

Identification of Systemically Important Banks Using Network Theory

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Abstract

Identification of systemically important financial institutions became a major issue in the wake of the global financial crisis. Both supervision and lender of last resort activity need supporting tools to determine systemic importance of individual institutions. Several countries are using indicator-based methods in the identification of systemic importance which focuses on market shares of each bank in different fields of banking. In this paper our main objective was the extension of these methods using measures of network theory. The position of an institution in the financial network and the characteristics of its partners may enhance the possible contagious effects of its default. We constructed an index that contains this information and can be simply inserted into indicator-based methods. Using market indicators we tested our index on the Hungarian FX swap market and we found that our new index is a good tool for the identification of systemically important institutions. Our analysis also highlighted that during the most intensive period of the crisis some foreign banks' relevance increased significantly, which helped to ease the tension in the market.

JEL classification codes: G01, G15, G21

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1. Introduction

The global financial crisis highlighted that some financial institutions' were too big in size when compared to the real economy and that the issues affecting these institutions can have a fatal effect on the economy. For this reason, governments spared no effort to save these institutions. There are several global examples where governments or central banks gave guarantees, injected capital or lent funding to their most important financial institutions. They had to do it because the cost of a possible collapse seemed to outweigh the cost of bailout. The bill however, was footed by the taxpayers, which seemed to be unfair and had serious political consequences. Because of all these issues, identification of systemically important financial institutions again became a hot topic.

One of the main lessons of the crisis was that the biggest institutions have to be handled differently, even during normal times. According to the new Basel framework, systemically important institutions have to be more strictly regulated than their less important partners. Due to their central role and their interconnectedness, the failure of these institutions can send shockwaves through the financial system, which, in turn, can harm the real economy. Individual financial institutions may rationally choose outcomes to maximize their profit, but on a system-wide level these are sub-optimal because they do not take into account their possible negative effects during stress periods.

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Before the crisis, the systemic role of individual financial institutions was mainly assessed during the decision about lender-of-last-resort support. A survey about analysis techniques used in different countries found that in many cases authorities applied the same methodology in the assessment of systemic importance and decision on lender-of-last-resort activity. A wide variety of methods exist in practice, from traditional techniques (e.g. indicator-based approaches which focus on market shares) through complex quantitative models to qualitative criteria, which includes market intelligence (FSB, 2009). Indicator-based methods may include several different types of ratios (BIS, 2011). Usually, financial markets, financial infrastructure and financial intermediation are the focus of the examination, but the actual set of indicators can vary from country to country depending on the special characteristics of the investigated banking system.

Indicator-based methods mainly focus on each bank's market share in different parts of banking (from assets to liabilities, from notional values of OTC derivatives to payments cleared and settled; it may cover several fields, BIS, 2011). Our goal is to expand the traditional indicator-based method to take into account possible contagious effects through financial markets. Importance of a bank on a financial market may be different based on its role in the network of the market than based on its share in the turnover or stock.

In the literature, many different measures are used to evaluate the stability of the network or to assess the role of individual institutions. Iazetta and Manna (2009) used the so-called geodesic frequency (also known as "*betweenness*") and degree for assessing the resilience of the network. They found that the use of these measures helps in the identification of the big players in the system. Iori et al. (2008) dealt with the Italian O/N interbank market in their paper. They found that, based on degree, large banks have many small partners, which raises the risk of contagion in a network with high connectivity. Berlinger et al. (2011) also used network measures for the examination of individual institutions' systemic role.

A widely used tool for finding the systemically important banks in the literature is the core-periphery decomposition. For example, Borgatti and Everett (1999) examined this

phenomenon on a network made of citation data, and found three journals to be the members of the core. Van Lelyveld and Veld (2012) also used the core-periphery decomposition to analyze systemic stability of an interbank market. They found a strong core-periphery structure for the Dutch interbank market and showed that core banks had systemic relevance. Craig and von Peter (2010) used this core-periphery structure for the German interbank market. Their findings suggest that bank-specific features help to explain how banks position themselves in the interbank market. As tiering is not random but behavioral, there are economic reasons why the banking system organizes itself around a core of money-center banks. This finding also implies that “coreness” can be a good measure of systemic importance. There is a strong correlation between the size and position in the network, which suggests that measures on these characteristics are also good tools for the identification of systemic importance.

The crucial role of the FX swap market for the banking system became more obvious during the crisis than ever before. The FX swap market in Hungary was paralyzed for some weeks after the Lehman collapse. This in turn resulted in serious liquidity problems for some big Hungarian banks. These problems were reflected in the structure of the FX swap market. As Banai et al. (2013) have shown, the topology of the FX swap market changed significantly. Many players left the market and some others decreased their exposure significantly. Our current paper is founded on the same database as Banai et al. (2013). This unique dataset about the FX swap market was used to create and test a methodology for assessing systemic importance of individual institutions. While Banai et al. (2013) were focusing on the system as a whole; our main result is that we show how different institutions may have different reactions on a crisis. Moreover, our methodology can be used for other financial markets as well. We will start our paper with the short description of the FX swap and the market itself. It will be followed by the methodology, which contains all the measures and important network characteristics we used in our work. We will continue with a short description of the network of the FX swap market. Then we will show our main findings and our conclusion.

2. The FX Swap

An FX swap is a derivative financial market instrument with two legs. On “*the spot leg*” the counterparties exchange two types of currencies with each other and they swap them back on “*the forward leg*”. Both the “*spot*” and the “*forward*” exchange rates are determined at the beginning of the transaction. The pricing of a swap implies a swap spread, which is the difference between the yield differential of the two currencies priced in the forward premium (the difference between the forward and the spot exchange rates) and a reference yield differential. There are three interpretations of FX swaps:

- Temporary exchange of liquidity in different currencies;
- Temporary exchange of funding in different currencies;
- Lending against foreign exchange collateral.

Due to data constraints, we are only aware of a section of the Hungarian currency swap market where at least one of the counterparties is a Hungarian bank. The turnover of the forint/foreign exchange swap market was 5.6 times of the Hungarian GDP in the period analyzed - between 1 January 2005 and 10 January 2014. The Hungarian banking system’s gross HUF/FX swap exposure against foreigners was 22% of the total assets of the banking

system at the end of the period (which is nearly the 80% of loans granted to households and companies). These two figures indicate the significant role of the swap market in the Hungarian economy, behind which lies not only the broad range of applications of currency swaps but also macroeconomic factors. Before the financial crisis, the net foreign debt of Hungary, and hence foreign funding need of the banking system, increased markedly. Net foreign debt equals the sum of open long forint positions of the different sectors in the economy (Páles et al., 2010), which means that one of the sectors had to undertake this open forint position. Foreigners were unwilling to undertake the position, which is why the bulk of the position was undertaken by the domestic private sector through the balance sheet of the banking system, which opened the on-balance sheet foreign exchange position of the banks. According to edict 2000/244, the banking system is subject to capital requirement after its open foreign exchange position¹, which is why it is incentivized to close its open on-balance FX position off-balance. Banks typically close on-balance sheet open FX position by FX swaps (Páles et al., 2010). Non-residents play a significant role in the swap market, as 80% of the total turnover of the market is made up of cross-border transactions.

During the financial crisis of 2008 the swap market dried up. The liquidity of the market was 8 standard deviations below its long-term average before the crisis. Meanwhile swap spreads increased markedly. Spreads, which were around zero before the crisis, jumped to hundreds of basis points. This means that in this period one could receive forint funding (against foreign exchange collateral) through FX swap at an interest rate several percentage points below the reference money market interest rate. In order to manage the liquidity shock to the swap market, the Central Bank of Hungary (MNB) introduced new, and in-part, temporary measures. Different foreign currency liquidity providing FX swap instruments were introduced by the central bank. The central bank instruments contributed to the easing of market tensions and moderation of swap spreads (Csávás-Szabó, 2010; Fábián-Mátrai, 2012). Today there are still some euro liquidity providing tools in the toolkit of the MNB.

3. Methodology

3.1. Adjacency Matrices

Now we introduce some tools from network theory as a brief introduction. Let us consider a financial market with N banks and let B be the matrix of bilateral exposures. In other words is the amount of HUF paid on “the spot leg” of the swap to bank j from bank i (let B_{ij}). This matrix defines a directed and weighted network without loop edges². If $B_{ij} > 0$, there is a directed link from i to j and naturally the edge weight is B_{ij} . Furthermore if bank i is lending to and borrowing from j at the same time, we use the difference of the weights. Usually in network researches there is a minimal interest in the size or the direction of the transactions. This is true because the fact that there is a link between two banks provides enough information and it makes it easier to understand some network measures.

¹ If total foreign exchange position exceeds the 2% of own funds before deduction of transgressions, then capital requirement of foreign exchange risk is 8% of open foreign exchange position.

² An edge that connects a node to itself.

Let D denote the adjacency matrix of a directed and unweighted network, i.e.

$$D_{i,j} = \begin{cases} 1 & \text{if } B_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Similarly we can define the undirected adjacency matrix,

$$A_{i,j} = \begin{cases} 1 & \text{if } D_{i,j} = 1 \text{ or } D_{j,i} = 1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

And finally we also introduce the matrix of an undirected and weighted network,

$$W = B + B^T \quad (3)$$

where B^T denotes the transpose of B .

Distance and Components

The distance between two given nodes i and j is the minimum number of steps that have to be taken from i to j . This is the length of the shortest path between two nodes and it is denoted by $d(i,j)$. Naturally if the network is undirected, $d(i,j)$ equals $d(j,i)$. If the network is weighted, the distance is the sum of the weights.

For many network measures the network has to be weakly connected. This means every node can be reached from all other nodes on an undirected path. In other words the distance between two given nodes is finite. If the network is disconnected, we consider only the giant weakly connected sub-graph.

Clustering Coefficient

For a given node i the clustering coefficient is specified to be the probability of i node's two neighbors are connected to each other. In other words the average clustering coefficient shows the ratio of extant triangles to potential triangles (in this case triangle can be defined as three nodes which are connected to each other).

Degree Distribution

Another important measure of the network is the degree distribution. It shows the frequency of nodes with degree k . It is usually divided by the total number of nodes in the network, but we are only going to use the frequencies.

Small-World Networks

In a small-world network the average shortest path length between all pairs of nodes is relatively small compared to the size of the network. Moreover, small-world property usually means that the average distance is proportional to the logarithm of the number of nodes, i.e.

$$\text{Average path length} = c \log(N) \quad (4)$$

where c is a constant.

Scale-Free Networks

A network is scale-free if its degree distribution follows power law. In other words, if we denote the frequency of nodes with degree k by $p(k)$, we have

$$p(k) = ck^{-\gamma} \quad (5)$$

where c is a normalization constant and γ is a positive parameter which usually lies in the $[2,3]$ interval (Barabási and Albert, 1999).

3.2. Centrality Measures

Degree Centrality

In a directed network the in (out) degree of a given node is the number of incoming (outgoing) links. If the network is undirected, degree is defined to be the number of connections to other nodes. We use the normalized degree, which means every degree is divided by the maximal possible degree. More precisely the degree centrality of a given node i ,

$$f_i = \frac{1}{N-1} \sum_{j=1}^N A_{i,j} \quad (6)$$

We also define the normalized weighted degree as the sum of the edge weights, i.e.

$$s_i = \frac{1}{\text{Total volume}^3} \sum_{j=1}^N W_{i,j} \quad (7)$$

A financial institute with high degree is important for several reasons. First, because of the drop out of a high degree institution its counterparties may not find new partners to make new contract. Second, the partners of a high degree bank can suffer significant losses after its collapse. And third, a panic effect of high degree institution's default may be significantly higher than that of a marginal bank.

Closeness

For a given node i the closeness is defined as the reciprocal of the average of the length of the shortest paths started from i to all other nodes. More precisely if $c(i)$ denotes the closeness centrality of node i we have,

$$c_i = \frac{N-1}{\sum_j d(i,j)} \quad (8)$$

We note that in the literature sometimes closeness is defined as the reciprocal of the sum of the length of the shortest paths instead of average (von Peter, 2007), and sometimes closeness simply means the multiplicative inverse of the maximum of the shortest paths started from i (Berlinger et al., 2011).

Closeness centrality (just like betweenness) focuses on the position of a node in the network. High closeness usually means that a node has many partners, or its partners are in central position. Furthermore higher closeness implies that problems may spread faster through the network. Otherwise, if a node has lower closeness centrality, it means participants are far away from that node, so it could infect a few nodes only.

Betweenness

Betweenness can be defined as the number of shortest paths going through a node. Shortest paths started from or ended at i are ignored. If we want to compare the betweenness for different graphs with different sizes, we have to normalize with the maximum number of shortest paths going through a node.

This measure focuses on the presence or absence of intermediary role. If a node has high betweenness, it means several banks are connected with each other through this node. The betweenness centrality is commonly used to identify vulnerability.

³ In this case total volume is the sum of the weights.

Eigenvector

Eigenvector (or prestige) centrality defines the importance recursively. The main idea is if a node is connected to important nodes strongly, then this node is also important. Naturally we could use the weights to measure how strong a connection is. The importance of a given node i can be expressed as the dot product of the weights and centralities. More precisely if $e(i)$ denotes the eigenvector centrality of node i , then the following formula holds,

$$ei = \frac{1}{\lambda} \sum_j W_{ij} e_j \quad (9)$$

where λ is a normalizing constant. Moreover we get an eigenvalue problem,

$$We = \lambda e \quad (10)$$

In other words the centrality vector is the eigenvector corresponding to λ . In general, many solutions exist, but in this case every value has to be non-negative. If we choose the eigenvector corresponding to the largest eigenvalue, the centrality vector will be non-negative (see Perron-Frobenius theorem). Furthermore, we normalize a vector by dividing by its Euclidean norm.

Unlike the previous measures, eigenvector centrality takes edge weights into account, so it can provide more information.

Aggregated Centrality Index

These five centralities try to measure the different properties of the network. It would be better if we could use only one index to describe how important a node is. Therefore, for a given node i we define an index called Aggregated Centrality Index (ACI) in the following way,

$$ACI_i = \frac{\left(\frac{f_i + s_i}{2} + b_i + c_i + e_i \right)}{4} \quad (11)$$

where $b(i)$ stands for the betweenness of i .

3.3. Random Networks

Since we used random networks during our analysis, as a final point of the methodology it is important to define the main characteristics of these networks. At first we introduce the Erdős-Rényi network, the most commonly used random model. Let us consider N nodes and create links between all pairs with probability p independent from other links. We are going to use the Erdős-Rényi model to compare the clustering coefficients. If the ratio of the clustering coefficients is close to 1 we say there is no structure in the network.

For a given network G we create an Erdős-Rényi model with the same number of nodes and p is defined as

$$p = \frac{\text{average degree in } G}{\text{number of nodes} - 1} \quad (12)$$

Our database consists only of transactions reported by domestic banks, thus the probability of two foreign banks are being connected is zero. Hence, we have to use another random model. Let us denote by GDD the sub-graph of domestic banks (domestic nodes and links between domestic banks). Moreover, we create a bipartite Erdős-Rényi graph, where the two disjoint sets are the domestic and the foreign banks. This means domestic banks can be connected to foreign banks and similarly, foreign banks can be connected to domestic banks only. Naturally

we try to create domestic-foreign type links only with probability p . Finally, we define the modified Erdős-Rényi model as the union of *GDD* and the bipartite random graph.

4. Characteristics of the Network

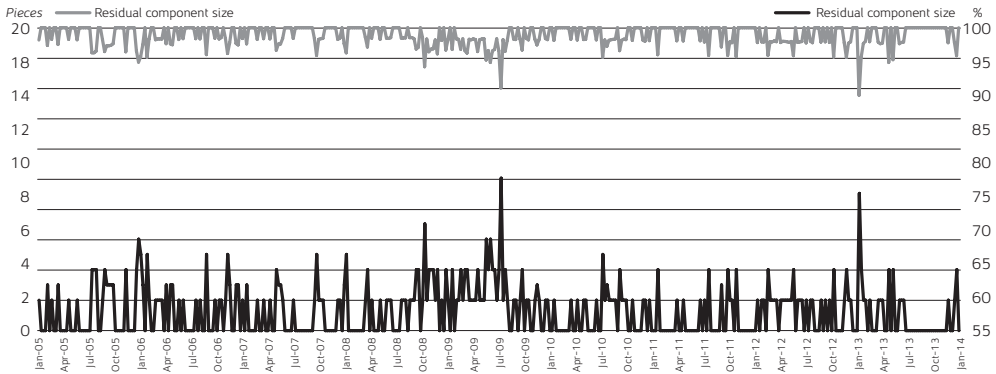
Our examination begins with a short analysis of the network itself. Since different types of networks behave differently during an idiosyncratic shock, we first have to know the characteristics of the investigated market's network. For instance Albert et al. (1999) showed that in case of a random network the effect of a random shock and a shock of central nodes are similar to each other. On the contrary, small world networks are stable for a random shock but they are sensitive to the behavior of the biggest players (Albert et al., 1999; Newman, 2003). It means that crisis of central nodes enhances and speeds up contagion (Markose et al., 2010). This example is clear evidence of the importance of network characteristics during the identification of systemically important financial institutions.

Banai et al. (2013) provided a deeper insight into the network topology of the Hungarian short term FX swap market. Although this time our dataset contains all the transactions independent from their maturity, the findings of that paper are still true. It is not surprising since about three quarters of the transactions have a maturity of one or two days. During the examination of the network, most of the conditions were the same as in Banai et al. (2013) but the dataset's time-frame is longer. Our novel dataset contains all the FX swap transactions between 1 January 2005 and 10 January 2014. Both domestic and foreign participants appear as nodes in our graphs, but we excluded the MNB. Since our objective is finding those private institutions that can threaten the sound functioning of the system, the inclusion of MNB could have distorted our results. Our focus was solely on credit institutions: for example non-financial corporations were left out. We can leave them out due to their marginal role in the market. Domestic banking groups were consolidated; therefore all the member institutions of a domestic banking group are represented by one node. However, we have not consolidated foreign groups for the following reason: consolidation was not intended since intragroup relationships may differ from one bank to another and we do not have a priori information to make this distinction. Therefore, taking these intragroup relationships into account provides us with new information. For this reason all the foreign banks have their own node in the graph. This differentiation between domestic groups and the whole group is supported by the fact that domestic central bank and supervisory authority is responsible for the domestic sub-consolidation of banks. The edges between nodes are based on transactions in the observed period and not on stocks. We aggregated transactions of every five workdays to compose the matrices of the graphs. HUF value on the spot leg was summed up between the participants: we gave a positive value for the transactions where the bank got foreign currency on the spot leg and negative value vice versa.

The first interesting characteristic of the FX swap market's network is that the graph is not connected in several cases (Figure 1). Considering graphs of one trading day, we can see many separate parts. In some cases, daily graphs contain about ten separate parts. For methodological reasons we need connected graphs. We had to find a frequency that does not hide actual market movements but one that is small enough to contain most banks and their usual relationship with each other. On a one week frequency more than 90 per cent of the nodes composed one connected graph during 434 weeks from the observed 435 weeks between 2005 and early 2014.

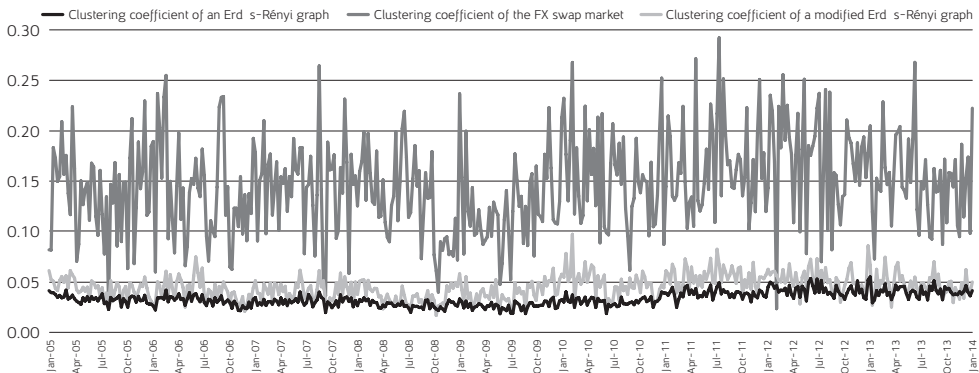
This disintegration of the network can have two possible reasons. First of all, it can be explained by the aforementioned data constraint. To the best of our knowledge foreign banks that are active on the Hungarian FX swap market also do business with each other. We only see the contracts where at least one partner is a Hungarian institution. Second, a strong relationship between the parent bank and its Hungarian subsidiary can also be the cause of disintegration of some banks. Since the main objective of the identification of systemic importance is supporting policy actions, these problems do not threaten our goal.

Figure 1: Number of Nodes out of the Biggest Weakly Connected Component (on a 1 Week Frequency)



Source: Authors' calculation

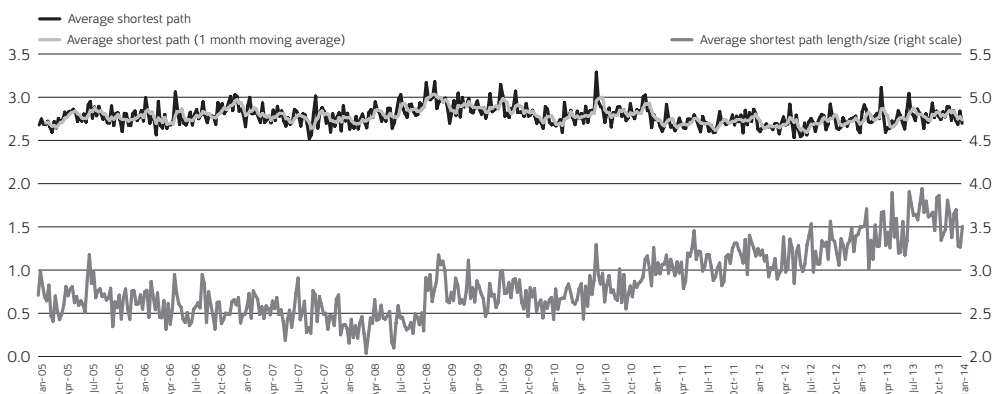
Figure 2: Clustering Coefficient of the FX Swap Market's Graph and Erdős-Rényi Random Graphs



Source: Authors' calculation

In most cases graphs of financial markets differ significantly from random graphs. We generated two random graphs to check this phenomenon. It is important because – as we mentioned before – random graphs behave differently during shocks. First, we compared our graph with an Erdős-Rényi random graph with the same average degree. Second, we also used a modified Erdős-Rényi random graph for comparison. In the latter case, we used different probabilities for edges between two domestic participants or two foreign participants, or one domestic and one foreign participant. Of course due to special characteristics of our database the probability of an edge between two foreign players was 0. Clustering coefficient of the FX swap market's network was significantly higher for every weekly graph than that of random graphs (Figure 2).

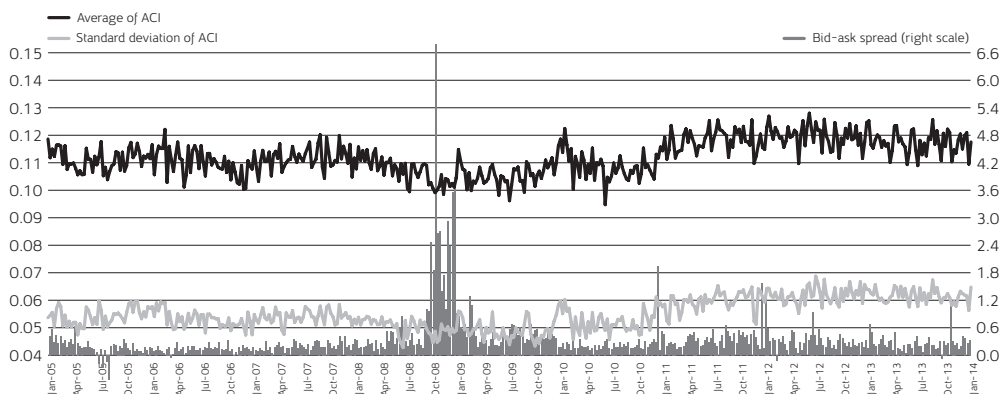
Figure 3: Dynamics of Average Shortest Path of the Network



Source: Authors' calculation

We further examined the most important characteristics of the graph and found that its degree distribution follows power law. Using k for the degrees $p(k)=61.2*k^{(-1.8)}$ power function is good approximation for the degree distribution. As a characteristic of power law distribution, few nodes have high degree and many have low degree. The few nodes with high degree connect as a center to the other nodes. The average shortest path of the network is also an important characteristic of the network. Social networks are usually characterized by relatively low average shortest path, which means that every node can be reached from every other in a relatively small number of steps. It increases the probability of contagion. When the average shortest path is small compared to the size of the network we may talk about a “small world” network (Pető-Békési, 2009; Newman, 2003). Figure 3 implies that the network of the FX swap market is a “small world” network. Average shortest path is about 3 to 4 per cent of the size of the network, which is very low. High clustering coefficient and low average shortest path together is an evidence of “small world” characteristics. According to Albert et al. (1999) and Newman (2003) this means that the stability of the network is sensitive to the behavior of the central players. For this reason central players can be considered as systemically important.

Figure 4: Statistics of ACI and Bid-Ask Spread on the Market



Source: Authors' calculation

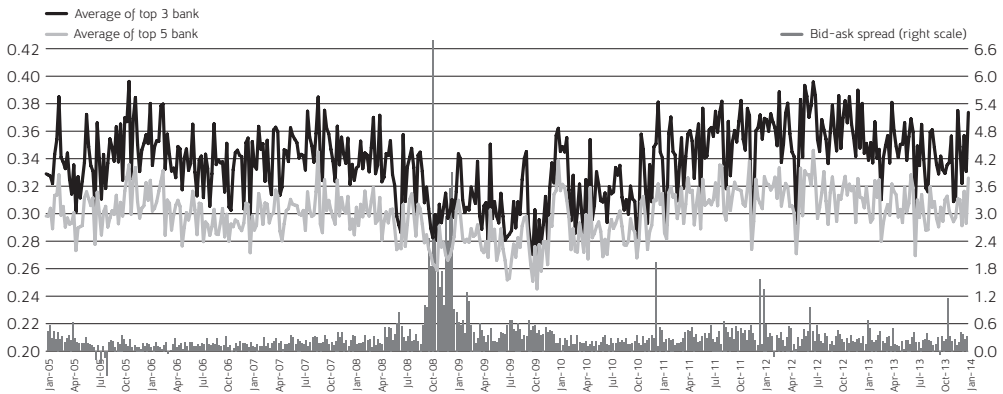
5. Results and Findings

5.1. Dynamics of ACI

Before analyzing individual banks we took a look at dynamics of ACI's basic statistics. Banai et al. (2013) found that after the collapse of the Lehman Brothers many institutions left the Hungarian FX swap market and some others decreased their activity. As a result, the network became more cliquish. Since mostly marginal institutions left the market the relevance of the average player and of central players became more crucial than before the crisis. We wanted to see whether ACI has a similar implication. It may confirm the suitability of the new index.

First of all we counted the average ACI of the banking system through the entire observation period from 2005 (Figure 4). A declining trend could be seen from late 2007 with the lowest then being after the Lehman collapse. The Lehman collapse in itself did not cause a major decline in the average ACI. From mid 2009 an increasing trend started and peaked in the first half of 2010. The most important information about the dynamics of ACI is that after the end of 2010 it started to increase. At the end of our observation period it was still on a historically high level. It coincides with the view in Banai et al. (2013), i.e. the cliquishness of the network increased. The difference between banks broadened significantly. The relevance of the big players became more crucial to the whole system.

Figure 5: ACI of Top Banks and the Bid-Ask Spread on the Market



Source: Authors' calculation

During the identification of systemically important banks, our main focus was not on the average of the banking system but on the biggest, most connected institutions. For this reason we analyzed the ACI of top institutions (Figure 5). We wanted to see whether there was any co-movement in the index and market indicators during turmoil. The idea behind this expectation was that an institution may be deemed as systemically important if its activity significantly influences the operation of the entire market. In other words, if a systemically important bank decreases its activity, significant changes have to be observed in market indicators. We illustrated this in Figure 5, the dynamics of the FX swap market's bid-ask spread and the average ACI of the top 3 and top 5 institutions with the highest value.

A negative relationship between the two time series (i.e. times when the bid-ask spread widens, the average ACI of the top banks usually decreases) implies that the reduction in the top banks' importance causes the jump in the bid-ask spread. We found this negative relationship in the data, especially with respect to the financial crisis of 2008/9. It means that a significant change in the behavior of a top institution probably has a significant effect on the entire market. We have to emphasize that this co-movement during turbulent periods characterized less the average of ACI (Figure 4). It implies that the index can make a clear distinction between institutions. All these findings confirm that ACI is a good tool for the identification of systemically important institutions.

5.2. Domestic versus Foreign Banks

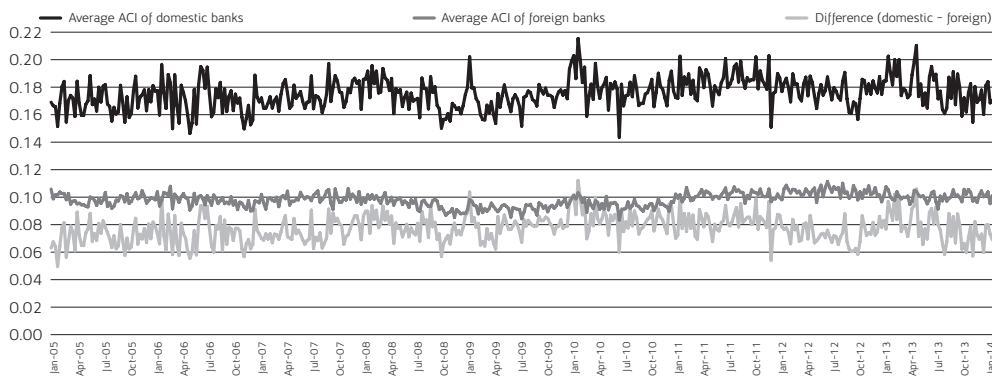
Compared to the commonly examined financial network (i.e. the network of the interbank deposit market) the FX swap market has a special characteristic. Namely, that many participants are foreign banks. As a consequence, some portions of the network are invisible to us but to the best of our knowledge in most contracts at least one participant is Hungarian. We also have to emphasize that the identification of systemically important institutions is important for policy reasons (e.g. lender of last resort activity). It implies that businesses between two foreign participants are out of our focus since Hungarian authorities have no right to take any actions to save these foreign banks. Finally, we have to add that this tool for identifying systemically important institutions can be used in other markets (e.g. interbank deposit market) where we may not be faced with this problem.

The inclusion of foreign banks made it possible to draw conclusions on the difference between foreign and domestic players considering their systemic importance. The analysis of the two groups of banks (e.g. domestic and foreign banks) is also a good check of the methodology. According to Banai et al. (2013) foreign banks are characterized by preferential trading. It means that foreign banks would rather do business with a small number of counterparties. The value of the contracts may be extremely high with the most trusted partners. This phenomenon became more obvious during the crisis. Our experience was that foreign parent banks were committed to their subsidiaries in Hungary and supported them during the most intensive period of the crisis. They ensured FX liquidity for the subsidiaries either on-balance sheet or off-balance sheet (Banai et al., 2010).

As a first step we counted the average ACI for the two groups through the whole observation period from January 2005 to January 2014 (Figure 6). The average ACI of foreign institutions was surprisingly stable during this period. It did not show strong movements even in the most intensive periods of the crisis. It may be the result of two adverse effects. On the one hand, as shown by Banai et al. (2013), many players left the market or decreased their activity at the onset of the crisis. Most of these institutions were foreign banks. *Ceteris paribus* the weaker activity of foreign banks would have resulted in a decreasing ACI. But on the other hand – as we mentioned before – some foreign parent banks supported their Hungarian subsidiaries by providing them FX liquidity. Their intensifying activity on the market enhanced their importance in the market and increased their ACI, which then offset the first effect. The dynamics of domestic banks' average ACI was significantly different. We experienced higher volatility during the crisis period. Parallel with the substantial rise of bid-ask spreads (as we have seen on Figure 4) average ACI of domestic banks decreased. It confirms the aforementioned view that this index can explain systemic importance of institutions. Finally, the difference

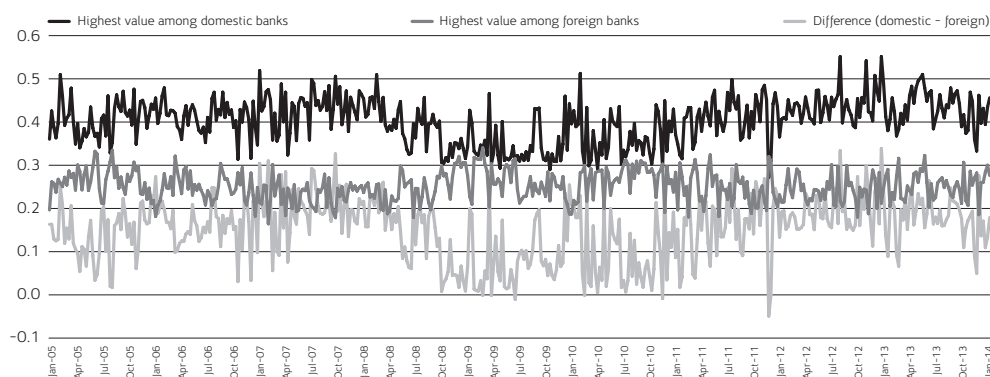
between the average ACI of the two groups is significantly positive through the whole period, i.e. domestic banks' average ACI was higher in every observed week. This is mainly due to the property of the database that there are no trades among foreign institutions.

Figure 6: Dynamics of Average ACI of Foreign and Domestic Banks



Source: Authors' calculation

Figure 7: Dynamics of Highest ACI of Foreign and Domestic Banks



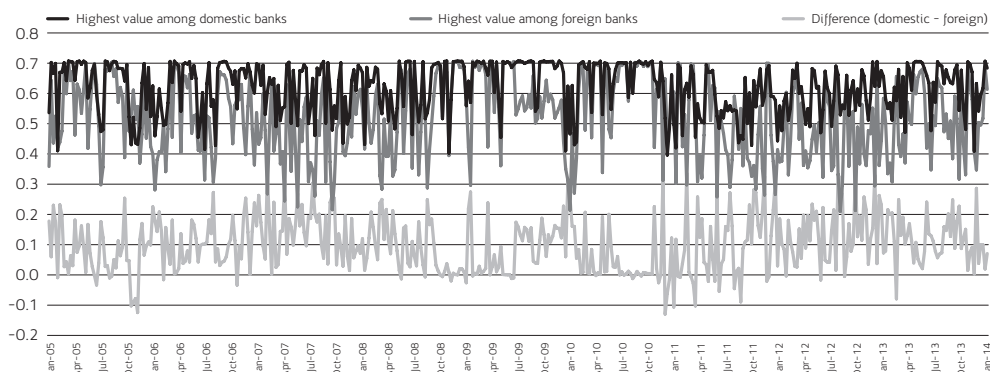
Source: Authors' calculation

Of course analysis of systemic importance has to focus on individual institutions and not on the average. We have to find those banks that have outstanding effect on the market. For this reason, during the comparison of foreign and domestic banks we checked the dynamics of the highest ACI of each group (Figure 7). The results show that the highest ACI value of foreign institutions increased during the most intensive times of the crisis. Since some foreign parent banks supported their subsidiaries, this result fits our expectations. The role of the biggest foreign players⁴ became more relevant. It supports our idea in the former paragraph. At the same time some big domestic banks seemed to cut down on their activity. We analyzed this trend in the previous chapter so in this part our focus is on the difference.

⁴ The number of these banks was very low. The 2 highest ACI increased only during that time.

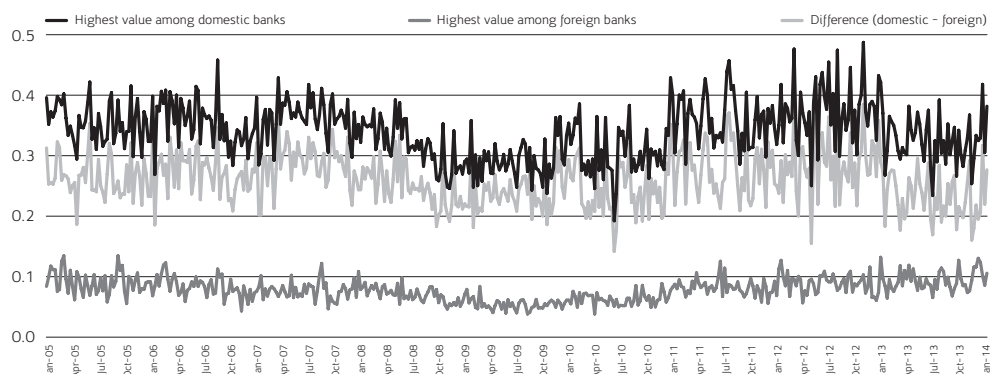
As we can see on Figure 7 before the crisis the most important domestic institution's ACI was much higher than that of the most important foreign bank. This difference evaporated several times after the Lehman collapse. In 2011, with the exit of some marginal players, the top domestic ACI increased and thus the difference between the domestic and the foreign value returned to its pre-crisis level.

Figure 8: Dynamics of Highest Eigenvector of Foreign and Domestic Banks



Source: Authors' calculation

Figure 9: Dynamics of Highest Degree among Foreign and Domestic Banks



Source: Authors' calculation

We checked the sub-indices of the highest ACIs as well - as we wanted to find those characteristics that explain the difference between the two groups. Figure 8 shows the eigenvector, figure 9 the degree, while the figures of betweenness, weighted degree and closeness are in the Appendix. Two of the sub-indices (namely eigenvector and weighted degree) contain information not just on the position of an institution but also on the size of its contracts. If we focus only on the top institutions of the two groups, we find that in most cases the domestic bank has higher relevance but from time to time this difference between the two ratios disappeared. This result implies that top foreign banks have a direct connection with central banks of the network and that the sizes of their contracts are relatively high. In the case of weighted degree, similar tendencies can be observed. The main difference is that

the index of the top foreign bank was only higher than that of the top domestic bank during the most severe period of the crisis. It supports the view of the foreign parent banks' strong commitment. Finally, closeness is also supporting this view. In some cases, closeness of top foreign bank is also very similar to that of the top Hungarian bank. It can happen when the foreign bank has a close connection with central Hungarian banks.

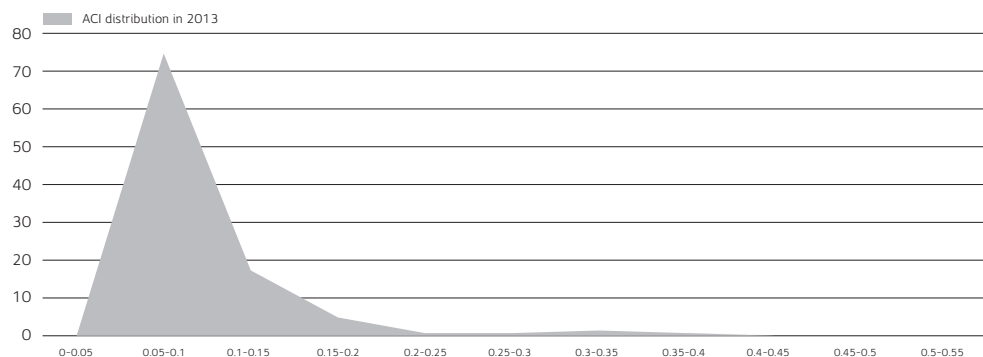
The rest of the sub-indices (namely degree, closeness and betweenness) show a different story since they are significantly higher for the top domestic banks. As we mentioned before, foreign banks pick their partners and for this reason the number of partners (i.e. degree) is limited even for the top foreign institution (data constraint also has a negative effect on foreign banks' degree, Figure 9). The difference between the two groups' highest closeness and betweenness tells us that foreign banks are not in a central position of the network. It also means that the importance of foreign institutions rather stems from the size of business with their partners and not the number of their partners.

The findings above coincide with our expectation. Like many papers have shown before (e.g. Banai et al., 2010; De Haas and Lelyveld, 2009), foreign parent banks supported their subsidiaries during the crisis. For this reason systemic importance of the top foreign institutions became more crucial for the stability of the network.

5.3. Using ACI

In the last two sub-chapters we showed that the ACI is a good tool in the identification of systemically important institutions. It was able to capture the tendencies we observed on the swap market in the last couple of years. Our main objective was finding a tool that could expand the traditional indicator-based approach in identification of systemic importance. ACI is a good measure that can be easily implemented in any framework and takes into account possible contagious effects. Indicator-based methods usually use standard scale for all indicators. The theoretical maximum of ACI is 1 and the minimum is 0. According to our experiences none of the institutions take these values. To fit the index to the standard scale of the indicators historical experiences may be used.

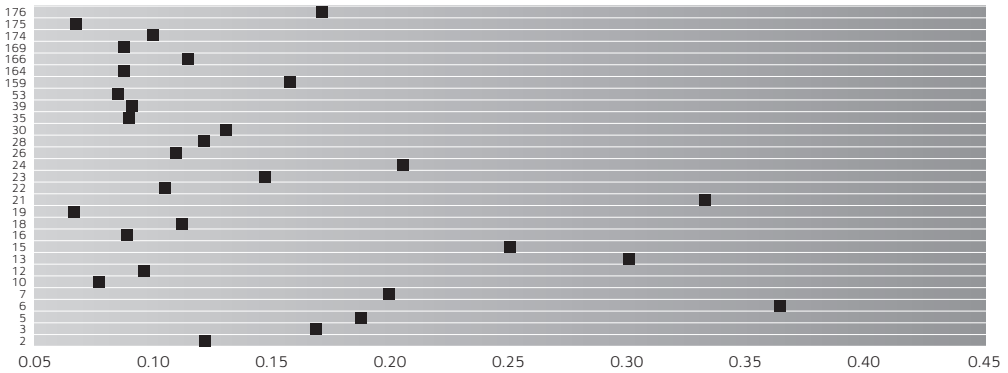
Figure 10: The Distribution of the ACI in 2013



Source: Authors' calculation

The distribution of the ACI has a significant positive skewness (Figure 10). Most of the banks in the market have low centrality indices. Banai et al. (2013) found that many of these marginal players left the market in the last couple of years and their exit did not threaten the stability of the market. These experiences also suggest that institutions with low ACI should not be considered as systemically important banks.

Figure 11: Heat Map Using ACI



Source: Authors' calculation

Note: Numbers on the vertical axis are identification numbers of banks. Most of the small institutions were left out of the table due to lack of place. They would not change the picture.

We used our dataset to show an example. As a first step we have to decide on the time frame or which periods should be used in the analysis. It can be important since - contrary to traditional indicators - network characteristics can change quickly. For this reason a very short or a very long observation period can somewhat distort. For the decision we have to examine the dynamics of network characteristics. As we have seen before, in 2013 network of the FX swap market was relatively stable, network indicators did not change considerably. For this reason we decided to use 2013 in our example. We counted the ACI for each bank on each week and as a final result every bank got the average of the weekly results. As Figure 11 shows, the index was able to make a clear ranking between banks for this time period. In addition, it was also able to make a clear distinction between some groups of banks. Most of the banks have a very low ACI and we identify a group of four banks that have outstanding value. We consider them as systemically important.⁵

⁵ We decided not to show the exact results of traditional indicator based methods, as they are confidential. However, we examined the differences of the two methods. We found that the order of the top 5 banks was the same with the two methods but significant differences were seen among the next 5 banks. This cross check confirms our method but at the same time it suggests that indicator based methods and network characteristics should be used together.

6. Conclusions

In many countries, public budgets had to bear an extreme burden to save some of their leading banks and at the same time to avoid the collapse of the banking system. For this reason systemic importance of financial institutions came into the spotlight during the crisis. As a main lesson, crisis governments, central banks and regulatory authorities learnt that these big institutions have to be more strictly monitored and regulated. These new challenges and the so-called lender-of-last-resort activity of central banks call for new tools in the identification of systemically important financial institutions.

Many countries (especially smaller countries) are using indicator-based methods in the identification of systemically important institutions. This approach uses several indicators that focus on individual institutions' market share in different fields of banking. The simplicity of this method gives the authorities a chance to make a proper decision and act quickly. But indicators based on market shares do not contain information on contagious effects. Our main objective was to extend these methods with a simple tool that takes into account possible contagion through financial markets.

We constructed the Aggregated Centrality Index, which contains different network measures for individual institutions. Both unweighted (degree, betweenness and closeness) and weighted (eigenvector and weighted degree) centrality measures were taken into account, since the size of the contracts may significantly increase systemic importance. This is especially true for the FX swap market.

Our new measure, the ACI was tested on our novel dataset which contains all the FX swap transactions from January 2005 to January 2014. We have shown that during market turmoil – when bid-ask spreads raise, i.e. market liquidity worsens – the ACI of top banks usually decreases significantly. It implies that waning activity of top banks has a significantly negative effect on market liquidity. As a result, our index can capture important systemic information.

We made an analysis about the differences between domestic and foreign banks, which also confirmed that the ACI is a good indicator of systemic importance. We found that the relevance of foreign banks increased significantly during the most intensive period of the crisis. In several cases foreign institution had the highest ACI in the whole system. This had never happened before the crisis. Many papers found that the activity of foreign banks in the region contributed positively to the stability of financial systems. Our findings support these papers. Later the difference between domestic and foreign top ACIs returned to its pre-crisis level, which is in line with the findings of Banai et al. (2013), who stated that some banks on the periphery of the network left the market.

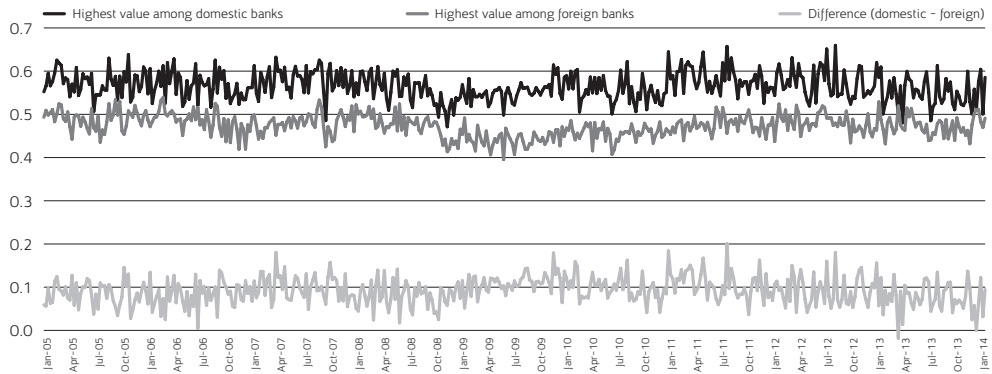
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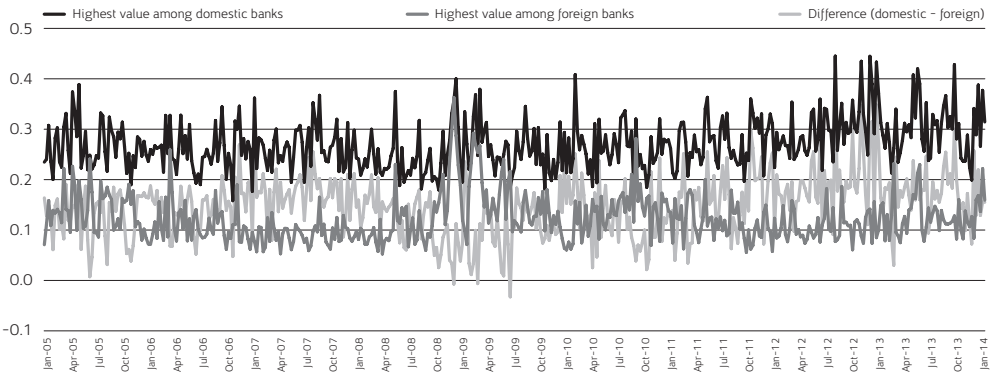
Appendix

Figure A1: Dynamics of Highest Closeness Among Foreign and Domestic Banks



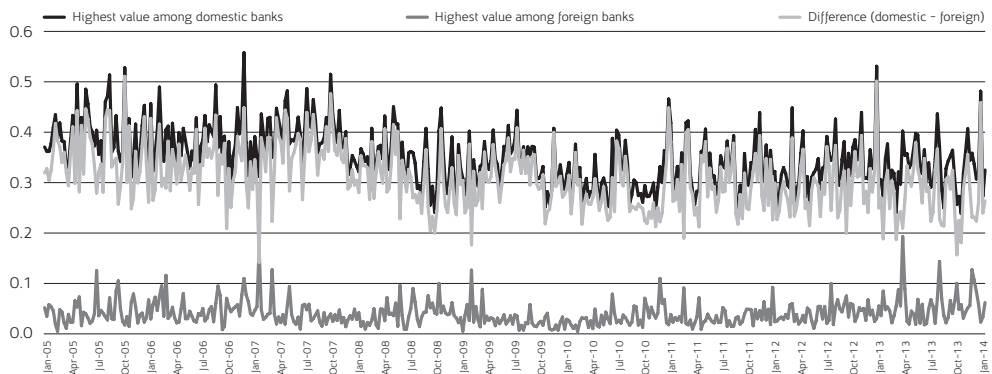
Source: Authors' calculation

Figure A2: Dynamics of Highest Weighted Degree Among Foreign and Domestic Banks



Source: Authors' calculation

Figure A3: Dynamics of Highest Betweenness Among Foreign and Domestic Banks



Source: Authors' calculation