month of settlement records to analyze the average network structure during the month. There is also research that focuses on daily changes in the shape of the network caused by transaction and settlement developments. This includes Soramäki *et al.* (2006), mentioned below, which examined the impact that the 9/11 terrorist attacks had on U.S. interbank payment flows using a daily analysis, as well as Imakubo and Soejima (2010), which use BOJ-NET data to analyze payment recycling (the use of funds received for the next payment) during the day, and show substantial network structure differences between the morning and afternoon.

Hence analysis based on transaction and settlement data requires selecting a period of observation that suits the purpose, including the time span that network structure is to be examined. When using stock data, the choice of time periods becomes irrelevant,

10. As opposed to the concept of betweenness centrality, degree is referred to as local centrality, because it does not take into account indirect links.

11. The BOJ's current account is used by authorized financial institutions to deposit and withdraw banknotes, and also used for sending and receiving funds for various other purposes. Specifically, BOJ current account transfers are used for the settlement of funds, and the settlement of payments on transactions for Japanese government bonds (JGBs) and other securities, between two financial institutions, as well as for final settlement of transactions made on private-sector deferred net settlement (DNS) systems. In addition, the BOJ makes deposits to and withdrawals from current accounts to settle open market operations that it conducts with financial institutions, various loans, the receipt and payment of treasury funds, and the receipt and payment of funds in conjunction with the issuance and redemption of JGBs.

12. The BOJ provides a central depository service for JGBs. This settlement is executed by the delivery versus payment (DVP) system. DVP is a mechanism aimed at avoiding failures to receive either securities or payment by ensuring that a delivery of securities occurs if, and only if, payment occurs. DVP accounts for approximately half of all settlements through the BOJ current account, both in volume and value of transactions.

but data as detailed as the maturity dates (and payment timing) of the individual credits/debits are often unusable, and thus must be ignored when running simulations and other dynamic analysis.

Inaoka *et al.* (2004) focused on the distribution of each node's degree within the network structure. A network created by randomly selecting two nodes and establishing a link between them is called a random network. The probability of a given node being selected is given by the network density (or connectivity), and thus the degree distribution within a random network is a Poisson distribution. Within a real social network, however, there are a large number of high-degree nodes with a very large number of links, and in most cases the links are unlikely to have been formed randomly. Actual studies of degree distribution have found many such distributions that have extremely long tails and adhere to a power law distribution. Inaoka *et al.* (2004) showed that in the payment network using the above-noted data, the power law distribution was observed not only in degree but also in the number of transactions for each transacting pair. They also showed, using a graphical picture of a network comprising 354 nodes and 1,727 links (network density of 2.8 percent $=1{,}727/{}_{354}C_2$), that the financial institutions with by far the highest degree and strength (as measured by the number of transactions) were centrally positioned within the payment network.[13] They further confirmed that a comparison of degree distribution and the distribution of number of transactions for each transacting pair in month-long observations of the network taken every third month from June 2001 until December 2002 showed no change in the tendency to follow a power law distribution.

Contrast this with Soramäki *et al.* (2006), which use data from Fedwire, the settlement system operated by the U.S. Federal Reserve System, to examine the structure of the daily flow of settlement funds. Their paper is not limited to interbank transactions, but also analyzes the structure of the network created by the entire flow of funds among financial institutions as well as Inaoka *et al.* (2004).[14] It uses various network statistics for the 62 trading days in the first quarter of 2004 to observe daily changes in network structure, and found that there were daily changes in the network density, average distance, degree distribution (the power indicator of the power law distribution), and the size of the network as expressed in number of nodes and the value and volume of settlements, and also found a pattern of seasonality at the beginning of the month, the end of the month, and at mid-month when an increase in bond settlements results in increased network size and density.

The paper also uses the concepts of assortative and disassortative to examine node affinity, with the former indicating greater affinity among similar nodes, and the latter indicating greater affinity among dissimilar nodes. Soramäki *et al.* (2006) focus on the

13. A power law distribution follows a distribution for which the exponent remains the same even when multiplying the stochastic variable by a constant. Such distributions are therefore also called scale-free, and a network that follows a power law distribution is called a scale-free network. The reasons why social networks tend to be scale free are shown by a number of theoretical models that look at the issue from the network creation mechanism, that is, from the events that create links between nodes. The network creation mechanism is valuable not just for understanding the current structural characteristics, but also for knowing how the network may change in response to exogenous shocks and how a collapsed network recovers. Although addressed in these theoretical models, this is beyond the scope of this paper.

14. Furfine (2003) attempts an analysis of contagion by extracting federal funds transactions from Fedwire settlement data.

correlation of the degree of the two nodes ending each link, and finding that correlation to be negative, show that nodes with a small number of links tend to favor links with nodes which have a large number of links and vice versa, and therefore that settlement networks are disassortative. This is further confirmed by the negative correlation between a node's degree and its average nearest neighbor degree (ANND).

The clustering coefficient, a statistic for measuring the ease with which multiple nodes within a group are able to form links, is found by dividing the number of links within a given sub-network, defined as all links connected to a given node (but not including that node), by the total number of links possible within the sub-network. The clustering coefficient could also be thought of as measuring the density of a local network consisting of all the nodes linked to the node in question, and in a random network, would be the same as average density. Soramäki *et al.* (2006) found the distribution of the clustering coefficient for each node ranged widely from zero to one, and was considerably larger than the network's average density of 0.3 percent.

The links between nodes have a tendency to cluster in social networks. Personal contact networks, for example, cluster by such social attributes as proximity to each person's residence and workplace. The realistic number of human links for a man is limited compared with the number of nodes (total population), and therefore link density tends to be sparse and clustered based on proximity. Despite this, in a social network it is possible to have both clustering and a short average distance, as is the case when measuring the distance of people with quite different social attributes and finding that distance to be short, with connections established in very few steps (legs).

Soramäki *et al.* (2006) also found that the settlement networks studied were highly clustered, but also had sparse network density and a short average distance: 2.62 during the period observed. This type of network, known as a small-world network, is seen in many different types of social networks, including personal friendships and corporate associations. The attributes of a small-world network are likely to include a small number of hubs and the presence of shortcut links with distant nodes, and there are many empirical studies of actual networks that support this. In a personal network, people with a large number of acquaintances are equivalent to hubs, and links that connect differing social attributes are equivalent to shortcuts.

Soramäki *et al.* (2006) also found the presence of sub-networks serving as hubs for the entire network. They showed that although the network comprised more than 6,600 nodes and more than 70,000 links on the first day of the observation period, 75 percent of the network's total settlement value was paid and received within a sub-network comprising only 66 nodes and 181 links, and 25 of these nodes comprised another highly dense sub-network. The paper did not discuss the role played by this core network, but we think it likely that it equates to a hub for an overall network comprising a very large number of nodes, and thus has the small-world characteristics noted above.

### C. Research Using Transaction Data

When using settlement data to analyze the interbank transaction network, it is often difficult to isolate interbank transactions from settlement data. Particularly because the focus is on the flow of funds, it is necessary to identify the start and end of a funds transaction and then use only the settlement data at the start. In this paper as well as in Furfine (2003), which analyzes contagion in federal funds transactions, various artifices are used to extract interbank transaction information from the settlement data. In contrast, Iori *et al.* (2008) use transaction data to analyze the transaction network, because Italy's transitioning of interbank transactions to an electronic brokering system (e-MID: electronic Market for Interbank Deposits) made it possible to use data on individual transactions for overnight instruments made within that system. That paper uses comparisons between 1999 and 2002 to check for structural changes in the interbank market and analyzes the impact on daily changes brought by the buildup of reserve deposits.

Looking at changes in the degree distribution that occurred during both years, Iori *et al.* (2008) found a substantial decline in the overall out-degree distribution because bank mergers resulted in a decline in the number of banks participating in e-MID to 177 from 215, but saw an increase in in-degree distribution. This indicates that banks decreased the number of banks that they sent payments to overall, but increased the number of banks that they received payments from. In addition, changes in the out-strength distribution, which looks at monetary totals, indicated a tendency for the top-ranked banks to decrease their value of transactions and for the lower-ranked banks to increase their value of transactions, and changes in the in-strength distribution showed that top-ranked banks increased the value of payments received. This shows that while the top-ranked banks were major providers of funds in 1999, the lower-ranked banks increased their role in providing funds in 2002, and the smaller value of funds provided to each counterparty by the lower-ranked banks was offset by the top-ranked banks increasing the number of banks from which they received funds, while the lower-ranked banks focused their payments on the top-ranked banks.

Iori *et al.* (2008) suggest that these structural changes can be attributed to (1) a rising demand for funds in regional economies during the 1999 boom, which made the lower-ranked banks less inclined to provide funds on the interbank market, and the reverse of this during the subsequent economic contraction; and (2) the introduction of the euro at the start of 2001, which encouraged the top-ranked banks to provide funding to foreign banks through voice-brokered transactions outside of the e-MID system, and the tendency for the banks to seek funding in the domestic interbank market.

An analysis of daily changes seems to show banks making fine adjustments to deposit reserve balances on the final day of the reserve maintenance period to ensure that they met reserve requirements. There was first of all a tendency, on and immediately prior to the final day, to increase both the value and volume of transactions, and in particular increases in volume occurred irrespective of bank size. From the perspective of network topology, this suggests a tendency for both the degree and the clustering coefficient to increase. The clustering coefficients except the final day and several days prior to the day were not significantly higher than a random network, which is a different result than that of Soramäki *et al.* (2006). We think that this lack of network clustering reflects the vertical relationship in the transactions going from the top-ranked banks to the lower-ranked banks, and to the small number of horizontal links between the same layers. Iori *et al.* (2008) provide visual confirmation of this with graphs.

Another tendency that was observed both for the top-ranked and the lower-ranked banks was that of focusing transactions on specific counterparties.[15] This tendency gets weaker, however, as the final day of the reserve maintenance period approaches. Iori *et al.* (2008) note the reason for this is that getting funding to meet reserve requirements takes precedence over counterparty selection, and this tends to result in an increase in transactions with banks not normally transacted with. The increase in the clustering coefficient noted above reflects this, and the decline in the network diameter approaching the final day is consistent with an increase in links, that is, the number of legs on the shortest declines because new links can be created.

There are few examples of such network analysis using transaction data of individual financial institutions because of limited access to that data. As far as we know, Italy is the only market where it was possible to use transaction data from an electronic brokering system to analyze the interbank monetary transaction network. This paper tries to examine the structure of interbank transaction as well as Soramäki *et al.* (2006) and Iori *et al.* (2008) using a combination of network statistics. Table 1 shows a comparison of the literature in terms of the statistics used and the network structure found. This paper shows that the small world, scale-free, and disassortative characteristics identified in the literature can also be observed in the Japanese interbank transaction network, and also shows that this network has a two-tier structure, made up of a core and a periphery, and that there is heterogeneous way to link the periphery to the core.

## III. Structural Changes in Interbank Transactions

### A. Data

The BOJ provides a current account for authorized financial institutions. The account is where financial institutions keep their required reserves, and also functions as a settlement asset for monetary and securities transactions between financial institutions, including the BOJ.[16]

Transactions in the BOJ's current account are settled through BOJ-NET, and it is possible to extract the settlement data of interbank transactions. However, some errors are generated in the data identification, because we use the transaction practices for the interbank markets such as values and counterparties of the transactions. In addition, the settlement data include the monetary flows both at the time of initial payment and at the time of repayment, making it necessary to extract the data at the time of initial payment in order to examine the transaction structure correctly.[17]

15. This is based on the participation ratio, which measures the extent that strength is concentrated on some links, and is given by the square of an individual link's share of strength.

16. In addition, it has the role of holding reserves for payment of banknotes.

17. The simulation of liquidity shock transmission in Appendix 1 uses the funds flow for both the initial payment and the repayment. For example, when examining the impact in the case some financial institutions become unable to settle, the flow at repayment is more important than the flow at initial payment. Likewise, when examining the secondary effect of an institution suspending an initial payment because the repayments it expected to receive did not materialize, it is also necessary to look at the flow of funds at initial payment.

**Table 1 Comparison with Earlier Empirical Studies**

| | Müller | Inaoka *et al.* (2004) | Soramäki *et al.* (2006) | Iori *et al.* (2008) | This paper |
|---|---|---|---|---|---|
| Data type | Large value exposure | Settlement data | Settlement data | Transaction data | Settlement data |
| Data source | Bank regulators | BOJ-NET | Fedwire | e-MID | BOJ-NET |
| Sample period | At end-December 2003 | Last month in quarter from June 2001 to December 2002 | Daily during 2004/Q1 | Daily in 1999–2002 | December in 1997 and in 2005 |
| Number of financial institutions | Approx. 300 | 546 | 5,086 (daily average) | 215 (1999), 177 (2002) | 444 (1997), 354 (2005) |
| Network visualization | Yes | Yes | Yes | Yes | Yes |
| Network statistics used in study | | | | | |
| 1. Degree | ○ | ○ | ○ | ○ | ○ |
| 2. Connectivity | ○ | | ○ | ○ | ○ |
| 3. Reciprocity | | | ○ | | |
| 4. Strength (value) | ○ | ○ | ○ | ○ | ○ |
| 5. Strength (number) | | ○ | ○ | ○ | ○ |
| 6. Distance | | | ○ | | ○ |
| 7. Average distance | ○ | | ○ | | ○ |
| 8. Diameter | | | ○ | ○ | |
| 9. Influence domain | ○ | | ○ | | ○ |
| 10. Betweenness | ○ | | | | |
| 11. Clustering | | | ○ | ○ | ○ |
| 12. K-core | | | | | ○ |
| 13. Affinity | | | ○ | ○ | ○ |
| Presence of power law distribution (see note) | – | 1, 5 | 1, 4, 5 | – | 1, 4, 5 |
| Exponent in the distribution | – | 2.3 (1), 2.1 (5) | 2.11 (1-in), 2.15 (2-out), 1.9 (4-out), 1.2 (5-out) | – | 2.0–3.4 (1), 1.6 (4-in), 1.8 (4-out), 1.7 (5-in) |
| Network structure | Centralized network<br>Sub-network | Scale free | Scale free<br>Small world<br>Disassortative<br>Core sub network | Structural change<br>Monthly cycle<br>Disassortative<br>Core and peripheral | Scale free<br>Small world<br>Disassortative<br>Core and peripheral |

Note: Where a power law distribution was observed, the numbers in parentheses refer to the numbered network statistics in the leftmost column in the above table. The in-out following the number shows whether the statistic was measured for a receipt (-in) or payment (-out) in a directed network (e.g., 1-in is the in-degree).

Next, we compare monetary transaction data for December 1997 and December 2005 while identifying the main characteristics (Table 2). Out of all the financial institutions that deal with the BOJ's current account, the number that had transactions in December 2005 was 354, 20 percent less than the number that did so in December 1997. In addition to a less active interbank transaction, we attribute this to the smaller number of financial institutions as a result of bank mergers. The same trend is evident when looking separately at the number of counterparties for payments and for receipts. In 1997, there were roughly the same number of financial institutions that made a payment as the number that received a payment, but in 2005 there was a bigger decline in the number that made a payment.

Meanwhile, the number of pairs of transacting institutions actually increased by 24 percent, to 1,709 pairs from 1,383 pairs, indicating more diversified transaction pairings. Out of the total 98,346 possible pairings for the 444 institutions that had a transaction (${}_{444}C_2$), there were actually 1,383 transaction pairs. The ratio of actual pairings to possible pairings (the network's average density) was 1.4 percent, which is very low. In 2005 there were fewer institutions with a transaction than in 1997, and a larger number of pairings, but the average network density was still quite small at 2.7 percent. This means that the interbank transaction network is sparse. Interbank transfers are thus conducted through the pairing of a limited number of institutions, and the transaction structure of the interbank market can be expressed as the pattern of transaction pairing and the value and volume of transactions for each pair.

Next, we see in Table 2 that both the total volume and total value of transactions during the month declined by about 30 percent relative to 1997. Although changes in the settlement practice for unsecured interbank money market were a major reason for this large decline (as explained below), this also appears to strongly reflect the decline in the money market transactions brought by the monetary easing policy.

### B. Transaction Structure in December 2005

Looking first at the December 2005 transaction values for each subsector, asset management trusts had roughly a 50 percent share of both the volume and value of interbank loan supply (including the supply from investment trusts under the asset management trusts), which is clearly the major source of funds supplied to the interbank market (Table 3), followed by the major banks and the regional banks, each of which accounted for more than 10 percent of transaction value. The major banks used to be the primary receivers of interbank loans, but the continued decline in bank lending has increasingly given them a funds surplus, and turned them into providers of funds partly (they are still receivers of funds on a net basis). Funds provided by money brokers have been very small, in terms of both value and volume, compared to their fund receipts. Money brokers now specialize in brokering unsecured interbank transactions (except for intraday unsecured transactions) between fund providers and recipients, and do not become a counterparty in settlements. Consequently, the numbers in this paper, based on settlement data, probably capture deals by money brokers in the secured and intraday interbank markets. The small sum of funds provided through such brokerage is indicative of the weak demand for short-term loans in the interbank money markets.

**Table 2 Summary of Interbank Transaction Data**

| | December 1997 | December 2005 | Change |
|---|---|---|---|
| Number of financial institutions with an interbank transaction during the period | 444 | 354 | –20% |
| Of the total, the number with a payment | 387 | 263 | –32% |
| Of the total, the number with a receipt | 393 | 297 | –24% |
| (Reference) Number of financial institutions with a BOJ current account | 710 (end of fiscal 1997) | 585 (end of fiscal 2005) | |
| Number of pairings of institutions with a transaction | 1,383 pairs | 1,709 pairs | +24% |
| Above as percentage of total possible pairings | 1.4% ($= 1{,}383/{}_{444}C_2$) | 2.7% ($= 1{,}709/{}_{354}C_2$) | +1.3 percentage point |
| Total number of transactions | 56,858 | 18,940 | –67% |
| Number of transactions for each institution (payments/receipts): | | | |
| Average | 243/168 | 71/63 | –71/–63% |
| Median | 49/30 | 13/6 | –73/–80% |
| Number of transactions for each pair: | | | |
| Average | 41.1 | 11.1 | –73% |
| Median | 16 | 2 | –88% |
| Total transaction value | ¥1,145 tril. | ¥322 tril. | –72% |
| Average value per transaction | ¥20.2 bil. | ¥17 bil. | –16% |
| Transaction value for each institution (payments/receipts): | | | |
| Average | ¥4.90 tril./¥3.38 tril. | ¥1.22 tril./¥1.08 tril. | –75%/–68% |
| Median | ¥441 bil./¥113 bil. | ¥143 bil./¥12.1 bil. | –67%/–89% |
| Transaction value for each pair: | | | |
| Average | ¥829 bil. | ¥18,861 bil. | +127% |
| Median | ¥76.3 bil. | ¥20 bil. | –74% |

Note: Average and median calculations only include financial institutions that had a transaction.

**Table 3 Value and Volume of Transactions by Subsector (December 2005)**

| | Transaction value (¥ trillions) | | | | Transaction volume (number) | | | |
|---|---|---|---|---|---|---|---|---|
| | Payments | | Receipts | | Payments | | Receipts | |
| Major banks | 40.4 | 13% | 62.3 | 19% | 1,186 | 6% | 2,535 | 13% |
| Trust banks | 20.2 | 6 | 11.7 | 4 | 1,260 | 7 | 582 | 3 |
| Regional banks | 44.8 | 14 | 5.8 | 2 | 2,543 | 13 | 492 | 3 |
| Regional banks II | 15.0 | 5 | 0.1 | 0 | 1,111 | 6 | 42 | 0 |
| Credit unions | 2.0 | 1 | 2.1 | 1 | 323 | 2 | 631 | 3 |
| Securities companies | 1.9 | 1 | 7.9 | 2 | 181 | 1 | 677 | 4 |
| Foreign banks | 9.9 | 3 | 23.0 | 7 | 586 | 3 | 931 | 5 |
| Foreign securities companies | 1.4 | 0 | 8.1 | 3 | 100 | 1 | 377 | 2 |
| Foreign trust banks | 8.0 | 2 | 0.0 | 0 | 191 | 1 | 11 | 0 |
| Money brokers | 13.0 | 4 | 186.6 | 58 | 552 | 3 | 11,680 | 62 |
| Asset management trusts | 146.8 | 46 | 0.9 | 0 | 9,657 | 51 | 118 | 1 |
| Securities financial companies | 5.3 | 2 | 6.1 | 2 | 95 | 1 | 356 | 2 |
| Affiliated financial institutions | 11.2 | 3 | 5.9 | 2 | 1,009 | 5 | 390 | 2 |
| Public financial institutions | 1.9 | 1 | 1.6 | 1 | 100 | 1 | 89 | 0 |
| Total | 322.4 | 100% | 322.4 | 100% | 18,940 | 100% | 18,940 | 100% |

Note: Percentage indicates share of total. Because these are cumulative totals of transaction flows, they differ from the investments/loans measured on a stock basis. Since this data is based on the initial transaction to investigate directions of loan flow, payments/receipts do not balance for each subsector. Analysis focused on settlements looks at both sides of the transaction, since all funds settlements are important, whether at the transaction start (initial funding) or end (repayment). Because figures are subsector averages, in some cases a specific firm can strongly impact the average, and in some cases there are substantial differences within a subsector.

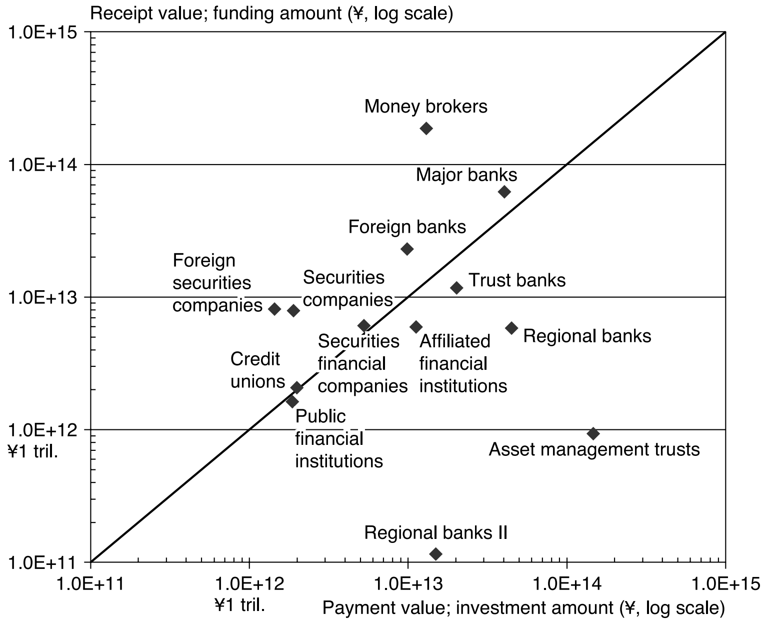
Money brokers account for the largest share in receivers of interbank funds, in terms of both volume and value, followed by the major banks and foreign banks. The flow of interbank market funds between subsectors shows a considerable amount of interbank direct dealing (DD) and direct settlement,[18] as well as a substantial amount of funds money brokers' receive from asset management trusts, around one-third of the total funds provided (Table 4). Data on the balance of payments and receipts for each subsector show foreign securities companies, securities companies, and foreign banks as the biggest net receivers of funds (Figure 1).

18. In addition to DD, we think the data also include a substantial amount of transactions in which money brokers make the match of demand and supply but the settlement is done directly between banks. We refer to this as direct settlement to distinguish it from DD.

**Table 4 Flow of Interbank Funds between Subsectors (December 2005)**

| Receipts (¥ trillions) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Payments | Major banks | Trust banks | Regional banks | Regional banks II | Credit unions | Securities companies | Foreign banks | Foreign securities companies | Foreign trust banks | Money brokers | Asset management trusts | Securities financial companies | Affiliated financial institutions | Public financial institutions | Total |
| Major banks | 7.0 | 2.2 | 2.4 | 0.0 | 0.0 | 2.8 | 8.5 | 0.3 | 0.0 | 14.7 | 0.2 | 0.0 | 1.5 | 0.5 | 40.4 |
| Trust banks | 4.2 | 0.3 | 0.6 | 0.0 | 0.0 | 0.6 | 0.9 | 0.1 | 0.0 | 12.7 | 0.4 | 0.2 | 0.1 | 0.2 | 20.2 |
| Regional banks | 7.4 | 1.4 | 1.0 | 0.0 | 0.0 | 1.8 | 1.3 | 0.3 | 0.0 | 30.3 | 0.1 | 0.8 | 0.4 | 0.1 | 44.8 |
| Regional banks II | 3.2 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 11.4 | 0.0 | 0.0 | 0.0 | 0.0 | 15.0 |
| Credit unions | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.5 | 0.0 | 0.0 | 1.4 | 0.0 | 2.0 |
| Securities companies | 0.5 | 0.6 | 0.2 | 0.0 | 0.0 | 0.1 | 0.3 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 | 1.9 |
| Foreign banks | 0.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 4.5 | 0.0 | 4.4 | 0.0 | 0.0 | 0.0 | 0.0 | 9.9 |
| Foreign securities companies | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.4 |
| Foreign trust banks | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 8.0 | 0.0 | 0.0 | 0.0 | 0.1 | 8.0 |
| Money brokers | 6.0 | 0.3 | 0.5 | 0.1 | 0.0 | 1.0 | 3.4 | 1.1 | 0.0 | 0.0 | 0.0 | 0.2 | 0.1 | 0.3 | 13.0 |
| Asset management trusts | 30.9 | 5.8 | 0.1 | 0.0 | 0.0 | 0.8 | 3.8 | 0.9 | 0.0 | 97.1 | 0.1 | 4.7 | 2.4 | 0.0 | 146.8 |
| Securities financial companies | 0.0 | 0.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 5.0 | 0.0 | 0.0 | 0.0 | 0.0 | 5.3 |
| Affiliated financial institutions | 1.6 | 0.5 | 0.6 | 0.0 | 2.1 | 0.3 | 3.0 | 0.6 | 0.0 | 2.3 | 0.0 | 0.1 | 0.0 | 0.1 | 11.2 |
| Public financial institutions | 0.7 | 0.2 | 0.1 | 0.0 | 0.0 | 0.2 | 0.0 | 0.2 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.3 | 1.9 |
| Total | 62.3 | 11.7 | 5.8 | 0.1 | 2.1 | 7.9 | 23.0 | 8.1 | 0.0 | 186.6 | 0.9 | 6.1 | 5.9 | 1.6 | 322.8 |

**Figure 1 Balance of Payments and Receipts by Subsector**




Network analysis frequently uses visualization with graphs, and Figure 2 shows an example of this technique to look at the receivers of funds provided by 64 regional banks. Money brokers were the biggest receivers, followed by major banks. Securities companies and foreign banks also received these funds.

**C. Comparison with December 1997**

Next, we compare with December 1997, which was before the introduction of RTGS and before the implementation of quantitative easing. Transactions outstanding declined by almost half from 1997 to 2005, to ¥21 trillion from ¥39 trillion, while the transaction flow, shown in Table 5, declined even more, by around 75 percent. This difference between the changes in stock and flow can largely be attributed to systemic changes in the handling of brokering unsecured loans by money brokers (these transactions, which used to be settled by flowing the funds through the broker’s account, are now, with the introduction of RTGS, settled directly between the payer’s and receiver’s accounts). Changes in settlement practice aimed at reducing the amount of funds settled, such as netting repayments and their paired payments, have also served to reduce the flow totals. Accordingly, the change between 1997 and 2005 reflects changes in the settlement system as well as structural changes in interbank transactions, and more accurately should be viewed as structural changes in both payments and settlements. Looking at the 1997 flow of funds between subsectors with this in mind, we can summarize that all subsectors both provided funds to and received funds from money brokers, that is, they played the role of a hub in interbank money markets (Table 6).

**Figure 2 Receivers of Funds from Regional Banks**

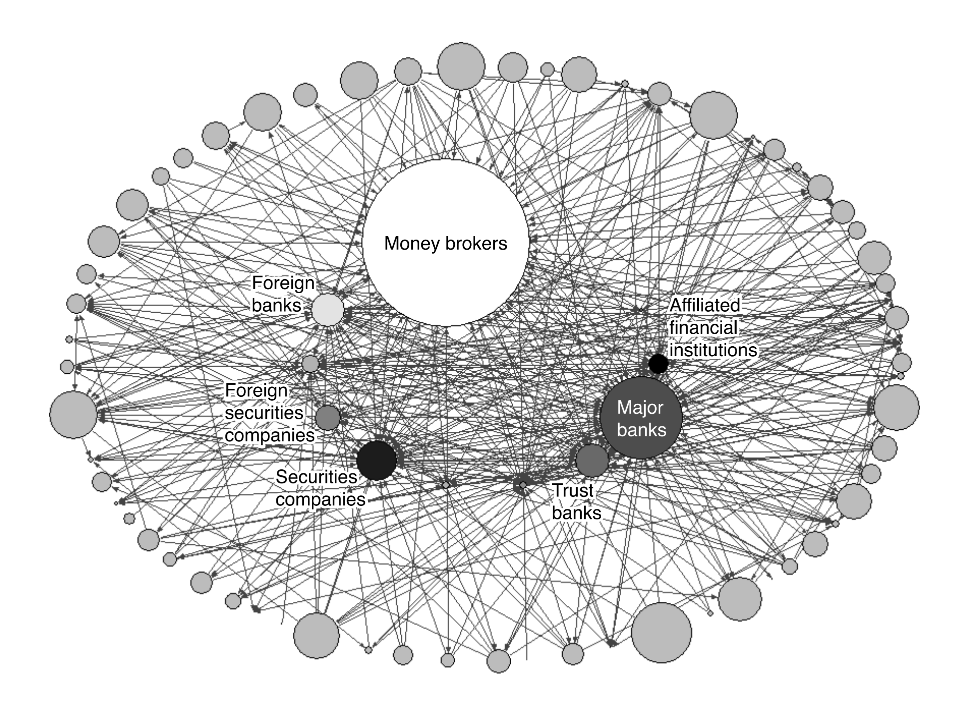



**Table 5 Comparison of Value of Transactions by Subsector**

| | December 1997 (¥ trillions) | | | | December 2005 (¥ trillions) | | | |
|---|---|---|---|---|---|---|---|---|
| | Payments | | Receipts | | Payments | | Receipts | |
| Major banks | 78 | 6% | 450 | 35% | 40 | 13% | 62 | 19% |
| Trust banks | 283 | 22 | 82 | 6 | 20 | 6 | 12 | 4 |
| Regional banks | 81 | 6 | 65 | 5 | 45 | 14 | 6 | 2 |
| Regional banks II | 23 | 2 | 14 | 1 | 15 | 5 | 0 | 0 |
| Credit unions | 6 | 0 | 3 | 0 | 2 | 1 | 2 | 1 |
| Securities companies | 29 | 2 | 15 | 1 | 2 | 1 | 8 | 2 |
| Foreign banks | 35 | 3 | 62 | 5 | 10 | 3 | 23 | 7 |
| Foreign securities companies | 4 | 0 | 13 | 1 | 1 | 0 | 8 | 3 |
| Foreign trust banks | 5 | 0 | 2 | 0 | 8 | 2 | 0 | 0 |
| Money brokers | 698 | 54 | 548 | 43 | 13 | 4 | 187 | 58 |
| Asset management trusts | – | – | – | – | 147 | 46 | 1 | 0 |
| Securities financial companies | 1 | 0 | 14 | 1 | 5 | 2 | 6 | 2 |
| Affiliated financial institutions | 27 | 2 | 12 | 1 | 11 | 3 | 6 | 2 |
| Public financial institutions | 8 | 1 | 2 | 0 | 2 | 1 | 2 | 1 |
| Total | 1,281 | 100% | 1,281 | 100% | 322 | 100% | 322 | 100% |

Note: Figures in percentage column indicate share of total.

**Table 6 Flow of Interbank Funds between Subsectors (December 1997)**

| | Receipts (¥ trillions) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Payments | Major banks | Trust banks | Regional banks | Regional banks II | Credit unions | Securities companies | Foreign banks | Foreign securities companies | Foreign trust banks | Money brokers | Asset management trusts | Affiliated financial institutions | Public financial institutions | Total |
| Major banks | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 2 | 0 | 72 | 0 | 0 | 0 | 78 |
| Trust banks | 9 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 272 | 0 | 0 | 0 | 283 |
| Regional banks | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 81 |
| Regional banks II | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 0 | 0 | 0 | 23 |
| Credit unions | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 1 | 0 | 6 |
| Securities companies | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 1 | 0 | 0 | 29 |
| Foreign banks | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 28 | 0 | 0 | 0 | 35 |
| Foreign securities companies | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 3 | 0 | 0 | 0 | 4 |
| Foreign trust banks | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 5 |
| Money brokers | 437 | 79 | 63 | 14 | 2 | 13 | 60 | 4 | 2 | 0 | 12 | 10 | 2 | 698 |
| Securities financial companies | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| Affiliated financial institutions | 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 23 | 0 | 0 | 0 | 27 |
| Public financial institutions | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 8 |
| Total | 450 | 82 | 65 | 14 | 3 | 15 | 62 | 13 | 2 | 548 | 14 | 12 | 2 | 1,281 |

### D. Daily Developments during December 2005

To observe the structure of interbank transactions on average, we analyze cumulative transactions for the month. The daily changes in these transactions have a seasonal pattern within the month, however, and thus the structure of transactions changes daily. We attribute this variation to institutional factors, such as the last day of the reserve maintenance period and the day that JGBs are issued, as well as to calendar (day-of-the-week) factors. We briefly confirm this as follows. Figure 3, which shows daily changes in both the value and volume of transactions in December 2005, suggests a tendency for the value and volume of transactions to increase approaching the final day of the reserve maintenance period (the 15th of every month). There is also a notable increase, particularly in volume, prior to a weekend or consecutive holidays. JGBs used to be issued on the 20th of the month, and both the value and volume of transactions also increase around this time. When simulating a liquidity shock using actual data, it is necessary to take into account the flow characteristics of the relevant day when choosing the day and when interpreting the results. The simulation in Appendix 1 uses the last day of the reserve maintenance period, which is the day with the largest transaction amount.

**Figure 3 Daily Developments in Value and Volume of Transactions**

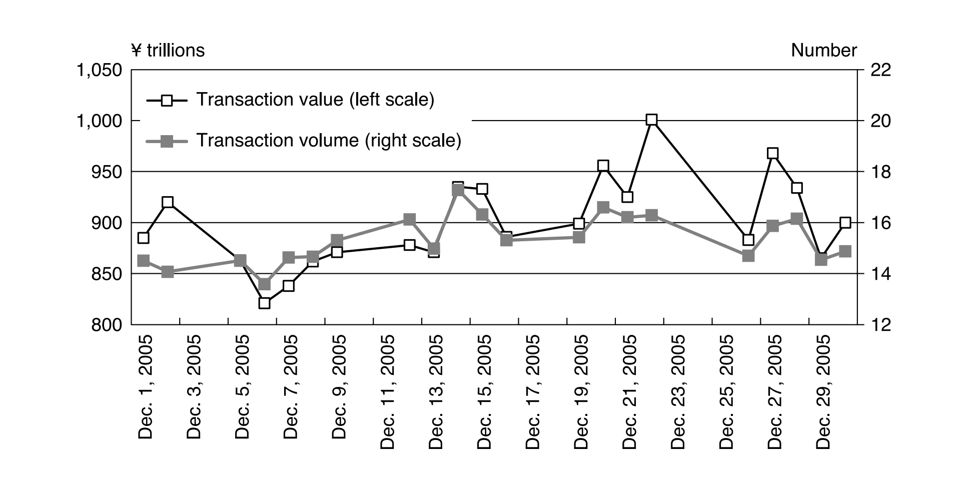
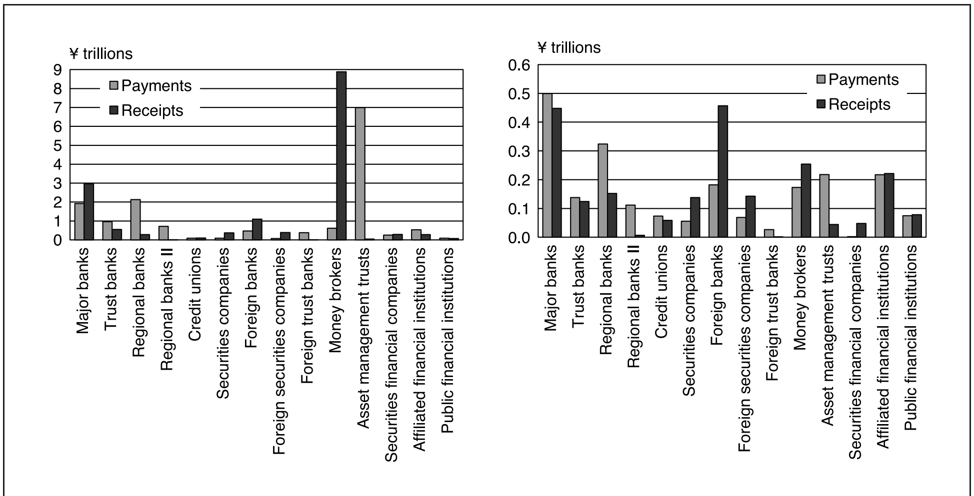



**Figure 4 Daily Transaction Value: Mean and Standard Deviation for 21 Trading Days**




The magnitude of daily change in transactions differs by subsector. Figure 4 shows the average over the 21 trading days in the month, and the volatility, of daily changes in funds payments and receipts. Asset management trusts and money brokers both show more volatility with large transaction values, but payments by money brokers show greater volatility to the lower average. This suggests that even if there is a funds surplus on average, demand for funds arises on specific days of the month, and this draws an increase in payments by money brokers. Foreign banks have high volatility relative to the average transaction amount, particularly in receiving payments. In contrast, although the major banks on average have a large value of receipts, their payments are more volatile, the opposite of the pattern exhibited by foreign banks, securities companies, and foreign securities companies. These characteristics reflect interbank market conditions under quantitative easing, and we would expect both the pattern within the month and the subsector characteristics to change depending on the period observed.

## IV. Structure of Interbank Transaction Network

### A. Overview

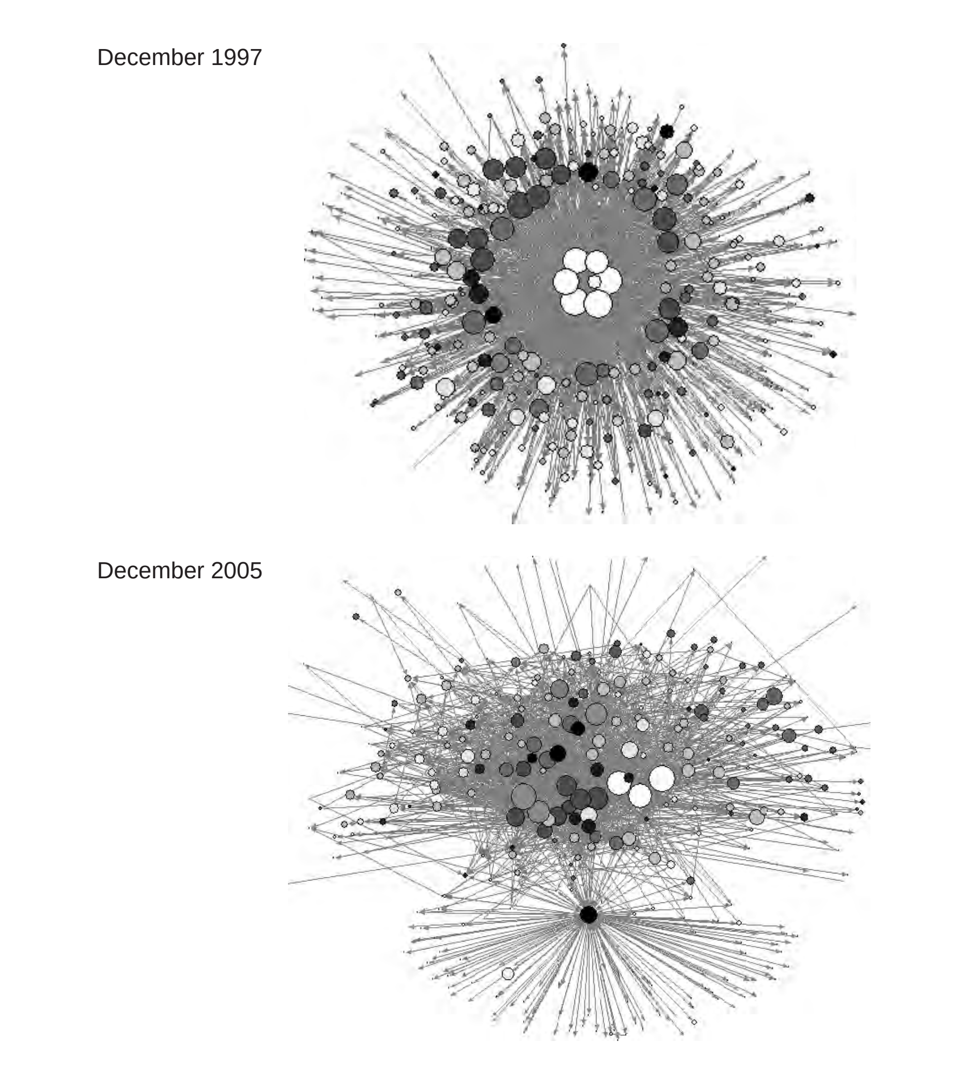
Network analysis frequently uses graphs to visualize network shapes. Following this, Figure 5 is a graphical depiction of the network, that is, the transactions in the interbank market. Each node represents a financial institution, and each link denotes the presence of a transactional relationship observed during the month. The network was built around a hub of money brokers in 1997, but changed to a decentralized network in 2005. Figure 6 shows a pattern diagram of this. The left panel depicts a star-shaped (centralized) network in which each node is linked only to the hub, and this is a fairly accurate depiction of the network in 1997. Table 6 above also confirms that almost all funds flowed through money brokers.

In contrast to this, the right panel in Figure 6 is known as a complete network wherein each node is connected to all other nodes, but as shown in Table 2, links in the actual transaction network are extremely sparse, and not all nodes have a high degree, as is the case in a complete network. A closer look at the bottom panel in Figure 5 for 2005 reveals that the network is not completely decentralized, and financial institutions with larger transaction amounts (larger size of circles) are located close to the center and appear to have fairly dense links (see the note to Figure 5 for an interpretation of node positioning). Next, we use network statistics to look, one by one, at the characteristics of the type of complex network depicted in Figure 5.

We start by confirming the distribution of degree and strength for each node, broken down by payments and receipts. This looks at the number of transaction counterparties each financial institution had during the month, as well as the gross transaction value. Figure 7 (top) compares 1997 and 2005 for each financial institution, in order of highest in-degree. In 1997, links were concentrated on seven money brokers, which is all there were that had in-bound links with at least 10 financial institutions, but in 2005 there was an increase in the number of institutions besides money brokers with a large number of links, to a total of 53 with at least 10 in-bound links. We think the increase in high-degree institutions would cause the decentralization seen in Figure 5. In addition, the institutions with a small number of links in 1997 wound up reducing their number of links even further. This could be interpreted as a narrowing of in-bound links to smaller financial institutions as a result of the reduction in funding needs caused by sustained monetary easing policy. Nearly the same phenomenon could be observed with changes in the out-degree distribution, although for smaller financial institutions the reduction in the number of outbound links was smaller than the reduction in in-bound links.

Looking next at the distribution of in-strength and out-strength (value of receipts and payments) shown in Figure 8, the top-ranked institutions had disproportionately high transaction values, and this tendency was more pronounced in 2005 than in 1997. We think one reason is that mergers between money brokers and between the major banks resulted in a consolidation of the top-ranked institutions. There was a downward

**Figure 5 Interbank Transaction Network**




Note: We produced this graph using the network analysis software Pajek, and the drawing is based on the Kamada-Kawai algorithm, which uses the attractive and repulsive forces between linked nodes, and positions the nodes with the greater number of links closer to the nodes with many links (the repulsive force acts between nodes, but this is superseded by the resultant force of attractive forces acting within the node group). Nodes connected by a single link have a strong repulsive force between them, resulting in nodes being positioned farther apart. Nodes are positioned overall to minimize the total energy from all attractive and repulsive forces, but because results are initial node-positioning dependent, creation of the graph requires repeated attempts until stable results can be achieved. The sizes of the circles within the graph are proportional to the log of strength (transaction value), while color identifies the subsector. The Kamada-Kawai algorithm does not require data on strength or on the weight of each link (the value and volume of transactions for each pair), but estimates node positioning based only on whether there is a link.

**Figure 6 Star-Shaped Network (Centralized) and Complete Network (Decentralized)**

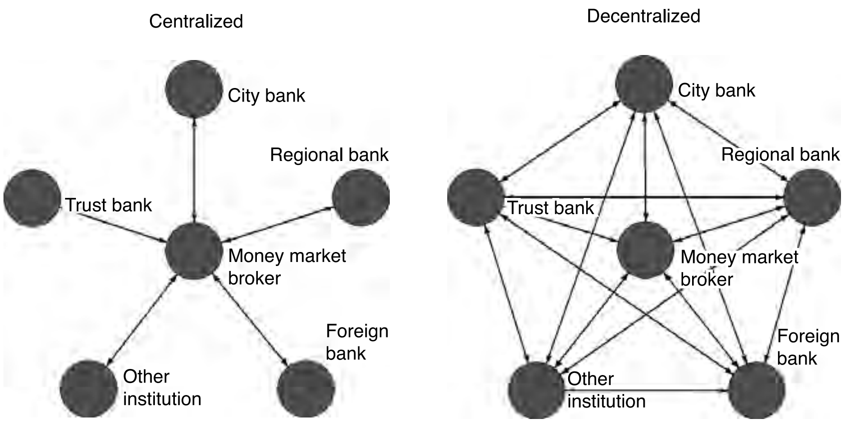



**Figure 7 Distribution of Degree by Direction of Funds Flow (In Log Form)**

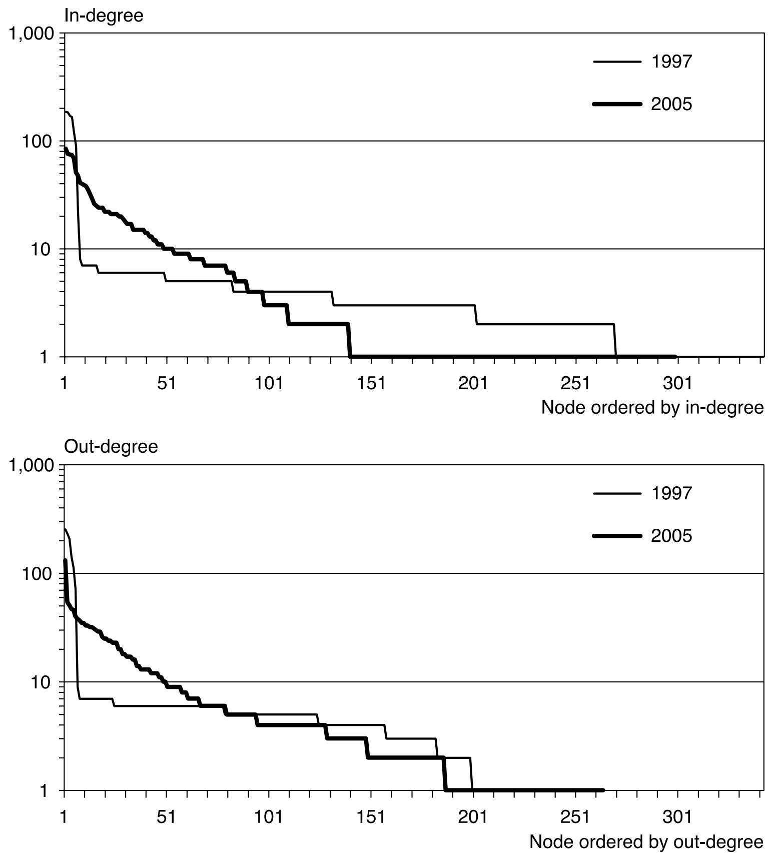
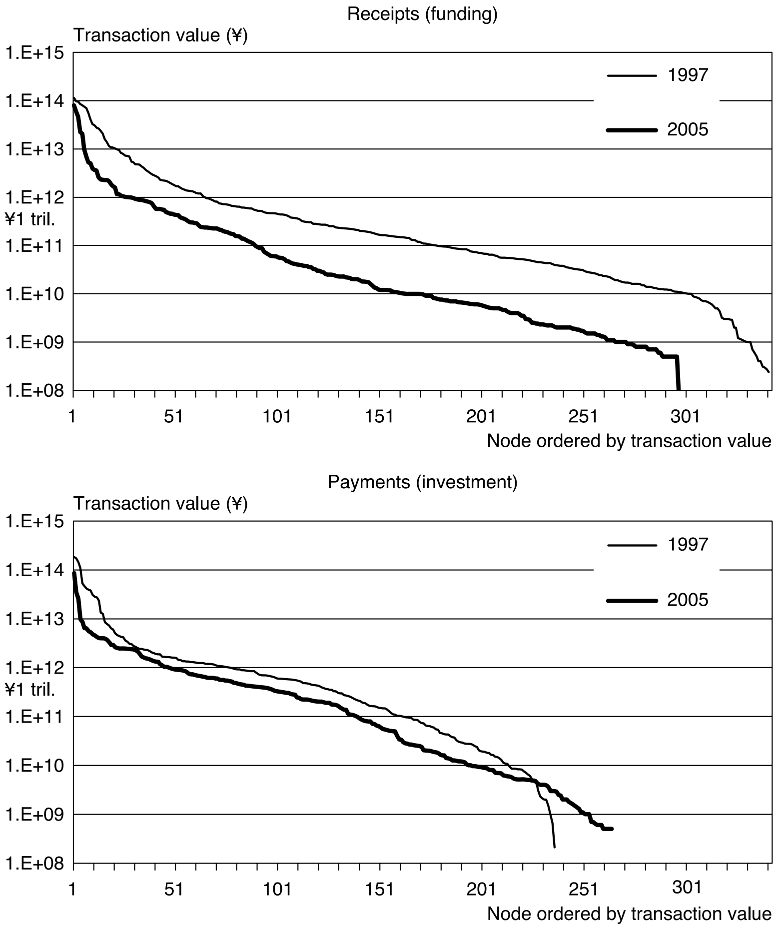


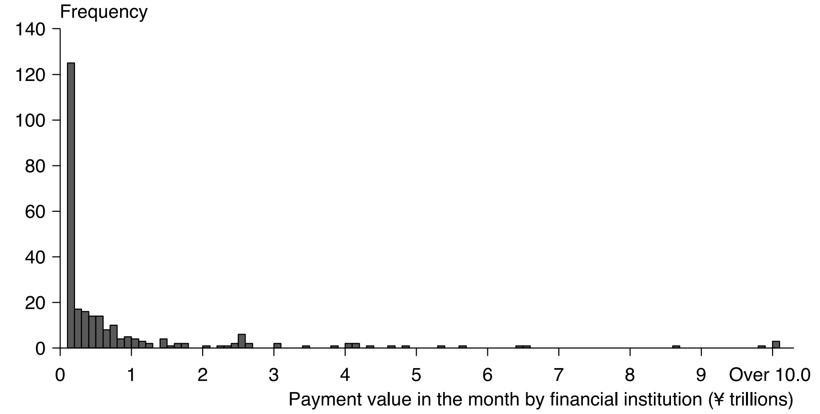
**Figure 8 Distribution of Valued Degree by Direction of Funds Flow (In Log Form)**




shift in the overall distribution both for receipts and payments, reflecting the decline in interbank transactions described in Section III. The downward shift was greater for receipts than for payments, but since for any given period total payments and total receipts must balance out, a comparison of payments and receipts in 2005 shows that the top receiving institutions had a relatively greater increase in transaction values than the top paying institutions, confirming that only some of the top-ranked receivers absorbed the overall excess in payments.

A histogram of the transaction value distribution by financial institution shows a very long tail (Figure 9), a characteristic of not only the degree distribution but also the distribution of the value and volume for each transaction pair. In many cases, this long-tailed distribution can be expressed as a power law distribution $p(x) \sim x^{-\gamma}$, and we confirm this actually follows the distribution identified in the earlier studies of Section II. See Appendix 2 for details.

**Figure 9 Long Tail Property: Distribution of Transaction Values**



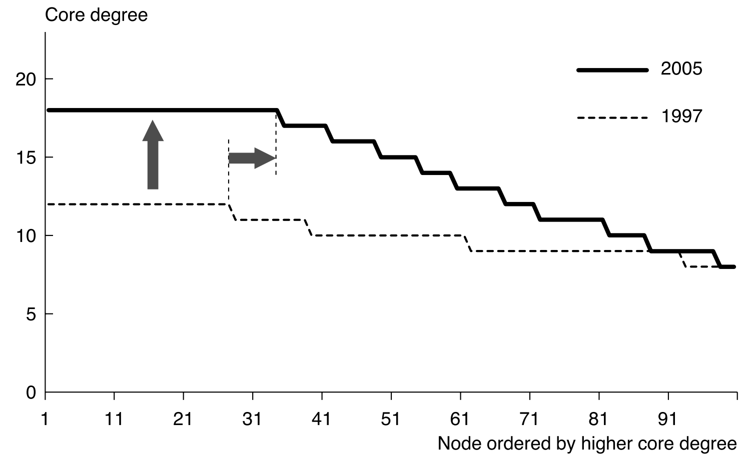

The fact that these degrees follow a power law distribution suggests that interbank transaction networks are neither complete networks, star-shaped networks (pure hub and spoke networks), nor random networks. High-degree nodes within a transaction network are the equivalent of hubs in a star network, but the other nodes are not all linked only to the hub, and there are some nodes of middling degree. Network theory developed theoretical models that involved a network creation mechanism to explain the emergence of the power law distribution of a degree widely seen in social networks. The inducement that creates links between nodes and the mechanism of network growth are particularly important for the emergence of the power law distribution. Section IV.D provides more detail regarding the inducements of link creation in the interbank transaction network.

### B. Two-Tier Structure with Core and Periphery

Figure 5 shows that even as the network becomes more decentralized, there still exist portions of the network that serve as a core. We tried to identify these financial institutions at the core of the transaction network using the statistic called core degree (Figure 10). A core is a high-density sub-network, all of whose members have at least $k$ links, and is close to a complete network, where all members are linked with each other. This $k$ is called the core degree.[19] Figure 10 shows the 34 financial institutions with the highest core degree $k$ (18) in 2005. Creating a sub-network out of these, all 34 members would have at least 18 links. The number of financial institutions increases as the core degree hurdle is lowered, but given the lack of any standard for what constitutes a core, we built our sub-network of those financial institutions with the highest core degree $k$. This core network comprises money brokers, major banks, asset management trusts, trust banks, major securities companies (both domestic and foreign), affiliated financial institutions, and some major regional banks. These subsectors were positioned

19. The core described here is defined as a $k$-core. Network theory also uses another concept of an $m$-core.

**Figure 10 Core Degree**




at the core of the interbank transaction network. The change from 1997 shown in Figure 10 makes it clear that (1) links within the core have a higher density (core degree has increased) and (2) the number of nodes in the core has increased. This implies that the network has become more decentralized in line with the growth of the core. Table 7 shows the average degree and average core degree for each subsector, calculated by the degrees of individual institutions.

We measured the clustering coefficient to observe the relationship between the nodes comprising the core portion of the network and other nodes. As noted in Section II, the clustering coefficient measures the link density of a sub-network comprising all the nodes linked to a given target node. Figure 11 plots the relationship between clustering coefficient and degree for each financial institution. Institutions located in area A of the figure have an extremely high number of links, but a low clustering coefficient, and are nearly the same financial institutions that comprise the core described above. The large number of links implies that these institutions are connected to nodes outside of the core on the network periphery, and thus function as a hub for the entire network. The clustering coefficient of these nodes shows a low average density despite belonging to the core, because the sub-network includes these peripheral nodes.

Institutions in area B, meanwhile, have a small number of direct links, but form a close-knit network with the transaction partners, which appear to transact only with a small number of select institutions. Some regional banks, foreign banks, and foreign securities companies were included here. Institutions in area C have a small number of fragmented transaction partners, and thus either have a few links to the core or form a local, small-scale network outside of the core. We revisit this below using different statistics.

The network statistics described above show us regarding the interbank transaction network in 2005 that (1) it had a two-tier structure with a core and periphery, (2) nearly

**Table 7 Changes in In-Degree, Out-Degree, and Core Degree: Average by Subsector**

| | December 2005 | | | December 1997 | | |
|---|---|---|---|---|---|---|
| | In-degree | Out-degree | Core degree | In-degree | Out-degree | Core degree |
| Major banks | 31.2 | 32.0 | 18.0 | 6.4 | 4.5 | 10.4 |
| Trust banks | 10.1 | 11.8 | 10.8 | 2.9 | 4.2 | 6.9 |
| Regional banks | 5.6 | 8.9 | 9.7 | 3.0 | 3.9 | 7.0 |
| Regional banks II | 1.5 | 3.1 | 3.5 | 2.9 | 2.9 | 5.6 |
| Credit unions | 1.1 | 1.7 | 1.9 | 1.0 | 1.0 | 1.5 |
| Securities companies | 12.0 | 6.2 | 7.5 | 5.4 | 2.3 | 3.7 |
| Foreign banks | 7.0 | 2.1 | 6.2 | 3.6 | 2.2 | 5.4 |
| Foreign securities companies | 7.3 | 2.9 | 8.2 | 2.4 | 0.9 | 2.2 |
| Foreign trust banks | 1.0 | 2.3 | 2.8 | 2.0 | 0.4 | 2.4 |
| Money brokers | 76.7 | 36.7 | 18.0 | 133.9 | 146.9 | 12.0 |
| Asset management trusts | 20.3 | 41.7 | 18.0 | – | – | – |
| Securities financial companies | 9.3 | 4.0 | 8.0 | 3.0 | 2.0 | 5.0 |
| Affiliated financial institutions | 26.8 | 56.3 | 17.5 | 5.3 | 3.5 | 7.3 |
| Public financial institutions | 9.0 | 6.6 | 8.8 | 4.5 | 3.0 | 5.0 |

Note: Subsector averages use zeros for the statistics of financial institutions without links. Core degree is calculated for an undirected network using both in-bound and out-bound links.

**Figure 11 Clustering Coefficient and Degree**

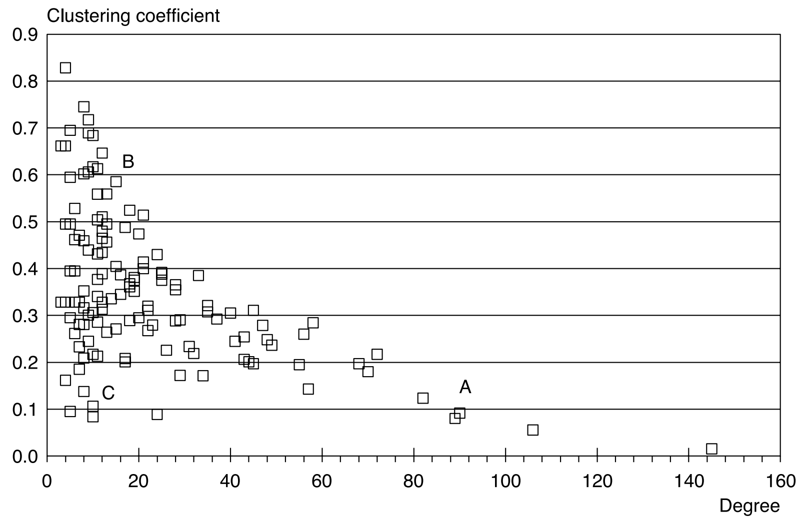
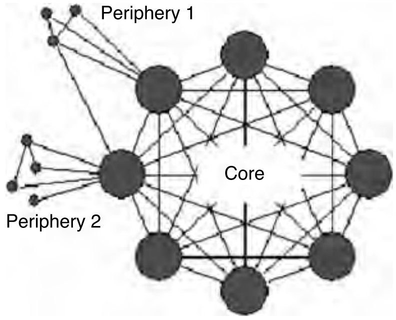


**Figure 12 Two-Tier Structure with Core and Periphery**



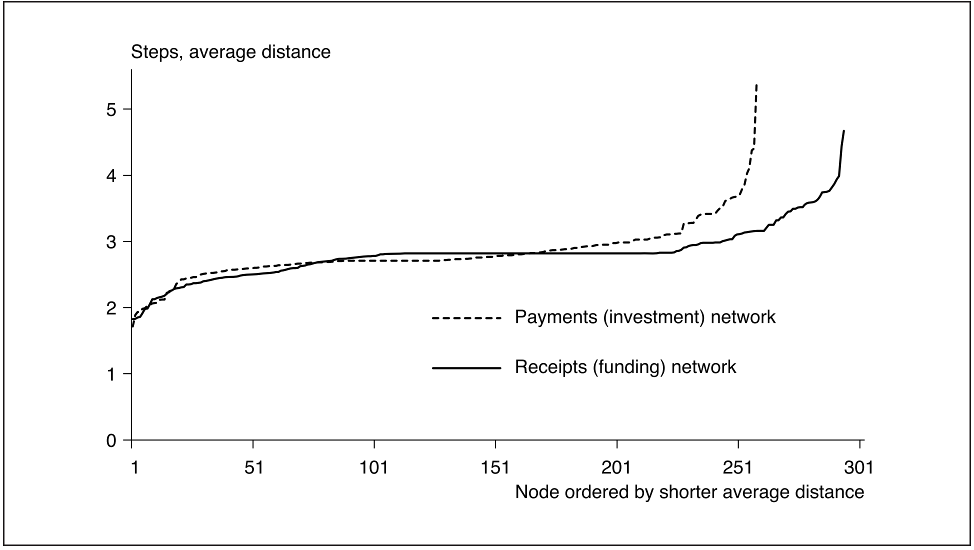

all members in its core were linked to every other member in what was close to a complete network, (3) the core served as a hub for the periphery, and (4) the periphery had clustering (there were either mutual links among a small number of peripheral members, or links to a certain node of the core. Figure 12 diagrams this concept, which we think can represent one of properties of the actual network in the bottom panel of Figure 5.

**C. Small-World Network**

The structural changes that have occurred in the interbank transaction network are critical from the systemic risk perspective. The mechanism by which liquidity shocks caused by delayed or failed settlements at some financial institutions are propagated to the entire interbank market, or likewise absorbed in the process of propagation, depends greatly on network topology. The literature confirms that the entire payment and settlement network is connected through a very small number of steps. In this paper as well, we measure the number of steps required for a given financial institution to reach other financial institutions throughout the network and the average number of the steps, namely, average distance.

The distribution of average distance in 2005 showed that the top 200 nodes were linked to all other nodes in the network in no more than three steps, on average, an indication that the interbank transaction network represents a very small world (Figure 13). As explained in Section II, a small-world network has a small number of links relative to the number of nodes and thus sparse network density, and a tendency to cluster among nodes of similar relevancy. Despite these properties, the network's average distance is short and can reach a very wide domain in only a few steps. Recent research on social networks has shown that these interesting features can be attributed to the presence of a small number of hubs and short-cut links, and in our study this appears to be the role played by the core described above. Particularly because the core is nearly a complete network, even if two given peripheral nodes are not linked to the same hub, they can be linked via a single step within the core.

**Figure 13 Average Distance for Each Node**




The influence domain, expressed in the number of reachable nodes, is defined not only by the domain of direct links (the domain reachable in a single step), but by any number of steps. Figure 14, which shows the domain reachable in $1, 2, \ldots, N$ steps by order of largest degree in the horizontal axis, makes it clear that a substantial portion of the network is reachable in two steps. In a small-world network, it is possible for a shock originating in one portion of the system to easily spread to the entire network, and thus the financial system's small-world property suggests the potential presence of systemic risk.

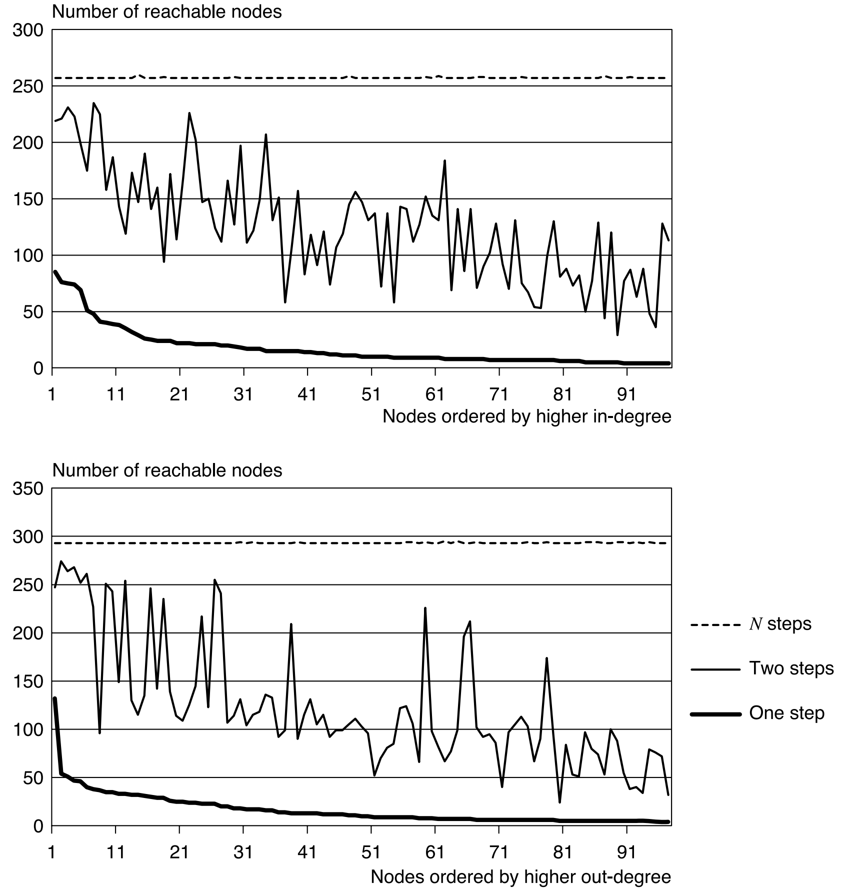
### D. The Periphery's Links to the Core

The network structure we have seen so far reflects what drives individual financial institutions to select their transaction counterparties. Although it is self-evident that institutional factors in the settlement and interbank markets described in Section III are important determinants of the structure, there must be an economic rationale (the need for an efficient, easy-to-use market that makes it easy to initiate transactions freely, securely, and at low cost) behind the system design and the various actual constraints faced by the market participants. Given these backgrounds, the interbank markets developed and formed transaction relationships that determined the network structure.

Some studies are investigating theoretical models generating networks that can mimic the small-world and scale-free properties observed in the real world. Such models include the preferential choice model,[20] where a greater number of links makes linkage more attractive to other nodes, models in which the tendency of a node to attract links from other nodes is determined proportional to certain criteria other than

20. Links between websites over the Internet also follow a power law distribution. The idea is that once a website reaches a certain level of recognition, its links expand rapidly, resulting in more visitors and accelerated growth in the number of its links. It has been shown that the creation of a power law distribution can be explained by a combination of a preferential choice model and a network growth model.

**Figure 14 Domain of Each Node**



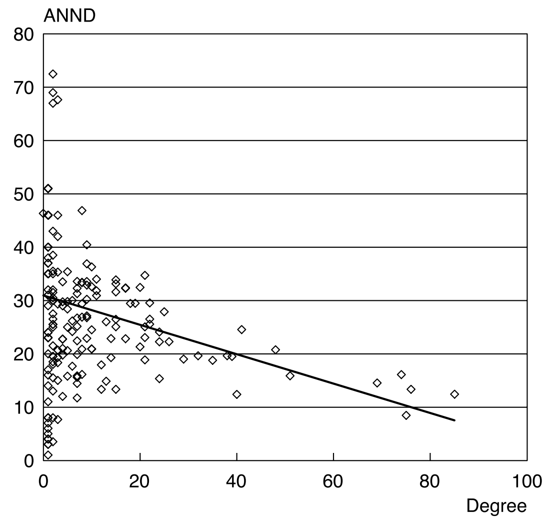

Note: The maximum domain differs between a receipt network (top panel) and a payment network (bottom panel), because some nodes only do one of either sending or receiving payments. The one-to-two-link domain also differs in a bidirectional network.

the existing number of links, and models in which the affinity between nodes gives a likelihood to connect each other, that is, links are more easily formed the higher or lower the similarity.

Figure 15 looks at the affinity between nodes in the transaction network. The horizontal axis shows the degree for each node, while the vertical axis shows the average nearest neighbor degree (ANND), which is the average of the degrees for all nodes directly connected to the node in question.[21] The figure confirms that the larger degree a financial institution has, the lower average of degrees its counterparties have, and vice

21. In Figure 15, the number of links on the horizontal axis is in-degree, and the average number of links for each institution on the vertical axis is the out-degree ANND. The graph has the same shape regardless of the 2 × 2 pair of in-degree and out-degree examined.

**Figure 15 Affinity: Disassortative**



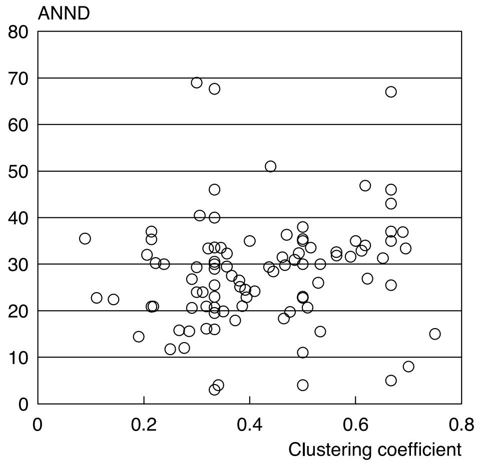

versa. It is noted that many financial institutions have a small degree and counterparties with a small average of degrees, which will be discussed below.

This would imply a tendency for institutions with a small degree to form ties with institutions with a large degree. A network relationship in which links are more likely with similar nodes is called assortative, and that where links are more likely with dissimilar nodes is called disassortative. Overall, the interbank transaction network tends to be disassortative in terms of degree. This tendency that has been confirmed by Soramäki *et al.* (2006) for the Fedwire settlement network in the United States and by Iori *et al.* (2008) for Italy’s interbank transaction network.

In addition, the large number of samples in the lower left of Figure 15 also shows an affinity for linkage between low-degree institutions. This suggests that there are two types of peripheral networks, (1) those with strong linkage to the core and (2) those with relatively weak links to the core. This suggests a difference from earlier studies in the sense that the network cannot be viewed simply as disassortative. Figure 16 plots the ANND on the vertical axis (as in Figure 15) and the clustering coefficient on the horizontal axis for nodes with a degree of 20 or less, that is, peripheral nodes. The group located in the upper right is composed of nodes within those described in (1) above (with strong links to the core) that are densely clustered among peripheral nodes, while those in the upper left are composed of nodes within those described in (1) above with a strong tendency to link only with the core. The group located in the lower left equates to those nodes in (2) (with relatively weak links to the core) with few links to other peripheral nodes.[22]

22. Nodes located in the lower right quadrant have a large clustering coefficient, and we think this coefficient is larger because of the large number of nodes with a small degree and the presence of links within a small

**Figure 16 Two Peripheries**




### E. The Network and Systemic Risk

We take a qualitative look at the interbank transaction network characteristics described above from three perspectives, to see what they imply regarding the stability, and robustness to shocks, of interbank transactions.

First, we take the perspective in which interbank market participants play an important role. This can be uniquely identified based on each financial institution's transaction data. Specifically, institutions that are connected with a large number of other institutions (have a high degree) and have a large value and volume of transactions (have a high strength) are important to the interbank market not only as senders and receivers of funds, but also in terms of contagion triggered by settlement delay/failure.

Also important is their positioning within the network when taking into account the indirect impacts. If the institution is part of the network's densely linked core, it may have a large impact on other important market participants as well as on peripheral nodes linked to the core. The former suggests network interdependency in which a node's importance is determined by the importance of its counterparties, while the latter suggests that even for institutions without either a high degree or high strength, their importance as a supplier of funds increases locally if they send funds to peripheral nodes, and furthermore these nodes are not normally connected with other core members (i.e., have not established large credit lines that allow for immediate funding when necessary).

The second perspective relates to the network structure. If the core network malfunctions and its activities in money markets go down, or if there is a cascade of settlement failures within the core, the short average distance makes it possible that the

sub-network. For example, the clustering coefficient for a triangular network composed of three nodes and three links is one.

shock will immediately spread to the entire network. Shocks that arise on the periphery can reach the core through links with core members, and if the core does not absorb this shock, its spillover to the entire network may occur. Because core members are larger than institutions on the periphery, even if the core members are able to nearly absorb the shock within the core, there might be a risk that shock waves, albeit small, will head to the periphery in the process of absorption. Financial institutions on the periphery are small on average, making it conceivable that a small shock wave could have a large adverse impact on them.

A third perspective concerns the central bank's supply of liquidity when interbank money markets are under stress. The financial market turmoil triggered by the subprime crisis with collapse of the securitization markets expanded to short-term money markets in the United States and Europe, and led to a notable tightening of funding and a contraction of credit. The Fed and the European Central Bank (ECB) undertook dynamic and flexible operations while introducing new operational measures in an attempt to improve their ability to supply much liquidity and stabilize the market. A necessary condition to designing such measures is probably knowledge of the financial institutions through which liquidity provided by a central bank can be circulated more efficiently and effectively.[23]

Given the core/periphery two-tier network structure described thus far, it seems that the most efficient and effective way to ensure circulation of funds through the entire network is to focus the supply of liquidity on core members. This only holds during normal times, however, and there is a concern that when interbank money markets are under stress, and particularly when core members are under stress, the usual financial intermediation will fail to function. To cope with the stagnation of funds within the core and the inability of the core to supply funds to cover funds insufficiencies on the periphery for any reason, it may be necessary to give not only core members but also peripheral members access to the central bank's liquidity supplying facilities. In addition, even if all members of a local network clustered on the periphery are not linked to the core, as long as one member is linked to the core or can access the liquidity supplying facilities of the central bank, there is a possibility that funds can be redistributed internally among the local network. One measure implemented by the Fed in August 2007 was the Term Auction Facility, a new facility of supplying liquidity to depositary financial institutions. This can be seen as an additional way to directly supply liquidity to periphery members.[24]

We limit our discussion here to the qualitative characteristics that can be inferred from the network structure. Actual transaction networks, as shown graphically, are considerably more complex than the conceptual diagram in Figure 12, and a further quantitative examination would be necessary to know the accuracy of our observations

23. Of course, the actual network design must take into consideration such factors as the choice of means to supply funds, the length of the loan, collateral requirements, and central bank disclosures on liquidity supplied, all of which is information needed to make the proper choices.

24. The Fed has introduced various methods to supply liquidity to primary dealers, which are the equivalent of core members. Soramäki *et al.* (2006), which analyzed the Fedwire interbank payment network, found that 66 of the 7,000 participating financial institutions accounted for 75 percent of the value transferred, and that of those, 25 formed a densely connected core sub-network, or clique. Although the paper did not offer details, we conjecture this core sub-network included many primary dealers.

regarding the transmission of shock. Appendix 1, as a first approximation to a dynamic quantitative analysis, presents the simulation to examine how a liquidity shock is transmitted within the network, using actual data but under admittedly strong assumptions.

## V. Conclusion

The interbank market's transaction and settlement flows have changed substantially in the last decade. We extract data on interbank transaction from BOJ-NET's settlement data, and use network theory, which has increasingly been applied to the social sciences in recent years, to investigate the characteristics of the interbank market's complex fund flows as a transaction network, using a variety of network statistics. We also examine the structural changes in interbank transactions by comparing data for December 1997, which was prior to the implementation of RTGS in 2001 and implementation of the ZIRP in 1999, with data for December 2005, after RTGS was implemented and while the quantitative easing policy was in force.

We find that interbank payment flows have changed from a star-shaped network with money brokers mediating at the hub to a decentralized network with numerous other channels. Whereas in 1997 the linkages were concentrated on money brokers, in 2005 there were more institutions with multiple links, and this resulted in a decentralization of the network. We also find that those institutions that originally had a small number of links saw an even further decrease in the number of their links, and that this tendency was more significant for those receiving payments.

Within the decentralized network in 2005 was a core network comprising money brokers, major banks, asset management trusts, trust banks, major securities companies, affiliated financial institutions, and some large regional banks; this core was very densely linked and nearly a complete network. These core members served as a hub for financial institutions on the network's periphery, making it possible for nearly the entire network to be connected with an average of two to three steps of links. Links from the core to the periphery are heterogeneous, and there are local clusters on the periphery.

The structure of the network is a critical determinant of systemic risk. The mechanism by which liquidity shocks caused by delayed or failed settlements at some financial institutions are propagated to the entire interbank market, or likewise absorbed on the way of propagation, depends greatly on network topology. We therefore simulate a liquidity shock based on certain assumptions to quantitatively analyze the transmission of that shock, in addition to making a qualitative examination of the network structure.

Our analysis does not include looking at how financial institutions react to liquidity shocks or at how such a reaction affects the shock's propagation. To assess the interbank market's stability and robustness to shock, it would be worthwhile to examine how the network is changed by reactive behavior, and how this reduces the intermediary function of the interbank market.

This should be possible to achieve with a case study during a period of stress. For example, interbank markets in the United States and Europe have been under considerable stress since the summer of 2007, and this may suggest that the market transaction structure is shaped differently than usual. It would probably be useful to observe the process of change on a daily basis and examine, from the network perspective, whether financial institutions serving in each role, as well as the interbank market overall, became less functional. There are a variety of explanations for why financial institutions might change their behavior during this process, including for their own reasons such as the increasing difficulty for fund-raising, external reasons such as a contraction of credit to those financial institutions perceived as having an increased counterparty risk, and a greater hesitancy to supply funds within a less liquid market.

The study of such reactions and the reasons should also be useful when considering the mechanisms for recovery from a market malfunction. In particular, this is likely to provide implications for a central bank considering measures, including specific ways to supply liquidity, to deal with a liquidity crisis and restore market conditions to normal.

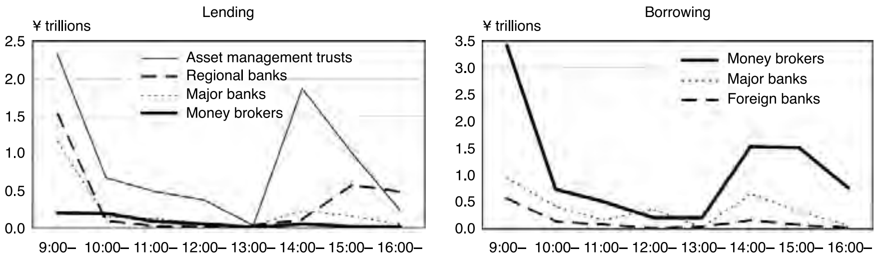
Also important is the relationship between market stability and efficiency during normal times. A market that prioritizes stability and robustness may be less efficient in financial intermediation, but it is also possible that there is not a tradeoff, but rather a complementary relationship, between the two. This paper does not look at the efficiency of financial networks, but we think that applying network analysis to an examination of them would be useful.

## APPENDIX 1: SIMULATING THE TRANSMISSION OF A LIQUIDITY SHOCK

To observe the structure of interbank transactions on average, we analyze cumulative transactions for the month. We also consider the implications that the characteristics of this structure have for systemic risk. It is very difficult to measure a network's dynamic reaction to shocks using a qualitative approach based on static structural information. In addition, as shown in Section III.D, the value and volume of transactions varies daily, as does which financial institutions lend and which borrow, and accordingly, the payment structure changes daily. How a liquidity shock, including funding shortages and settlement failure, propagates across the network when an RTGS system is in place depends strongly on information regarding settlement amount (which equates to the "thickness" of linkages) as well as on information regarding the order and timing of payments.

In this appendix, we run a simulation based on actual data as a first approximation, albeit under several strong assumptions. Although our analysis is of the transaction network, when examining a time series of funds flowing across the network from the perspective of contagion, it effectively becomes an analysis of the settlement network. Our simulation uses settlement data from the start of the transaction as well as data at the end of the transaction. A shock from a shortage of funds and settlement failure implies delays/defaults in the flow of repayments, and results in contagion effects whereby the non-arrival of expected repayments makes it necessary to suspend lending. Consequently, the timing and amount of flows at the start of the transaction are also important.

**Appendix Figure 1 Fund Lending and Borrowing by the Hour (December 2005)**




## A. Intraday Developments

Because the time of settlement is important to our simulation, we first look at the status of intraday settlements. Appendix Figure 1 shows the amount of BOJ-NET settlements every hour beginning with the 9:00 opening. In December 2005, most of the lending by the largest lender of funds, asset management trusts, occurred at around 09:00 and 14:15. We ascribe this second peak in the afternoon to these trusts lending their liquid funds on the interbank market after determining fund inflows and redemptions for that day. These funds include loans in the name of investment trusts on the secured interbank market as well as loans in the name of trust banks on the unsecured interbank market. Most lending by the major banks is on the unsecured interbank market, and nearly all of these loans are completed in the first hour (09:00 to 09:59). Lending by the regional banks peaks twice, from 09:00 to 09:59 mostly of unsecured loans, and from 15:00 to 16:59 mostly of secured loans. We think the latter funds are lent after settlements within the Data Telecommunications System of All Banks (Zengin System) are completed (settlement instructions in the Zengin System are completed by 15:30, and its final DNS timing over BOJ-NET is 16:15[25]). Reflecting this institutional design, money brokers' receipt of funds peak twice, from 09:00 to 09:59 and from 14:00 to 15:59.

The RTGS system, which settles each payment order individually, is less efficient than the DNS system, which settles orders netted out in batches. The RTGS system gives each financial institution an incentive to try to minimize its funding burden by receiving payments prior to making them. From the perspective of the counterparty receiving the payment, this delays receipt of funds and increases the uncertainty of the timing of receipts. Because the RTGS system itself has no mechanism to negate the moral hazard created by having to depend on receipts from counterparties to ensure fund payments, if a financial institution holds back payments to evade funding cost, it delays the payments from the financial institution that was expecting that payment. These payment delays are spread from institution to institution in a domino effect

25. The Zengin System, a private-sector settlement system operated by the Tokyo Bankers Association, executes inbound and outbound payments for bank transfers, wires, and other domestic small-scale payment instructions, as well as calculates the amount of transfer settlements. Through DNS with the Zengin System, all debits and credits are converted to bilateral debits/credits between the Tokyo Bankers Association and each financial institution, and the final unnetted amounts are settled using the BOJ's current account.

that develops into a system-wide gridlock.[26] When implementing RTGS in BOJ-NET, financial institutions and their association promoted settlements based on the repayment priority rule (repayments concentrated during the hour starting at 09:00) and the one-hour rule (settlement within one hour of execution), and otherwise took measures to avoid gridlock. BOJ-NET also introduced an overdraft system, through which the BOJ provides intraday loans up to the amount of collateral for use in settlements, as a way to ease intraday payment frictions.[27]

### B. Simulation Rules and Assumptions

We use data on transactions settled under these rules and practices to simulate a liquidity shock, as follows. As noted in the main text, the interbank transaction network has changed from a structure built around money brokers at the hub to a more decentralized structure, but money brokers are still the primary intermediaries in money markets. Within this context, one of the stress scenarios that we simulated is a liquidity shock in which there is an interruption of the settlement of funds sent from money brokers to foreign banks and to securities firms (domestic and foreign), which are the institutions likely to have less collateral available to use intraday overdrafts from the BOJ than are commercial banks.

We started each financial institution off with maximum liquidity, that is, the minimum required funds needed to settle all of that day's transactions without delay.[28] We also added a constraint that says financial institutions with delayed receipts cannot go elsewhere for funding in order to make a payment. Consequently, under the above liquidity shock the institution must wait until it receives a deposit from another financial institution (such as repayment associated with the maturing of a past transaction), and must temporarily suspend payments in the interim.[29]

This is not a realistic assumption, because in the real world a financial institution short of funds is likely to pursue other channels to obtain funding, while the central

26. There is a substantial body of literature on the contagion of payment delays under RTGS. McAndrews and Potter (2002) and Lacker (2004) both offer interesting research on payment delays in New York following the 9/11 terrorist attacks.

27. McAndrews (2006) classifies friction related to intraday liquidity transactions into three categories: search friction (from searching for a counterparty), timing friction (from protecting settlement deadlines), and incentive friction (between the incentives of each counterparty).

28. For financial institution $i$ at time $t$, with $v_{i,t}^{\text{out}}$ the amount of intended payment and $v_{i,t}^{\text{in}}$ the amount of intended receipt, we define $DL_{i,t}$, the intraday excess payment of financial institution $i$ at time $t$, as $\max\left[\sum_{s=0}^{t}(v_{i,s}^{\text{out}} - v_{i,s}^{\text{in}}), 0\right]$, $0 \leq t \leq T$ (with $T$ representing the time that the payment system closes). In this case, the upper-bound liquidity at the start of the business day for the entire payment system is maintained. In other words, if $UB = \sum_i \max_i DL_{i,t}$, every settlement will be completed according to schedule (there will be no payment delays).

29. Actually, settlements are often made in the order in which instructions are executed, which suggests that a first-in first-out (FIFO) rule is being used. Under FIFO, if there are instructions to make payments on two obligations that have not been paid because of a lack of funds—for example, a ¥1 billion transaction followed in the queue by a ¥500 million transaction—if a deposit of ¥700 million comes in from another bank, the ¥500 million transaction will not be settled until the ¥1 billion transaction is settled. For our simulation, however, we weaken that rule to a "bypass FIFO" rule, which in this case would mean that the order of execution would be ignored to allow the ¥700 million to be used for settlement of the ¥500 million transaction, even with the ¥1 billion transaction not having been settled yet. Because liquidity sinks (funds waiting on a payment), and a contagion of payment delays, are normally more likely to occur under FIFO than under bypass FIFO, there is a possibility that our results understate the payment delay contagion. The simulation in Imakubo and Soejima (2010) uses BOJ-NET settlement data under the FIFO rule.

bank is likely to supply funds so as to maintain a macro balance of funding supply-demand. Nevertheless, there is a possibility that when modeling payment behavior in response to a lack of funds and including this in the simulation, the assumptions will have a major impact on the simulation results. To first observe the transmission of a liquidity shock under the basic assumption that institutions will respond by delaying their own payments without seeking funds elsewhere, we ran the simulation under the constraints noted above.[30]

We ran our simulation on data for December 15, 2005, the last day of the reserve maintenance period and the day of the month with the largest transaction value. We used every transaction settled on BOJ-NET that day (excluding settlements of JGB transactions).

Individual transaction data comprises the sender of the transfer, the receiver of the transfer, and the time the transfer instruction was input.

**C. Simulation Results**

If settlements are done in the order that transfer instructions are input, settlement would be delayed because payments expected from money brokers were not made in this simulation. In some cases, payment delays were quickly fixed upon receipt of repayments, but in other cases they led to a cascade of delays. Appendix Figure 2 shows the status of delays. The horizontal axis shows delayed transactions in the left panel and shows transactions that never settled before closing time in the right panel, in both cases ordered by the time that transfer instructions were input. The vertical axis in the left for line charts shows the time of actual settlement after instructions were received, and also the time of settlement following the delay. The vertical axis in the right for bar chart shows the amount of transactions that were delayed.

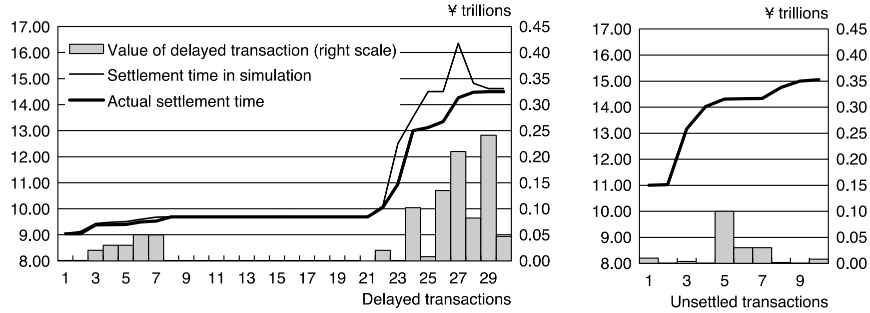
Excluding the ¥600 billion of payments from money brokers to foreign banks and both domestic and foreign securities firms, on that day there were 10,149 transactions for ¥59 trillion, of which 30 transactions (¥1 trillion) had delayed settlements and 10 transactions (¥200 billion) never settled that day. Most of the delays that occurred during the hour from 09:00 were only delayed slightly and were for very small values (transactions 1, 2, and 8–21 show as near zero in the left panel). After that, some relatively large transactions were delayed, and the time of delay was also longer.[31] The payment delays did not stay within the subsectors initially defined in the model as being directly affected by liquidity shock, but spread to financial institutions in other subsectors.

In addition, one of the delayed payments was for settlement of an outstanding negative balance on a private-sector DNS system. This suggests the risk that a liquidity

30. Simulations that assume rule-based reactions are known as behavioral simulations. There are other behavioral simulations with reactions given by either a neural network or linear judgment, as well as the variable parametric fitting approach based on a simple probability distribution of reaction deviations without regard to behavioral principles. There is a considerable body of literature that, like Imakubo and Soejima (2010), assumes rule-based reactions. Leinonen and Soramäki (1999) and Bech and Soramäki (2001) provide a summary of concepts used in settlement simulations. Our simulation here assumes a rule-based reaction whereby the financial institution does not seek funding when unable to pay, but waits until it receives funds.

31. Because it is unclear whether this characteristic is unique to the day selected for simulation or is common enough to occur on other days, we do not think any implications can be drawn from this simulation result alone.

**Appendix Figure 2 Simulated Contagion of Payment Delays**




Note: This simulation uses the BOJ-NET simulator developed by the Yajima Lab at the Tokyo Institute of Technology.

shock can affect not only transactions settled in the RTGS system but also those settled in other DNS systems.[32]

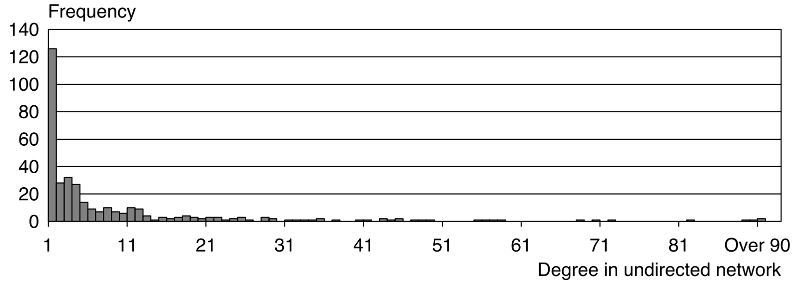
Even when financial intermediation between financial institutions breaks down, many of those institutions caught in the contagion of delays actually have the option of intraday overdrafts and supplementary loans through pooled collateral in the BOJ, and even without depending on these loans there are a variety of other market instruments that make funding available with some burden of a higher rate. This should make it possible to prevent transmission of the shock. That said, there might be a case of interest rates rising on some funding transactions, and of some delays in settlement time. Another conceivable action that could be taken ahead of time to deal with funding shortages is to hold reserves in excess of the reserve requirements.

## APPENDIX 2: POWER LAW AND SCALE-FREE DISTRIBUTIONS

Information on the degree distribution is critical to statistically understanding a network structure. If a given node has the probability $p$ of an average connectivity (total number of links $m/{}_nC_2$) with the other $n-1$ nodes, and the probabilities of linking with any other node are independent, then the probability that said node will have $x$ degree, $p(x)$ is given by the binomial distribution ${}_{n-1}C_x\, p^x (1-p)^{n-1-x}$. As the network size $n$ becomes larger, the binomial distribution can be approximated by a Poisson distribution, and thus the degree distribution of a random network (a network in which links between the $n$ nodes occur randomly at a given probability) follows a Poisson distribution. In a real network, however, the probability of a link forming between each node is neither uniform nor random, and $p(x)$ differs from a Poisson distribution.

32. Even if a DNS system is not completed by the scheduled time, private-sector settlement systems have risk management mechanisms in place that will initiate liquidity supplying measures in accordance with the situation. These measures provide a mechanism whereby a pre-selected liquidity supplying bank supplies funds to ensure settlement completed within that day.

**Appendix Figure 3 Degree Distribution for an Undirected Network (December 2005)**




Appendix Figure 3 shows the degree distribution in December 2005, where the frequency on the vertical axis divided by the total number of links $m$ corresponds to the distribution of $p(x)$. The figure shows that most of the nodes have a very small degree, the number of nodes declines rapidly as degree increases, but never becomes zero, and there are occasionally nodes with a high degree. Such a distribution can often be expressed as a power law distribution $p(x_i) \sim x_i^{-\gamma}$.

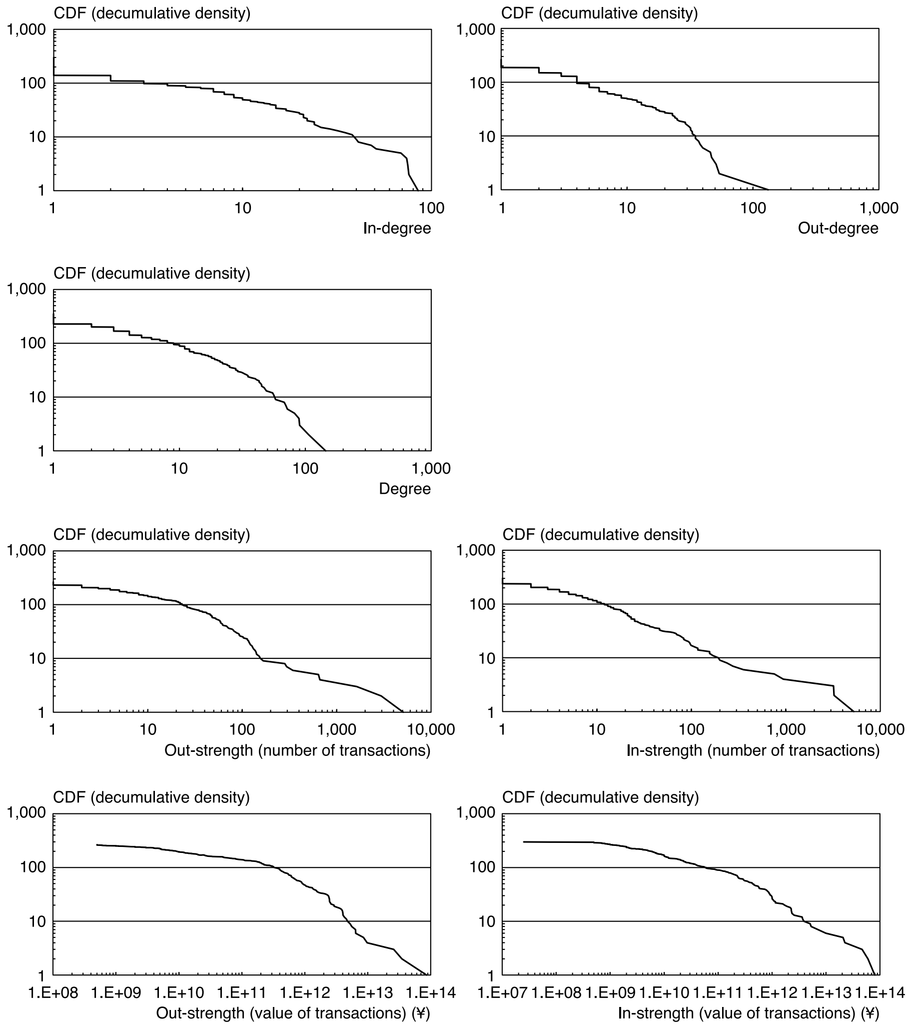
Power law distributions can be observed not only for the degree and strength of a network, but also throughout the man-made and natural world. Examples include a corporation's sales and number of employees, the population of cities and villages, the size of the glass shards from a broken window, the rate of change in asset prices, and the number of copies of a book that are sold. A power law distribution follows a distribution where the exponent remains the same even when multiplying the stochastic variable by a constant, that is, $p(bx_i) = ap(x_i)$, and thus is not dependent on the scale of the variables. This is why it is also known as a scale-free distribution. For example, company size based on amount of debt follows a power law distribution, and assuming that a large bank lends to large to mid-sized companies and a small bank lends to small to medium-sized companies, irrespective of the average difference in bank loan values, the distribution of loan amounts by company for the two banks will follow the same power law distribution.[33] This suggests that just as a large bank has customers that are large for it, a small bank has customers that, even with small absolute amounts, are large for it, and the failure of a large customer results in the same relative damage for both banks.

This lack of dependence on scale is known as self-similarity, or "fractality." A power law distribution has this fractality, and displays a characteristic that, when for example graphing the rate of change in the exchange rate or stock prices on various time scales (monthly, daily, every 10 minutes, every minute), all are so similar that it is difficult to tell which time scale the graph is based on.

33. The last graph in Box 7 of Bank of Japan (2006) shows how corporate loan balances follow a power law distribution.

A simple way to confirm a power law distribution is to confirm that a graph of the logarithmic forms of frequency (or probability found by dividing frequency by the total number of samples) and the probability variable $x$ are linear in shape. Here, we take the log of both terms in $p(x_i) = ax_i$ and get $\ln(p(x_i)) = \ln \alpha - \gamma \ln(x_i)$, where the slope $-\gamma$ is a straight line. The number of samples does not smoothly decline for every $x$, and the number of domains where there are no sample increases as $x$ gets larger. These cases are often depicted as a cumulative distribution in a log-log plot graph. Integrating the power law distribution's density function, the exponent of $-\gamma$ increases by one, and thus the power can be found using $-(\gamma - 1)$ as the slope of the cumulative distribution. Appendix Figure 4 looks at this in the context of the interbank transaction network. The payment network's in-degree cumulative distribution at the upper left shows, when excluding the top-two institutions and institutions with an in-degree of six or less, that it generally follows a power law distribution with slope $\gamma = 2.0$. In the undirected network (without regard to whether the link is for incoming funds or outgoing funds) in the second graph from the top on the left, however, the power rises from 2.0 to 3.4 passing 30 degrees. Not only here but in many other power law distributions, limitation of natural resource and other results in the sudden disappearance of nodes with a high degree. This can be expressed with a distribution wherein an $x$ larger than the cutoff level $x_{\text{cut}}$ declines exponentially: $p(x_i) \sim x_i^{-\gamma} e^{-x_i/x_{\text{cut}}}$.

**Appendix Figure 4  Power Law Distribution and Exponent: Degree and Strength**




Note: Distributions are shown for strength in number of transactions for each node and strength in value of transactions for each node, while the bottom two graphs look at the number and value of transactions for each pair of financial institutions.

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