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Network indicators for monitoring intraday liquidity in BOK-Wire+

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We describe the network properties of the Korean interbank payment system (BOK-Wire+), apply existing methodologies for identifying systemically important banks and develop a new intraday liquidity indicator that compares banks' expected resources for settling payments in the remainder of the day with their expected liquidity requirements. We use data only available to the Bank of Korea on banks' expected payments and build regression models for the remaining expected in- and outflows of liquidity. We find that the BOK-Wire+ system has more evenly distributed payment flows than interbank payment systems in other countries. We identify ten core banks and measure their network positions (SinkRank) and intraday liquidity risks. The metrics presented in this paper are especially suited for continuous oversight of intraday liquidity and systemic risks in payment systems.

1 INTRODUCTION

Interbank payment systems provide the backbone for all financial transactions. Virtually all economic activity is facilitated by transfers of claims by financial institutions.

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In turn, these claim transfers generate payments between banks whenever they are not settled across the books of a single bank. These payments are settled through interbank payment systems.

In Korea the system for settling large value interbank payments is the Bank of Korea Financial Wire Network System (BOK-Wire+). Due to the high value of the transfers settled through it by financial institutions, and its pivotal role in the functioning of the financial markets and the implementation of monetary and credit policies, its safe and efficient functioning is central for the Korean economy.

The environment related to large-value payment systems (LVPSs) has changed rapidly in recent years, and the interdependency among financial institutions has increased because of the diversification of types of transactions and the expansion of securities settlements. It is thus becoming even more important for central banks to analyze the network relationships of LVPS participants.

In addition, during the global financial crisis, financial institutions' intraday liquidity situation worsened and the authorities came to recognize that intraday liquidity management is crucial for financial stability. In this context the Basel Committee for Banking Supervision (BCBS) has published monitoring tools for intraday liquidity management (Basel Committee for Banking Supervision 2013), and the Bank of Korea (BOK) is seeking to establish a robust framework for the monitoring of financial institutions' intraday liquidity management in consideration of the network relationships of the LVPS.

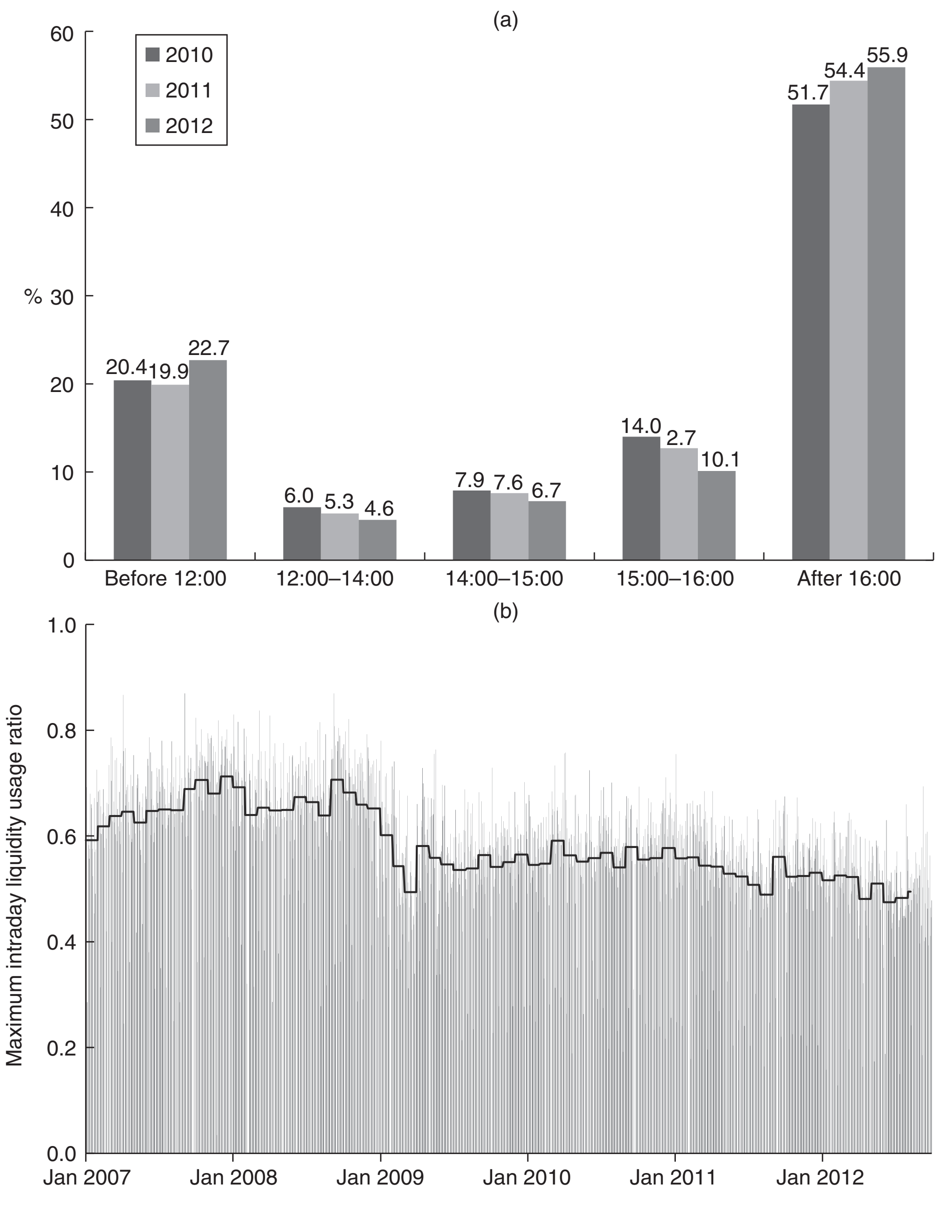
The objective of this paper is to provide a description of BOK-Wire+ with a focus on its network structure and banks' liquidity, to identify systemically important banks and to develop a set of indicators that would allow the BOK to assess the intraday liquidity and systemic risks in BOK-Wire+.

2 BOK-WIRE+ AND ITS NETWORK STRUCTURE

BOK-Wire+ is the real time interbank gross payment and settlement system owned and operated by the BOK. The main feature of this system is its use not only of the real time gross settlement (RTGS) mode of settlement but of a hybrid settlement mechanism[1] as well. BOK-Wire+ is used for the settlement of all short-term financial transactions (general funds transfers, interbank short-term lending/borrowing, third-party funds transfers), the cash legs of securities transactions, the Korean won (KRW) legs of foreign exchange settlements and the settlements for retail payment systems. BOK-Wire+ is also used for the implementation of BOK monetary policy operations and for the issuance and redemption of government and other public bonds.

[1] A hybrid settlement system combines the characteristics of an RTGS system and a netting system by adding bilateral and multilateral offsetting features to the RTGS system.

FIGURE 1 (a) Proportions of settlement through BOK-Wire+, by time of day; (b) maximum intraday liquidity usage ratio of all banks.



The proportions of the daily average values of fund transfers through BOK-Wire+ for 2010, 2011 and 2012 are given by time of day in part (a). In part (b), the gray bars show the MLUs of each day and the black line represents the average monthly MLUs.

The daily average volume and value of funds transfers through BOK-Wire+ amounted to 13 265 transactions and W226.1 trillion in 2012.[2] Looking at the daily average value of funds transfers made through BOK-Wire+ by time of day, in part (a) of Figure 1 on the preceding page, more than half of all settlements are concentrated between 16:00 and closing time (17:30).[3] Settlement concentration near the closing time is a potential risk factor in the operation of BOK-Wire+. If settlement transactions are heavily concentrated during the last hour of operation, settlement gridlock is highly likely. This could cause a failure to complete daily settlement because of the lack of time to resolve the situation, which might in turn result in systemic risk.

The maximum intraday liquidity usage ratio[4] (MLU) of all banks (from January 2, 2007 to September 28, 2012), which indicates banks' intraday liquidity usage relative to their intraday liquidity sources, was high during the global financial crisis (between September 2008 and October 2008), but returned to a lower level after the cuts of the base rate between October 2008 and February 2009. This means that banks managed their intraday liquidity more tightly in a stressed market situation. We also found that the trend of the proportion of opening balance in the banks' intraday liquidity sources (opening balances plus credit limit) was slightly downward during the crisis but its average value increased to the previous level for the base-rate-cut period. In addition, its volatility was higher during the base-rate-cut period than the crisis period resulting from high volatility of opening balances. This indicates that opening balances are more influenced by the external environment.

Recently, regulators and researchers have begun to understand and analyze payment systems through the lens of network theory. The general concept of a network is highly intuitive: a network describes a collection of nodes (eg, financial institutions) and the directed links among them. The links can denote different relationships between the nodes, depending upon the domain of analysis. In our context of a payment system, a link describes the value of payments sent by one institution to another on a given day.

The main premise of network analysis is that the structure of the links between the nodes matters for the systemic importance and liquidity risks posed by participants in the network. The riskiness of banks in the system cannot be evaluated in isolation. The analysis needs to take into account how liquidity flows in the network and how disruptions in these flows, which may not involve its direct counterparties, affect

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[2] The daily average volume and value are calculated with all transactions settled through BOK-Wire+. In contrast, transactions between the accounts of an individual institution are excluded when computing the network indicators in Table 1 on page 42.

[3] See Bank of Korea (2012) for more details.

[4] $\mathrm{MLU}_t = (\sum_i^n U_{i,t})/(\sum_i^n B_{i,t} + C_{i,t})$, where U is maximum intraday liquidity usage, B the starting balance and C the credit limit of bank i at day t.

a bank via the impact of the disruption to the counterparties of its counterparties. Earlier analyses applying network concepts to interbank payment systems include, for example, Soramäki *et al* (2007) for payment flows in the US Fedwire system and Becher *et al* (2008) for the UK interbank payment system, Pröpper *et al* (2009) for the Dutch interbank payment system, Boss *et al* (2008) for the Austrian interbank payment system and Embree and Roberts (2009) for the Canadian interbank payment system. Network metrics provide a more complete description of the payment system beyond summary measures such as number of participants and total value. They shed light on how interactions take place among the banks in the system. Two systems of equal size may differ substantially in their network structure and therefore their behavior and inherent risks. Network metrics provide the first step in describing the system from this perspective and can relate to the stability and efficiency of the system.

Table 1 on the next page shows a comparison of network metrics across selected interbank payment systems.[5] The BOK-Wire+ system has 125 participants, ie, in the same range as the Dutch TOP system. Around 18% of the possible links are used on a daily basis, a relatively large share compared with that of the TOP – probably a result of the less concentrated banking market in Korea. The Canadian large value transfer system (LVTS) is tiered, with fourteen large banks acting as correspondents to a number of smaller banks which may be interacting with either the LVTS members or other smaller banks using the LVTS members to settle large value payments. The network therefore has very high connectivity; it is almost a complete network, where all possible links are present. The connectivity in Fedwire is much lower, at 0.3%, due to the large number of possible links in a network of 5086 banks and the high concentration of payment activity among the most connected banks.

On average, participants in BOK-Wire+ transfer payments with forty-five other participants and the most connected participants receive payments from eighty-four counterparts and send payments to eighty-six. Reciprocity, ie, the share of reciprocal links, is very high. At 58% it is over three times what would be expected in an Erdős–Rényi (ER) network with the same connectivity[6] (the expected reciprocity in such a network is its connectivity, which is, in the case of BOK-Wire+, 18.1%). The high share of reciprocal links in all of the systems compared may be caused, for example, by preferential business relationships or similar business activities of linked banks (Soramäki *et al* 2007), or by the coordination of payments and liquidity (Embree and

[5] All metrics were calculated and the visualizations created with Financial Network Analytics (FNA) Lab software (www.fna.fi). The FNA commands are reproduced in Appendix C.

[6] In an ER model a network is constructed by connecting nodes randomly so that each node has an equal probability of being the source and target of a link. This model is often used as a benchmark to identify nonrandom network structures.

TABLE 1 Comparison of network properties of selected interbank payment systems (daily averages and standard deviations)

	System			
	BOK-Wire+ (Korea)	**LVTS (Canada)**	**TOP (Netherlands)**	**Fedwire (US)**
Period	Aug 2013	Apr 2004 –Dec 2008	Jun 2005 –May 2006	2005
Value	W190 tr	C$25.4 tr (pa)	€584 m	US$1.3 tr
Volume	11 672	4.4M (pa)	21 400	345 000
Number of nodes	122±5.9	14	155	5 086±123
Number of links	2871±471	N/A	1 182	76 614±6 151
Connectivity (%)	18.1±2.5	69.2±3.3	7.0	0.3±0.01
Degree (average)	45.4±6.9	N/A	9.2	15.2±0.8
Degree (maximum in)	84±8	N/A	N/A	2 097±115
Degree (maximum out)	86±10	N/A	N/A	1 922±121
Reciprocity (%)	58±6.0	89.3±2.5	63	21.5±0.03
Average path length	1.85±0.05	1.31±0.03	∼2.3	2.62±0.02
Average eccentricity	2.9±0.1	1.84±0.07	∼3.3	4.67±0.33
Average diameter	3.8±0.4	2.01±0.07	N/A	6.6±0.5
Clustering coefficient (%)	51.3±1.7	84.3±1.5	38.0	53.0±1

Not all papers report all metrics. Unavailable metrics are marked as N/A in the table. For TOP the standard deviations of the metrics are not available.
Sources: LVTS (Embree and Roberts 2009); TOP (Pröpper *et al* 2009); Fedwire (Soramäki *et al* 2007).

Roberts 2009). Like most payment networks, the BOK-Wire+ network is very dense. The average path length from one node to another is only 1.85, and even the most remote participants in the network are only a few steps from each other, resulting in an average diameter of 3.8 in the network. A disruption in a dense network cascades more quickly to all banks in the network than a disruption in a network where paths are longer.

The clustering coefficient in BOK-Wire+ is high, at 59.9%. The clustering coefficient measures the likelihood that two connections of a participant are connected as well, forming a triangle.[7] This concept originates from social network analysis, showing that two friends of any one person are often more likely to be friends as well. Extended to banking systems, we see in BOK-Wire+ and the compared systems that this type of clustering is also very common here. This could be due to the fact that most banks connect to a small set of core banks that are connected to each other, forming triangles in which two of the banks concerned are in the core and one in the periphery.[8] The expected clustering coefficient in a random ER network is its connectivity, ie, less than one-third of what we find for BOK-Wire+. High clustering creates additional interdependencies and may elevate the contagion of disruptions in the system, as these may not only cascade directly from one bank to another but also be amplified via their common neighbors.

The BOK-Wire+ network is characterized every day by a single strongly connected component allowing liquidity to flow freely in the network. This contrasts with many other economic networks (see, for example, Vitali *et al* 2011) that have bow-tie structures, where some of the nodes are in components where liquidity flows out to the strongly connected component, and certain of the participants are in components that receive liquidity from the strongly connected components.[9] Such a structure was also found for the Fedwire system, where 21% of the participants did not belong to the strongly connected component (Soramäki *et al* 2007).

Visualizing dense networks is difficult. One approach is to remove the insignificant links. Figure 2 on the next page shows the effects of this approach for a typical day (August 20, 2013) in BOK-Wire+. We start the series with the full network, and in subsequent frames keep only the largest links covering 99%, 95%, 90%, 75% and 50% of the total payment value. The full network contains many very small links that are not likely to be important for risks and liquidity flows. The smallest links, which together account for 1% of in total payment value, make up over a third of all links. The effect gets smaller as more of the small links are stripped out and the main links are revealed.

Figure 3 on page 45 displays the largest links, accounting for 75% of the payments of BOK-Wire+ and 75% of those of Fedwire in 2004. These subnetworks are formed of 70 participants and 286 undirected links in BOK-Wire+,[10] and 68 participants and 181 links in Fedwire. While the subnetworks are similarly sized in terms of their

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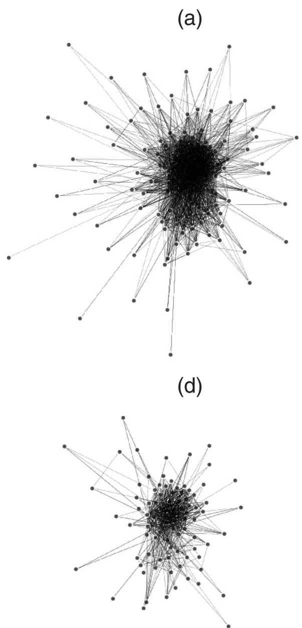
[7] Following Soramäki *et al* (2007), we calculate the clustering coefficient for each node as $C_i = m_{nn,i}/k_i(k_i - 1)$, where $m_{nn,i}$ is the number of links between neighbors of node i and k_i is the number of neighbors of node i (ie, its degree).

[8] We discuss the core–periphery structure of the network in the next section.

[9] These components are referred to (in the order of the flow) as the giant in-component (GIN), the strongly connected component (SC) and giant out-component (GOUT).

[10] For a better comparison with the Fedwire network, the Bank of Korea is excluded in this diagram and the 498 directed links are summed into 286 undirected links.

FIGURE 2 Effects on network structure of removing small value links.



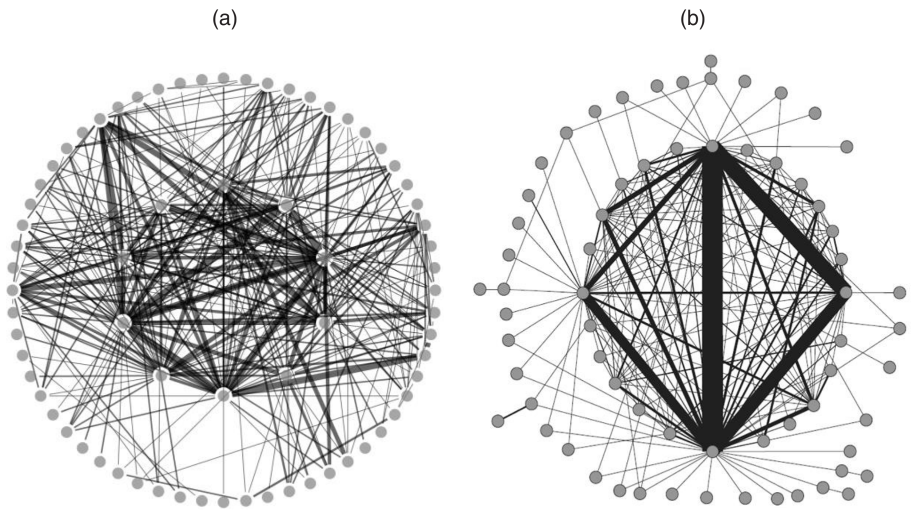
Each diagram shows the network structure containing the largest links, covering 99%, 95%, 90%, 75% and 50%, respectively, of the total payment value. (a) All links: 126 participants, 2973 links. (b) Top 99% of links: 111 participants, 1820 links. (c) Top 95% of links: 104 participants, 1247 links. (d) Top 90% of links: 89 participants, 934 links. (e) Top 75% of links: 70 banks, 498 links. (f) Top 50% of links: 33 participants, 189 links.

numbers of nodes, it can clearly be seen that there are more links and that the link values (links with higher values are shown as thicker widths of links) are more evenly distributed in BOK-Wire+ than they were in Fedwire.

3 ESTIMATING INTRADAY LIQUIDITY RISKS OF SYSTEMICALLY IMPORTANT FINANCIAL INSTITUTIONS

As may be seen from Figure 3 on the facing page, which shows the BOK-Wire+ network structure, the core of the network is composed of only a limited number of participants and they are tightly connected with each other. It is important for central banks to recognize which of the participants are systemically important, and to monitor their intraday liquidity needs properly to ensure the smooth functioning of the LVPS. In this context, we identify systemically important participants in BOK-Wire+ through core–periphery analysis (Craig and von Peter 2014) and SinkRank

FIGURE 3 Comparison of undirected links accounting for 75% of value.



The subnetworks of (a) BOK-Wire+ and (b) Fedwire (Soramäki *et al* 2007) are made up of the largest undirected links, covering 75% of the total payment value. The layout of BOK-Wire+ is based on the Bachmaier *et al* (2010) algorithm that minimizes link crossings.

(Soramäki and Cook 2013), and analyze their intraday liquidity risks using a new indicator developed herein, the Payment System Liquidity Indicator (PSLI).[11]

3.1 Core–periphery structure

Craig and von Peter (2014) introduced the concept of core–periphery, or tiered, structures for banking systems. The concept entails a small group of highly connected core participants and a larger group of less connected periphery participants. Many central banks and researchers have since applied this methodology, for example, in pursuit of identifying a set of systemically important banks. A perfect core–periphery system has the following properties

(1) The core banks are connected to each other.

(2) The periphery banks are not connected to other periphery banks.

(3) The core banks are connected to (some) periphery banks.

[11] We used settlement data of BOK-Wire+ from August 1, 2013 to August 30, 2013 for calculating the core–periphery structure and SinkRank, and from July 1, 2013 to September 30, 2013 for PSLI.

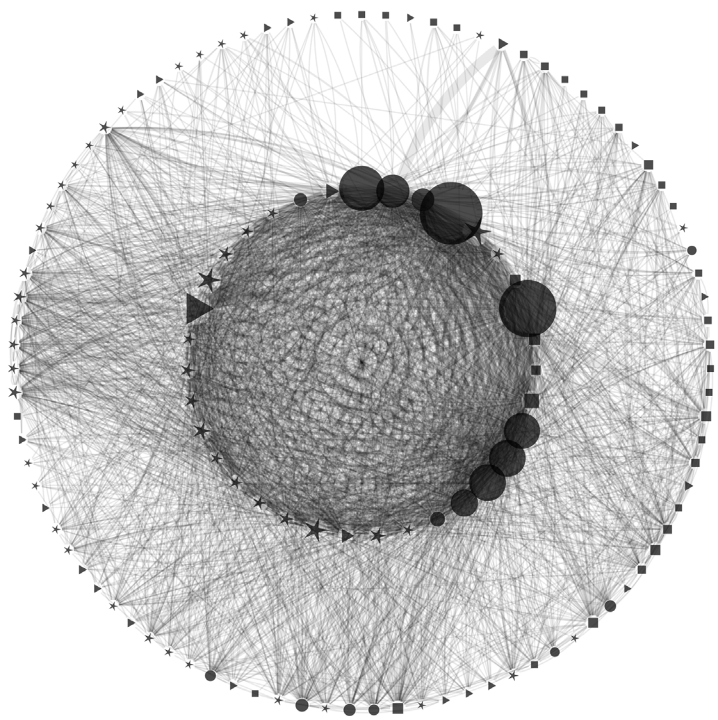
Craig and von Peter (2014) present an algorithm for approximating the core–periphery structure. The algorithm finds a classification of banks into "core" and "periphery" that minimizes the error score. For nodes classified as periphery the error is equal to the number of links that they have to other nodes classified as periphery, and for nodes classified as core the error is equal to the number of missing links to other nodes classified as core. The classification error is the sum of the nodes' errors.

Real banking systems deviate from perfect core–periphery structures, with some core banks not linked to all other core banks or some links present between periphery banks. Nevertheless, the core–periphery concept has proved useful for understanding markets and banking systems and for identifying important banks. For example, Craig and von Peter (2014) found a core–periphery structure in the German banking system, while also finding that bank-level features such as connectedness and balance-sheet size were helpful for predicting a bank's classification as core or periphery. The finding that large, well-connected banks are more likely to be in the core lends support to the core–periphery structure as a realistic model for banking systems. Craig and von Peter also found that the core–periphery classification of banks in the German system is stable over time. Fricke and Lux (2012) meanwhile reported similar findings for the (Italian) e-MID trading platform and Langfield *et al* (2013) reported a core–periphery structure in the UK interbank system.

We calculate the core–periphery structure for BOK-Wire+ and find that the model fits the data relatively well. The error rate (total number of errors divided by number of links on a given day[12]) is on average 17.1%, with a relatively small standard deviation of 1%. In comparison, the average error rate in a random ER network with the same number of nodes and links is much higher at 73%. The error rate reported by Craig and von Peter (2014) for the German banking network is in the same range, although slightly smaller at 12.2%. We can also compare the error with the network built with a Barabási–Albert model of growth and preferential attachment adapted for payment systems by Soramäki and Cook (2013). Such a scale-free network exhibits a small number of highly connected nodes that form the core, and a large number of nodes that connect to these. In a network built with this algorithm, and having roughly the same number of links, the error is smaller, at 6.2%. The Korean interbank network can be said to be close to a core–periphery structure, but not as close as a scale-free network would be.

[12] Recall that each link between periphery nodes accounts for one error, and each absence of a link between two core nodes accounts for one error. Core nodes that have no links to periphery nodes add an error for each missing outgoing or incoming link to the periphery nodes present.

FIGURE 4 Core–periphery structure of complete BOK-Wire+ network.



Nodes denote participants, and links net payment flows between participants. The sizes of the nodes are commensurate with the values of payments sent and received by the participants concerned. The nodes are shaped in accordance with the groups that the participants belong to: circle, domestic banks; square, foreign bank branches; star, financial investment companies; triangle, other.

Figure 4[13] shows the core–periphery structure of BOK-Wire+ on a representative day (August 20, 2013). Depending upon the day, we find between twenty and thirty-

[13] Financial institutions in Korea are commonly divided into six categories: banks, nonbank depository institutions, financial investment companies, insurance companies, other financial institutions and financial auxiliary institutions. Based upon the acts applicable to them, financial institutions providing similar services are grouped together. However, banks and financial investment companies perform key roles in the payment and settlement services, and there are unique differences between domestic banks and foreign bank branches regarding these services. We thus classify the participants of BOK-Wire+ into four groups in this paper: domestic banks, foreign bank branches, financial investment companies and others.

seven core banks and between eighty-five and ninety-six periphery banks.[14] The core banks are mostly domestic banks and financial investment companies. In relative terms, 59% of domestic banks are in the core. 19% of financial investment companies are in the core, 13% of others and only 6% of foreign bank branches are in the core (across the whole time period).

The structure is also found to be very stable across days, as the standard deviation of the error rate is very low. We find a total of forty-nine banks in the core on at least one day. Twenty-four of these are in the core on either all days or all but one. We find ten banks that are in the core on all of the twenty-one business days of August.

3.2 SinkRank

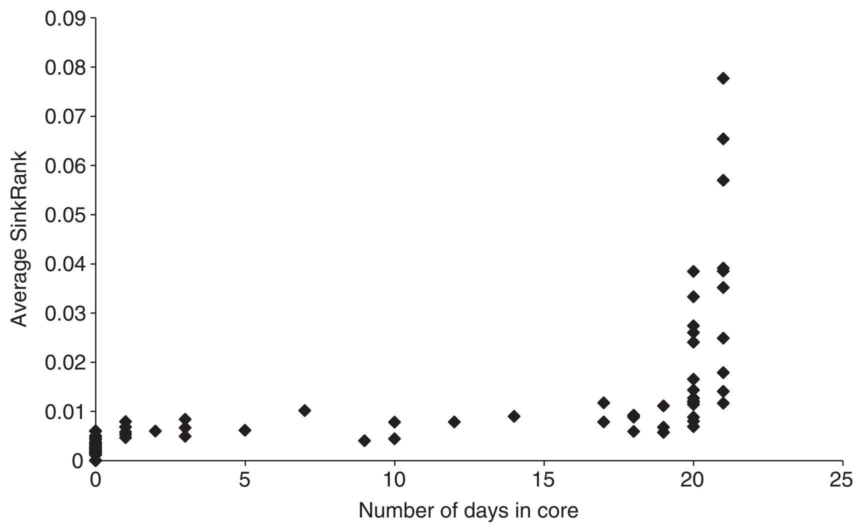
The metrics most often used for measuring the systemic importance of banks in a payment system tend to focus on local measures, such as the numbers or values of payments made or received, and ignore the system's network structure. Network-based centrality measures can give a more complete description of the importance of banks in the network. However, the existing network-based metrics have been developed with other applications in mind, and do not capture the salient features of payment systems, such as their dependence on smooth flows of liquidity reused by banks several times over the course of the settlement day to settle payments. Soramäki and Cook (2013) aim to improve this by presenting a new algorithm, SinkRank, for identifying the central nodes in payment systems.

SinkRank models the liquidity flows in the system using absorbing Markov chains in a directed and weighted network. The transition matrix for the Markov chain model is estimated on the basis of historical payment patterns. Each payment moves liquidity in the network, and the measure of interest in SinkRank is the number of random payments (along the links in accordance with their historical frequencies) that are needed to transfer a unit of liquidity anywhere in the network to the given "Sink" node. The faster liquidity moves to the sink node, the more important it is and the higher is its SinkRank.[15] The matrix algebra for calculating SinkRank is described in detail in Appendix A.

[14] The Wednesday of the second week of every month is the last day of the reserve maintenance period. Banks are often reluctant to settle transactions so as not to change their current account balances at the BOK on these days, and so the volumes and values of funds transfers through BOK-Wire+ are much smaller then than on other days. Without taking into account Wednesday, August 7, the structure is even more stable, with between thirty-three and thirty-seven core banks each day.

[15] The main difference between SinkRank and other centrality measures based on modeling random walks such as PageRank (Page *et al* 1999) is that SinkRank amends the underlying transition matrix (removing outgoing links from the sink node for which the measure is being calculated). In our model the disrupted node does not relay payments forward (as in PageRank), but rather all liquidity that reaches it stays there, as the liquidity would in an operations disruption of a bank in a payment

FIGURE 5 SinkRanks and frequency of system participants present in the core.



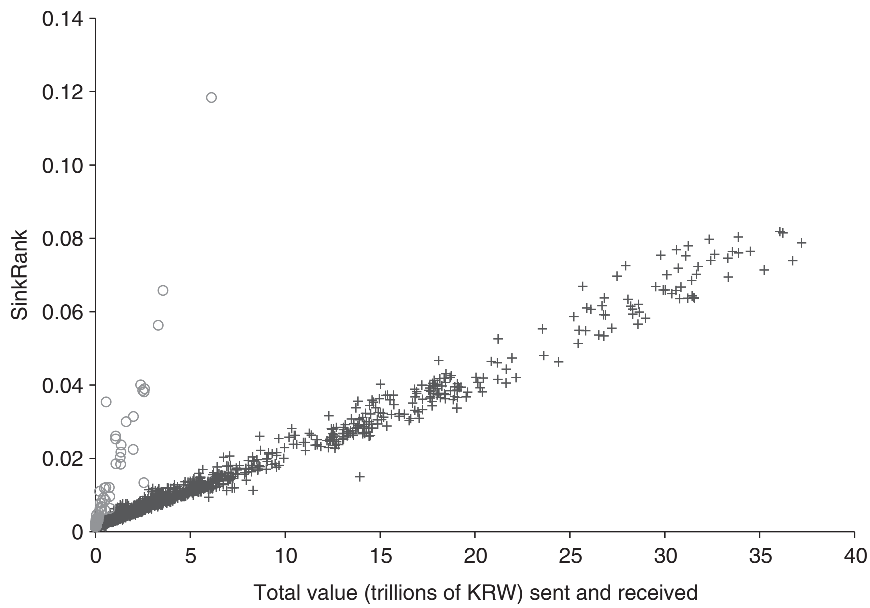
This graph shows the relationships between the daily average SinkRanks of the BOK-Wire+ participants and the numbers of days on which they are classified as core banks under the core–periphery structure.

Comparing core banks and banks with the highest SinkRanks, we first see that the five banks with the highest average SinkRanks are also in the core on all days (see Figure 5). The nineteen banks with the highest average SinkRanks are core banks on either all days or all but one day. The two measures thus point to the same conclusion.

The added benefit of SinkRank, however, is that it is on an interval scale and so can be used to identify outliers. A few banks have relatively high SinkRank scores even where they are only identified in the core on small numbers of days, and some banks that are frequently in the core have relatively low SinkRank scores. As can be seen in Figure 6 on the next page, SinkRank is positively correlated with the value of payments sent and received by a bank. We see one trajectory of SinkRank values (as gray circles) that is different from the others. In these observations, participants with relatively low payment values have high SinkRank values. These are values for a

system. SinkRank models the actual process of a payment system with an operational outage of a bank. This also allows us to identify nodes that are most affected by the disruption (ie, from which liquidity moves quickest to the sink). PageRank only gives us a measure of importance of a node, not of the vulnerability to a given disruption. The accuracy of all measures of systemic importance is hard to evaluate, as there are not enough large disruptions to statistically validate one measure against another. Therefore, a measure can mainly be validated on how well it describes the process being modeled.

FIGURE 6 SinkRanks and values of payments sent and received by system participants.



This graph shows the daily relationships between the SinkRanks of the BOK-Wire+ participants and the total values sent and received by them. Gray circles show participants with relatively low payment values that have high SinkRank values and relate to the exceptional day of Wednesday August, 7 (see footnote 14).

number of participants on the last day of the reserve maintenance period (August 7), and in fact the highest SinkRank for the whole period is observed on this date.

The SinkRank values of participants are highly skewed. Some 62% of participants have SinkRanks of less than 0.01, meaning that it takes on average 100 payments to move liquidity to the participant from a random other participant in the network. The SinkRanks of 95% of banks are below 0.04, meaning twenty-five payments on average to move liquidity to the sink from a random starting point in the network. The highest SinkRank of a participant during the month was 0.12. On this day only eight payments on average were needed to move liquidity to that participant from any other participant.

As already mentioned, the core–periphery structure and SinkRank yield almost the same conclusions on the set of systemically important participants in BOK-Wire+. SinkRank also differentiates the magnitude of systemic importance among the banks in the core. We focus our further analysis now on ten banks that were in the core on all business days of August. These were also the ten most important banks in terms of SinkRank.

3.3 Intraday liquidity risk monitoring indicator: PSLI

SinkRank measures the importance of banks' network positions. It does not evaluate whether a bank has the capacity to process payments or to withstand intraday liquidity shocks without propagating them further. To evaluate the bank's intraday liquidity needs we use a unique data set on trading data to develop a new metric called the Payment System Liquidity Indicator (PSLI), which captures both a bank's payment needs and its capacity to carry out payments.

For banks, the intraday liquidity sources consist of their reserve balances at the central bank (balance_{ijt}), their intraday credit limits at the central bank (limit_{ijt}) at time t on day j and their payments to be received from other financial institutions during the remainder of day j at time t (remaining credits, Rcredits_{ijt}). Their intraday demand for liquidity comes from payments to be made to other financial institutions during the remainder of day j at time t (remaining debits, Rdebits_{ijt}). Financial institutions manage their intraday liquidity risks by maintaining the inequality

$$\text{balance}_{ijt} + \text{limit}_{ijt} + \text{Rcredits}_{ijt} > \text{Rdebits}_{ijt}, \tag{3.1}$$

ie, a bank's intraday liquidity sources must be larger than its intraday liquidity demands. Note that a bank's balance, balance_{ijt}, can be either positive or negative up to the limit_{ijt} (which is denoted as a positive number here).

The BOK knows the reserve balances that banks hold at the BOK and the intraday credit limits that they have from the BOK on a real time basis. Often banks themselves or central banks do not know the values of all payments that banks need to make during the remainder of a day. The BOK, however, can access information on some payments related to securities settlements and foreign exchange (FX) settlements in advance, since they are reported to the BOK before the hours of operation on the settlement date by other institutions, such as the Korean Central Counterparty (CCP) and the Central Securities Depository (CSD), and by the Continuous Linked Settlement system (CLS) for FX settlement. In addition, some payments remain pending before they are settled, and must be included in the liquidity demand. In light of this information, the above inequality can be revised as follows:[16]

$$\begin{aligned}\text{balance}_{ijt} + \text{limit}_{ijt} + \text{KRcredits}_{ijt} + \widehat{\text{ERcredits}}_{ijt}& \\ > \text{pending}_{ijt} + \text{KRdebits}_{ijt} + \widehat{\text{ERdebits}}_{ijt},&\end{aligned} \tag{3.2}$$

which splits the remaining credits and debits into two components, credits and KEdebits, that are known by the BOK in advance due to the reporting by market infrastructures, and ERcredits and ERdebits, which are unknown but can be estimated on the

[16] We use the hat to denote an estimated value.

basis of historical payment patterns. In this paper we use linear regression models as described in Appendix B to estimate these values. The models take into account day of the week effects, the value already settled on the given day, effects related to reserve maintenance and to US holidays and the trade values of bonds and spot exchange, and provide accurate estimates for the values of expected credits and debits.

Finally, we use the above inequality for calculating the intraday PSLI, as bank i's ratio of projected liquidity demand to projected liquidity supply at time t on day j:

$$\mathrm{PSLI}_{ijt} = \frac{\mathrm{pending}_{ijt} + \mathrm{KRdebits}_{ijt} + \widehat{\mathrm{ERdebits}}_{ijt}}{\mathrm{balance}_{ijt} + \mathrm{limit}_{ijt} + \mathrm{KRcredits}_{ijt} + \widehat{\mathrm{ERcredits}}_{ijt}}. \tag{3.3}$$

If the PSLI of a given bank at a given time is greater than 1, the bank's expected liquidity needs are larger than its available resources and the bank is likely to experience high intraday liquidity pressure. If the value is less than 1, the bank's liquidity resources at the given time are sufficient to cover its expected intraday liquidity demand during the remainder of the day.

We can classify the core participants into three groups, depending upon their PSLIs at 09:00: participants with PSLIs of over 1, between 0.8 and 1, and below 0.8.[17] Participants with high PSLIs can be considered to have high probabilities of being subject to intraday liquidity risk and, correspondingly, those with low PSLI have low probabilities.

In addition to the absolute level of the PSLI, its volatility[18] is of interest and can represent a bank's pattern regarding intraday liquidity management, and it is likely that banks with high PSLI variability may have challenges in intraday liquidity management because it means their intraday liquidity needs change greatly from day to day. When looking at the payment and liquidity patterns of banks we in fact find that banks 58, 1, 28 and 31, whose volatilities in terms of PSLI are above average, have the least amounts of intraday liquidity sources. We can see the daily average levels and volatilities of core banks in Figure 7 on the facing page.

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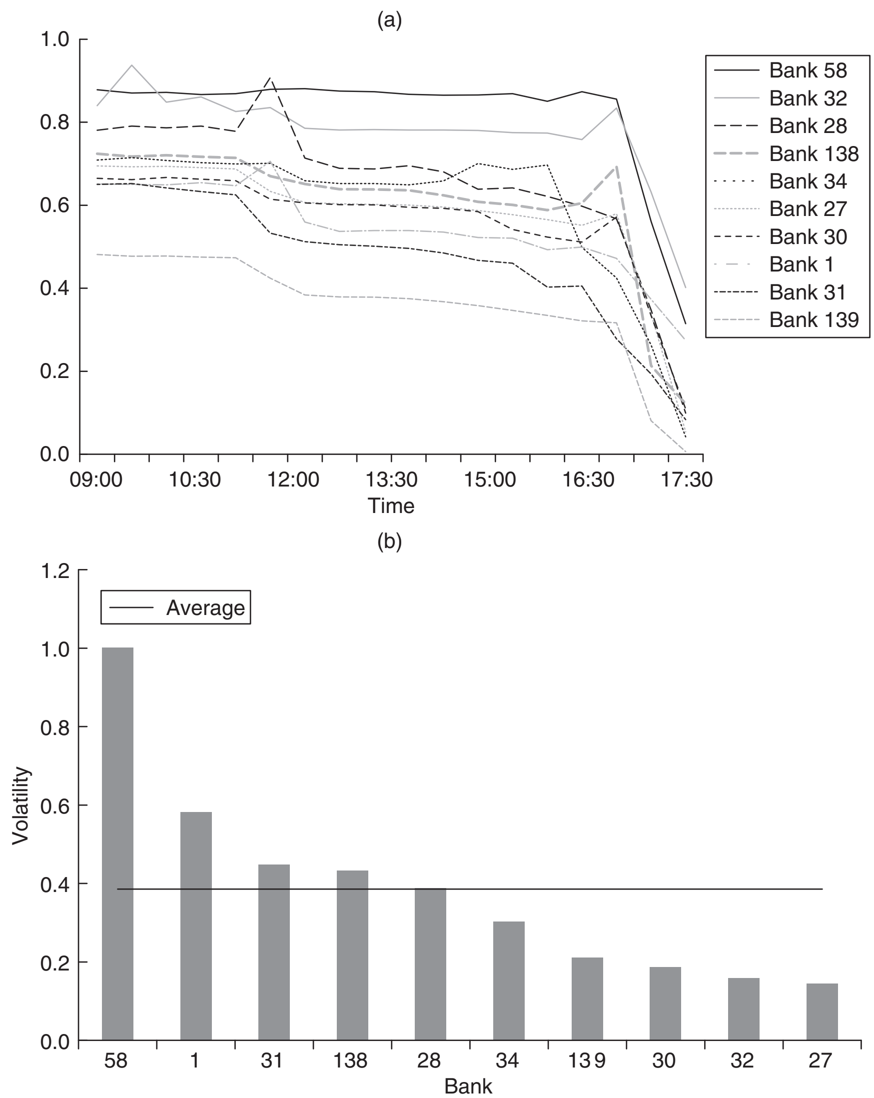
[17] We set 0.8 as a warning level for two reasons. First, a bank with a PSLI over 1 at a given time is not expected to have sufficient intraday liquidity sources to fulfill all of its expected payment obligations and we wish to capture banks that are near this threshold. Second, the estimation of PSLI contains some error, as we may be overestimating expected remaining credits or underestimating expected remaining debits. The mean absolute percentage errors of expected total credits and debits are 19.66% and 18.80%, respectively (see Appendix A) and the expected total credits and debits account for 50% of the denominator and 75% of the numerator of PSLI at 09:00. Therefore, the PSLI of a bank which does not have the capacity to process payments is highly likely to be over 0.8 even in the circumstance that overestimation of expected remaining credits and underestimation of expected remaining debits happen at the same time. We find 2016 such cases out of 11 780 observations during the third quarter of 2013.

[18] We calculate the PSLI volatility of a certain bank by summing the variance of PSLI of that bank every 30 minutes from 09:00 until 17:30.

FIGURE 7 Level and volatilities of core banks' PSLIs.



(a) The daily average levels of PSLIs of the different banks are drawn in by time of day. (b) The volatilities of their PSLIs (bars) and their averages (line).

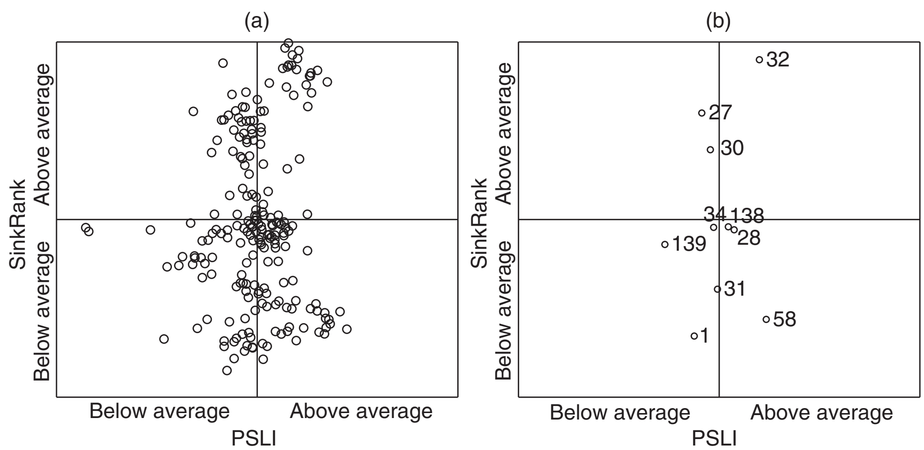
With these two dimensions, we can classify the ten core banks into six groups. This could be interpreted as indicating that the banks at the top left, bottom left and top center of Table 2 on the next page, which are in bold, are likely to have

TABLE 2 Classification of banks by level and volatility of PSLI.

	Level		
Volatility	**Above 1**	**Between 0.8 and 1**	**Below 0.8**
Above average	—	**58**	1, 28, 31, 138
Below average	—	32	27, 30, 34, 139

This table shows the classification of banks by their daily average PSLI levels at 09:00 and the volatilities of their PSLIs. The BOK needs to monitor the banks in bold more carefully.

FIGURE 8 Intraday liquidity risk (PSLI) and importance (SinkRank) of ten core banks (a) on individual days and (b) on average at 09:00.



Each dot represents a participant's PSLI at 09:00 versus its SinkRank on a certain day in part (a), and a participant's daily average PSLI at 09:00 versus its daily average SinkRank in part (b).

relatively high intraday liquidity pressures, so that the BOK needs to monitor them more carefully.

A further framework for understanding intraday liquidity risk and potential contagion is the quadrant presented in Figure 8. This plots SinkRank versus PSLI (at 09:30) and divides the plot area into four regions. In the bottom left area both the SinkRank and the PSLI are low, indicating that these banks do not have prominent network positions as regards their capacities to disrupt the system and have sufficient resources to cover their expected intraday liquidity requirements. These banks pose the smallest risk and account for 31% of the observations. On the top left (20% of total observations) we have those banks with important positions in the network but sufficient resources. On the bottom right (31% of total observations) are banks with relatively more limited resources but not important network positions. And on the top right are the banks that are most systemically important and most constrained in their resources, which would thus pose the greatest risk to the system. About 19% of the observations are present in this quadrant. In part (b) we see the average positions of individual banks in terms of their PSLIs and SinkRanks and find that only one bank is in the most risky quadrant, even though several other banks are very close to it.

4 CONCLUSION

In this paper we described the network properties of the Korean interbank payment system, and found them to be similar to those of other interbank payment systems studied. The system has more evenly distributed flows and relatively more banks that are important from a systemic perspective than the compared systems. From a total of 132 central bank account holders, we identified the core and periphery of the network and found the model presented in Craig and von Peter (2014) fits the data well. We found the core to be relatively stable over the days studied, and studied the ten banks that were in the core on each of the days in August 2013.

Next, we identified the most important banks in terms of their network positions, using the SinkRank algorithm developed in Soramäki and Cook (2013). Unsurprisingly, we found that core banks have higher SinkRank scores. Because neither the core–periphery analysis nor the SinkRank metric evaluate whether a bank has the capacity to process payments or to withstand intraday liquidity shocks without propagating them further, we then developed a new metric named the Payment System Liquidity Indicator (PSLI), which compares a bank's expected resources for settling payments in the remainder of the day with its expected liquidity requirements. We used data on banks' expected payments available only to the BOK and built regression models for the remaining expected in- and outflows of liquidity for each day. Using these, together with SinkRank (systemic importance of the bank) and PSLI (intraday liquidity risk), we were able to identify the banks that are most critical to the smooth functioning of the system.

Our work has made several contributions. First, we have suggested new metric appropriate for continuous oversight of intraday liquidity and systemic risks in payment systems. Most payment system monitoring indicators can only be calculated after the end of payment system operation on the settlement date, because actual settlement data is required to compute them. In contrast, our PSLI can be calculated on a real time basis during operating hours by using information on some payments related to securities and FX settlements which the BOK can assess in advance, and estimating the remaining credits and debits, and can thus be used for timely monitoring of the intraday liquidity risks of participants in BOK-Wire+. Second, we have studied the network structure of BOK-Wire+ and compared it with those of other LVPSs. The BOK-Wire+ network is characterized by a single strongly connected component allowing liquidity to flow freely in the network, similarly to other LVPSs, but it is different in that the link values between participants located in the core are more evenly distributed than they were in Fedwire.

This research can be extended in several ways. First, the model of liquidity flows underlying the SinkRank metric could (like the PSLI) be made time-dependent and based on regression models of expected flows in the complete system. Verification of the results is hard because actual disturbances are rare. In such cases the theoretical and statistical underpinnings have more importance. We believe that both the SinkRank and the PSLI correctly measure the systemic importance and liquidity risk by construction. However, it would be interesting to carry out counterfactual simulations where a number of different stress scenarios are simulated and the disruption measured and compared with the SinkRank and PSLI values of failing banks. Second, regression analysis could be improved by enabling the estimation of parameters of the regression model to be adjusted to reflect the stress situation. This improvement might be useful in predicting banks' intraday liquidity needs under stress, because the parameters of the regression model in this paper are estimated on the assumption of the market situation being the same as usual.

APPENDIX A. CALCULATION OF SINKRANK

We can represent the network of interest as a matrix M, where the rows and columns correspond to the nodes which, for convenience, we shall label as $1, 2 \dots, n$. The (i, j)th entry of the matrix corresponds to the link from node i to node j. If there is no link from node i to node j, that entry of the matrix is equal to 0. Otherwise, the (i, j)th entry of the matrix is equal to the weight of the link from node i to node j. We use as weight the value of payments sent by bank i to bank j on the day for which the measures are calculated. We then calculate the transition matrix of the system, P, by dividing each entry by its row sum.

To calculate the SinkRank, we number the nodes so that the absorbing node (ie, the node for which the SinkRank is calculated) comes last in the transition matrix. The transition matrix of the absorbing system is then equal to

$$P' = \begin{pmatrix} S & T \\ 0 & I \end{pmatrix},$$

where S is a square $(n-1) \times (n-1)$ matrix, 0 is a row vector (length $n-1$) of zeros and T is a column vector of length $n-1$. We then calculate the fundamental matrix $Q = (I - S)^{-1}$. The row sums of Q correspond to the expected number of steps before absorption for each possible starting value. We calculate the SinkRank of the absorbing node as the inverse of the simple average of Q's row sums, ie, $(n-1)/\sum_i \sum_j q_{ij}$. To calculate the SinkRanks for all nodes, we repeat the above process, setting each node in turn as the absorbing node.

APPENDIX B. REGRESSION ANALYSIS FOR EXPECTED DEBITS AND CREDITS

This appendix details the linear regression procedure used to calculate the expected remaining credit and debit values used in the PSLI indicator. We first computed the expected total credit (and debit) values by using regression results, and then obtained the expected remaining credit (and debit) values by using the expected total credit (and debit) values and the cumulative credit (and debit) values. These expected values were calculated at half-hour intervals for all business days in 2013 Q3.

B.1 Expected remaining credits

Step 1: calculating expected total credits using the regression model

To calculate the expected total credits to a bank, we fit a linear regression model (model 1) with the total credit as the response variable, and the bank, the day of the week and indicators for reserve maintenance days and US holidays, and the trade values of bonds and spot exchange as predictors. More specifically, we fit the following model:

$$\begin{aligned}\mathrm{Tcredit}_{ij} = \sum_{i}^{n} \beta_i^{\mathrm{credit}} + \gamma^{\mathrm{credit}} D_j + \delta^{\mathrm{credit}} R_j \\ + \zeta^{\mathrm{credit}} U_j + \eta^{\mathrm{credit}} \mathrm{bond}_{j-1} + \theta^{\mathrm{credit}} \mathrm{FX}_{j-2} + \varepsilon_{ij},\end{aligned}$$

where

- $\mathrm{Tcredit}_{ij}$ represents the total credits to bank i's settlement account on day j;
- $\beta_i^{\mathrm{credit}}$ is a constant effect for bank i;
- γ^{credit} is a vector of day of the week effects, except for Monday, and D_j a vector of day of the week indicators, except for Monday, for day j;
- R_j is an indicator of whether day j was the last day of the reserve maintenance period;
- U_j is an indicator of whether day j was a US holiday;

- bond_{j-1} is the trade value of bonds on day $j-1$;[19]
- FX_{j-2} is the trade value of spot exchange on day $j-2$;[20] and
- ε_{ij} is an error term, assumed to be normally distributed with different variance for each bank (heteroscedasticity).

We estimated the parameters of the above model by using fixed effect panel regression under heteroscedasticity with the data from ten banks (1, 27, 28, 30, 31, 32, 34, 58, 138 and 139) from July 1, 2012 to June 30, 2013. All coefficients of model 1 except for the trade values of bonds and spot exchange were statistically significant at significance levels of 5%, and the model's adjusted R-squared was equal to 0.9668. We reestimated the revised model (model 2), excluding the trade values of bonds and spot exchange, and found that all regression coefficients were statistically significant with p-values less than 0.039, and that the model's adjusted R-squared was equal to 0.9669. Please refer to Table B.1 on the facing page for the regression result.

Using the estimated parameters and information on the independent variables of the two models (the day of the week, the last day of the reserve maintenance period and US holidays, the trade value of bonds and the trade values of spot exchange for model 1; the day of the week, the last day of the reserve maintenance period and US holidays for model 2) during the third quarter of 2013, we obtained the expected total credits for the same ten banks using each model, and then computed the forecasting errors,[21] mean deviation errors[22] and mean absolute percentage errors[23] for each model to compare forecasting accuracy. The mean deviation error of model 2 was closer to zero and the mean absolute percentage error of model 2 was slightly smaller than those of model 1. However, we found that 95.1% of actual total credits were contained within a 95% confidence interval of total credit of model 1, and 94.9% of actual total credits within a 95% confidence interval of total credit of model 2. Please refer to Table B.2 on page 60 for detailed figures. Giving more weight to the result of confidence interval coverage, we concluded that predictions using the model 1 regression are better than those using model 2, and are quite reliable.

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[19] The settlement date for bonds is commonly one business day after the transaction date.
[20] The settlement date for FX (US dollar) is commonly two business day after the transaction date.
[21] Forecasting error(e_i) = actual total credit value$_i$ − estimated total credit value$_i$.
[22] Mean deviation error = mean(e_i).
[23] Mean absolute percentage error = mean$(|e_i/\text{actual total credit}_i|)$.

TABLE B.1 Results of regressions for expected total credits.

Model 1			Model 2		
	Coefficient	t		**Coefficient**	t
tue	−0.4463***	−4.71	tue	−0.4420***	−4.90
wed	−0.7733***	−7.72	wed	−0.7675***	−7.88
thu	0.4285***	4.72	thu	0.4529***	5.08
fri	−0.1974*	−2.17	fri	−0.1860*	−2.06
reserve_check	−5.0634***	−34.42	reserve_check	−5.0582***	−34.46
us_hol	−1.1194***	−6.80	us_hol	−1.1088***	−6.78
bond	−0.0014	−0.33	—	—	—
fx	−0.0145***	−1.14	—	—	—
_lreceiver_1	3.2454***	16.17	_lreceiver_1	3.0444***	29.52
_lreceiver_27	12.3990***	56.58	_lreceiver_27	12.2016***	90.57
_lreceiver_28	7.5387***	37.27	_lreceiver_28	7.3455***	69.65
_lreceiver_30	13.7615***	61.23	_lreceiver_30	13.5581***	93.65
_lreceiver_31	5.5641***	28.41	_lreceiver_31	5.3665***	57.94
_lreceiver_32	15.5196***	68.50	_lreceiver_32	15.3199***	104.16
_lreceiver_34	8.1727***	42.00	_lreceiver_34	7.9805***	88.51
_lreceiver_58	2.9636***	14.64	_lreceiver_58	2.7652***	26.27
_lreceiver_138	8.1447***	39.93	_lreceiver_138	7.9436***	72.84
_lreceiver_139	7.4039***	37.51	_lreceiver_139	7.2040***	74.81
Number of obs = 2 480			Number of obs = 2 490		
F(18,2462) = 4 018.74			F(16,2474) = 4 544.65		
Prob > F = 0.0000			Prob > F = 0.0000		
R-squared = 0.9671			R-squared = 0.9671		
Adj R-squared = 0.9668			Adj R-squared = 0.9669		

*, ** and *** represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Step 2: calculating expected remaining credits

The total credits to bank i's settlement account on day j are divided at time i into

- the cumulative credits to bank i on day j by time t and
- the remaining credit to bank i on day j from time t to the end of BOK-Wire+ operation,

as in the formula below. Using this relation with information on the cumulative credits which the BOK knows on a real time basis, and the expected total credits obtained from step 1, we calculated the expected remaining credits of the ten banks at half-hour

TABLE B.2 Comparison of measures of forecasting accuracy of regression models.

	Model 1	Model 2
Mean deviation error	–0.3822	–0.3529
Mean absolute percentage error (%)	19.66	19.41

intervals between 09:00 and 17:30 on each day of 2013 Q3:

$$\widehat{\text{ETcredit}}_{ijt} = \text{Ccredit}_{ijt} + \widehat{\text{ERcredit}}_{ijt} \Rightarrow \widehat{\text{ERcredit}}_{ijt} = \widehat{\text{ETcredit}}_{ijt} - \text{Ccredit}_{ijt}.$$

In the occasional event where the expected remaining credits were negative, we set the expected value to 0, since the credits are by definition positive. This correction creates a slight bias in the results, but in turn decreases their variance.

B.2 Expected remaining debits

Step 1: calculating expected total debits using the regression model

To calculate the expected total debits to a bank, we again fit a linear regression model (model 1) with the total debit as the response variable, and the bank, the day of the week and indicators for reserve maintenance days and US holidays, the trade value of bonds and the trade value of spot exchange as predictors. More specifically, we fit the following model:

$$\begin{aligned}\text{Tdebit}_{ij} = \sum_{i}^{n} \beta_i^{\text{debit}} + \gamma^{\text{debit}} D_j + \delta^{\text{debit}} R_j \\ + \zeta^{\text{debit}} U_j + \eta^{\text{debit}} \text{bond}_{j-1} + \theta^{\text{debit}} \text{FX}_{j-2} + \phi_{ij},\end{aligned}$$

where

- Tdebit_{ij} represents the total debits from bank i's settlement account on day j;
- β_i^{debit} is a constant effect for bank i;
- γ^{debit} is a vector of day of the week effects, except Monday, and D_j a vector of day of the week indicators, except Monday, for day j;
- R_j is an indicator of whether day j was the last day of the reserve maintenance period;
- U_j is an indicator of whether day j was a US holiday;
- Bond_{j-1} is the trade value of bonds on day $j-1$;

- FX_{j-2} is the trade value of spot exchange on day $j-2$; and
- ϕ_{ij} is an error term, assumed to be normally distributed with different variance for each bank (heteroscedasticity).

We estimated the parameters of the above model by using fixed effect panel regression under heteroscedasticity with the data from ten banks (1, 27, 28, 30, 31, 32, 34, 58, 138 and 139) from July 1, 2012 to June 30, 2013. As a result of the regression, all coefficients of model 1 except for the indicator of Friday, the trade value of bond and the trade value of spot exchange were statistically significant at significance levels of 1%, and the model's adjusted R-squared was equal to 0.9679. We again reestimated the revised model (model 2) excluding the indicator of Friday, the trade value of bonds and the trade value of spot exchange from model 1, and found that all regression coefficients were statistically significant with p-values less than 0.001, and that the model's adjusted R-squared was equal to 0.9681. Please refer to Table B.3 on the next page for the regression result.

Using the estimated parameters and information on independent variables of the two models (the day of the week, the last day of the reserve maintenance period and US holidays, the trade value of bonds and spot exchange for model 1; the day of the week, the last day of the reserve maintenance period and US holidays for model 2) during the third quarter of 2013, we obtained the expected total debits for the same ten banks using each model, and then computed the forecasting errors, mean deviation errors and mean absolute percentage errors for each model to compare forecasting accuracy. The mean deviation error of model 1 was closer to zero and the mean absolute percentage error of model 1 was smaller than those of model 2. In addition, we found that 94.1% of actual total debits were contained within a 95% confidence interval of total debits in both model 1 and model 2. Please refer to Table B.4 on the next page for detailed figures. On the basis of these results, we concluded that predictions using the model 1 regression are better than those using model 2, and are quite reliable.

Step 2: calculating expected remaining debits

The total debits from bank i's settlement account on day j are divided at time t into

- the cumulative debits by bank i on day j by time t and
- the remaining debits of bank i on day j from time t to the end of BOK-Wire+ operation

as in the formula below. Using this relation with information on the cumulative debits which the BOK knows on a real time basis, and the expected total debits obtained

TABLE B.3 Results of regressions for expected total debits.

Model 1			Model 2		
	Coefficient	t		**Coefficient**	t
tue	−0.2939**	−3.09	tue	−0.2692**	−3.49
wed	−0.5075***	−5.05	wed	−0.4879***	−5.67
thu	0.6049***	6.63	thu	0.6054***	7.93
fri	−0.0128	−0.14	—	—	—
reserve_check	−5.2343***	−35.43	reserve_check	−5.2310***	−35.50
us_hol	−1.0795***	−6.53	us_hol	−1.0934***	−6.82
bond	0.0037	0.87	—	—	—
fx	0.0001	0.04	—	—	—
_Ireceiver_1	3.0615***	14.87	_Ireceiver_1	3.1743***	31.34
_Ireceiver_27	12.0550***	38.07	_Ireceiver_27	12.1676***	130.47
_Ireceiver_28	6.7873***	28.69	_Ireceiver_28	6.9051***	80.15
_Ireceiver_30	13.5095***	59.61	_Ireceiver_30	13.6257***	87.87
_Ireceiver_31	2.8790***	34.04	_Ireceiver_31	2.9899***	32.92
_Ireceiver_32	19.3134***	56.84	_Ireceiver_32	19.4082***	89.10
_Ireceiver_34	8.2016***	14.30	_Ireceiver_34	8.3231***	118.77
_Ireceiver_58	2.3454***	68.63	_Ireceiver_58	2.4588***	26.63
_Ireceiver_138	7.6201***	42.56	_Ireceiver_138	7.7360***	87.08
_Ireceiver_139	6.0048***	11.62	_Ireceiver_139	6.1261***	56.87
Number of obs = 2 480			Number of obs = 2 490		
F(18,2462) = 4 159.70			F(15,2475) = 5 031.22		
Prob > F = 0.0000			Prob > F = 0.0000		
R-squared = 0.9682			R-squared = 0.9682		
Adj R-squared = 0.9679			Adj R-squared = 0.9681		

*, ** and *** represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

TABLE B.4 Comparison of measures of forecasting accuracy of regression models.

	Model 1	**Model 2**
Mean deviation errors	−0.0773	−0.0982
Mean absolute percentage error (%)	18.80	18.92

from Step 1, we calculated the expected remaining debits of the ten banks at each half-hour period between 09:00 and 17:30 on each day during 2013 Q3:

$$\widehat{\text{ETdebit}}_{ijt} = \text{Cdebit}_{ijt} + \widehat{\text{ERdebit}}_{ijt} \Rightarrow \widehat{\text{ERdebit}}_{ijt} = \widehat{\text{ETdebit}}_{ijt} - \text{Cdebit}_{ijt}.$$

Similarly to the case with the expected credits, in the occasional event where the expected remaining debits were negative, we set the expected value to 0 since the debits are by definition positive. This correction creates a slight bias in the results, but in turn decreases their variance.

APPENDIX C. FINANCIAL NETWORK ANALYTICS COMMANDS FOR NETWORK ANALYTICS, VISUALIZATION AND CALCULATION OF PSLI

```
# Create networks from payment data (in csv file payments.csv), summing up
# value and number of payments sent on each link

buildbytime -table payments.csv -time 1 -svcol sender -dvcol receiver -timecol
   time -datecol date -valuecol value -preserve false -weightoperation sum,count -
   dateformat yyyy-MM-dd -timeformat HH:mm:ss

# Exclude Bank of Korea from the analysis
dropv -v [Bank of Korea]

# Calculate size and order of the network
order
size

# Sum up number and value of payments on each network/day
sumap -scope network -p sum -savep total_value
sumap -scope network -p count -savep total_number

# Sum up value of payment sent and received by each bank/node
sumap -p sum -direction out -savep value_sent
sumap -p sum -direction in -savep value_received
sumap -p sum -direction undirected -savep value_total

# Calculate in/out degrees
degree -direction undirected -savep degree
degree -direction in -savep degree_in
degree -direction out -savep degree_out

# Identify maximum degrees for each day
maxvp -p degree
maxvp -p degree_in
maxvp -p degree_out

# Calculate connectivity
connectivity

# Calculate in/out reciprocity by each node
reciprocity -direction in -savep reciprocity-in
reciprocity -direction out -savep reciprocity-out
reciprocity -direction undirected -savep reciprocity

# Calculate average in/out reciprocity for each day/network
avgvp -p reciprocity
avgvp -p reciprocity-out
avgvp -p reciprocity-in

# Identify weakly and strongly connected components
clusterwc
clustersc
```

```
# Count number of weakly and strongly connected components on each day/network
countvp -p clustersc -e clustersc=1 -savep largest_sc
countvp -p clusterwc -e clusterwc=1 -savep largest_wc

# Calculate clustering coefficient on node and network level
clusteringv
clusteringn

# Calculate undirected/in/out average path lengths for each node and network
# averages
apl -direction undirected -savep apl
apl -direction out -savep apl_out
apl -direction in -savep apl_in
avgvp -p apl -savep apl
avgvp -p apl_out -savep apl_out
avgvp -p apl_in -savep apl_in

# Calculate undirected/in/out eccentricity and network averages
eccentricity -direction undirected -savep eccentricity
eccentricity -direction in -savep eccentricity_in
eccentricity -direction out -savep eccentricity_out
avgvp -p eccentricity
avgvp -p eccentricity_in
avgvp -p eccentricity_out

# Calculate network diameters
maxvp -p eccentricity -savep diameter
maxvp -p eccentricity_in -savep diameter_in
maxvp -p eccentricity_out -savep diameter_out

# Identify core and periphery nodes/banks and classification error. Mark nodes
# either as 'corebank' or 'peripherybank'
clustercp -saveerror true
setvp -p peripherybank -e clustercp=false -value 1
setvp -p corebank -e clustercp=true -value 1

# Count number of core and periphery banks in each network
sumvp -p corebank -savep core_banks
sumvp -p peripherybank -savep periphery_banks

# Calculate weighted sinkrank
sinkrank -ap sum

# Save all of the above results in an excel file
saveexcel -file network-stats.xls

# Create visualization for day 20 August 2013

# Drop all other networks except 20 August 2013
keepn -n 2013--08-20

# Identify threshold for link value where links larger than the value account
# for 75\% of the total value an drop all links smaller than it
cumpercentilea -p sum -percentile 0.75 -savep percent75
dropa -e sum<network.percent75

# Drop all nodes which have no links (i.e. have a degree of 0)
degree
dropv -e degree=0

# Merge reciprocal links (to make network 'undirected')
symmetrize -p sum -triangularize true
```

```
# Calculate coordinates for core--periphery network layout
cplayout

# Create visualization for the network using above coordinates
crtviz -arrow :false -awidth sum -vsize :::8 -vcolor :gray -
atransparency :::0.6

### Calculate PSLI ###

# Load deposits as a new node property
loadvp -table deposits.csv -ncol Date -vcol Participant

# Load credit limits as a new node property
loadvp -table credit_limits.csv -ncol Date -vcol Participant

# Calculate PSLI for each bank and each 5-minute interval between 8am and 22pm
psli -file payments.csv -openingtime 8:00:00 -closingtime 22:00:00 -interval 5
-overdraft Credit_Limit -fund Deposit -file PSLI
```

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