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Network properties and evolution of the Hungarian RTGS over the past decade

(A hazai nagy értékű fizetési rendszer hálózatának jellemzői és evolúciója az elmúlt évtizedben)

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Contents

Abstract

Since the 2008 economic crisis, network research has become increasingly prominent in the world of finance. The complex interrelations and financial interdependencies formed among financial market participants have proved to be critical in times of crisis. In this paper, we explore the network properties of the Hungarian RTGS (VIBER) and also seek an answer to the question of whether the network properties of the system have changed over the long term across the time windows considered, and if so, to what extent. Furthermore, we identify systemically important participants using a variety of network theory tools. We also explore methodologies which – by providing new perspectives for monitoring the evolution of systemically important participants – may contribute to improving the effectiveness of oversight in Hungary. To identify systemically important participants, we apply four methodologies, namely: the LSI index, the model capturing the relation of eigenvector and betweenness, diffusion centrality, and the model exploring the effect of combining multiple nodes. In the Hungarian RTGS, two distinct groups emerge: the first is comprised of participants that play a key role in the transmission of liquidity ("core"), and the other is the cluster of periphery participants. As the composition of the core has remained virtually unchanged, it can be considered stable. While the risk of contagion arising from an operational disruption increased at both the individual and aggregated level during the period under review, it is also apparent that no such link exists in the graph the removal of which would ultimately cut the communication between the banks originally connected by it. The results of each indicator showed that there were no significant changes regarding the network properties across the three time windows, confirming the robustness of the network properties of the Hungarian RTGS and its stability over time.

Journal of Economic Literature (JEL) codes: D85, E42, E5, G2, G21, L14
Keywords: Hungarian RTGS (VIBER), network research, financial networks, graph theory, topology, centrality indices, systemically important financial institutions (SIFI)

1 Introduction and motivation

Network theory provides us with a deeper understanding of financial networks. In everyday life, we encounter networks frequently. For instance, when we call someone's number, we use our provider's telecommunications network. In transportation, motorways also constitute a specific type of network system. In fact, even the human body itself is an extremely complex network. The formation of viruses also follows patterns that are characteristic of networks, as a result of which they are frequently analysed for prevention purposes, given the possibility that the identification of key actors (hosts) could be of critical importance in preventing viruses from spreading (An et al., 2016). *Schweitzer et al.* (2009) propose that the findings made in other disciplines and technological sectors (such as biology, telecommunications, health, etc.) with relevance to graph theory should also be used for the study of economic networks, arguing that the networks encountered in everyday life and those of financial markets share a number of similarities, and that the network structures occurring in various disciplines and specific economic processes follow a similar pattern, a similar "universality". Interbank relations are also fat-tailed[1] and scale-free,[2] i.e. there are few banks connected to a *very high* number of other participants. Thus, presumably, banks engaged in similar investment behaviours are likely to end up in the same cluster. Similar regularities can also be found in other areas including international trade networks, regional investment and ownership networks (Schweitzer et al., 2009).

The 2008 economic crisis focused attention on the network properties of money markets, payment systems, and the analysis of systemically important participants. Over the past decades, economic processes have become extremely complex, and the interrelations between individual financial institutions have strengthened. Consequently, an incident (operational disruption, bankruptcy, etc.) occurring at one point in the system can spill over and impact the rest of its participants. The 2008 economic crisis also highlighted the fact that in order to maintain financial stability, there was a need to identify systemically important participants both in the economy and in the field of financial infrastructures. Having gained increased prominence over the past decades, the science of network research is highly instrumental in responding to that need. For example, the network analysis of money markets has demonstrated that it is not necessarily (only) turnover and bank size that matters when determining the importance of the credit institution concerned in terms of systemic risk. It is much rather the number and quality of linkages a given system participant has; or more precisely, the number of its outgoing and incoming links, and the significance of those links (Wright,[3] 2009). Other aspects may also become dominant, such as how active a system participant is on the FX swap market (Lublóy, 2006). Another key lesson learned from the crisis is that the financial institutions with the highest degree of connectivity require particular attention even in stable, "crisis-free" periods, and it is essential for them to be monitored and supervised closely. Banks of relative significance have been bailed out by governments in a number of cases in order to prevent the collapse of the banking system, imposing extreme burdens on central budgets. This was one of the reasons why, in the aftermath of the crisis, the identification of systemically important participants gained more significance (Berlinger et al., 2015b, with particular regard to the chapter *Systemic Risks*).

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[1] "*Fat-tailed distributions*". The term refers to distributions where the probability of extreme events is higher than expected.

[2] *"The degree distribution of a random network follows a bell curve, telling us that most nodes have the same number of links, and nodes with a very large number of links don't exist. (...) In contrast, the power law degree distribution of a scale-free network predicts that most nodes have only a few links, held together by a few highly connected hubs. (...) A random network has a characteristic scale in its node connectivity, embodied by the average node and fixed by the peak of the degree distribution. In contrast, the absence of a peak in a power-law degree distribution implies that in a real network there is no such thing as a characteristic node. We see a continuous hierarchy of nodes, spanning from rare hubs to the numerous tiny nodes. (...) The degree exponent for the scale free model is γ=3, i.e. the degree distribution follows $P(k)\sim k^{-3}$."* (Barabási, 2014, pp. 70–71., p. 88)

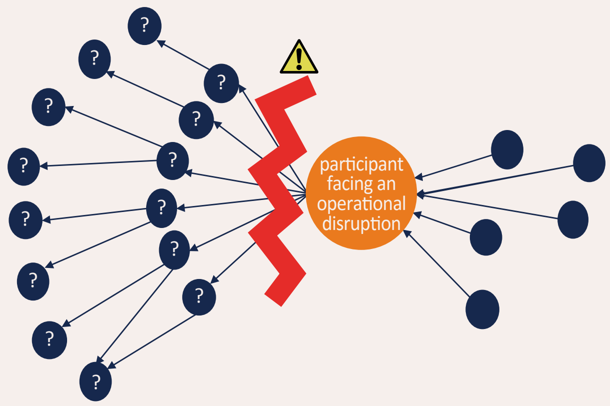
[3] Among other sources, references are made in Wright's work to Kimmo Soramäki, including Soramäki et al. (2006): The Topology of Interbank Payment Flows; and Soramäki et al. (2008): The Network Topology of CHAPS Sterling.

Financial infrastructures are of particular relevance to the execution of payments. In order to function, all financial markets require financial infrastructures. They enable the execution of transactions conducted in the market, while their role in the effectiveness of monetary transmission is also unquestionable. In this paper, we primarily focus on the network properties of the Hungarian RTGS (VIBER[4]). It is operated by the MNB primarily for the settlement of large-value and time-critical financial transactions. The system provides for the settlement of the cash leg of forint-based money and capital market transactions and other urgent customer payments. Due to real time settlements, transactions are finally and irrevocably executed in central bank money when sufficient funds are available (no netting[5]).

We seek to find the answers to the principal questions of our paper by applying various network theory solutions. In this paper, our aim is to locate the clusters within the Hungarian RTGS and to identify critical actors that are systemically important in terms of the transmission of intraday liquidity. Additionally, by means of graph and network theory, we wish to describe the network properties of the RTGS, and the significant changes occurring in those properties between 2008 and 2016. Since the crisis, some participants have merged, others have exited the market or have been wound up, new participants entered, and the financial infrastructure technology has also developed considerably. Each of these changes may have had an effect on the network of payment systems. We use numerous methods to find the answers to the questions raised above. For instance, we use *diffusion centrality*[6] to investigate the risk that a contagion emerging within the network may spill over. In terms of payment systems, this may be relevant from the perspective of how other system participants will be affected if a bank is faced with an operational risk (e.g. an operational disruption of the SWIFT messaging network prevents a given participant from submitting an item to the RTGS). This is notable since the RTGS network is a closed system. Despite each participant being connected to all others, in the event of the "drop-out" of a systemically important participant a contagion risk may arise. This is because an important system participant tends to receive liquidity from a large number of participants, while also transmitting significant amounts of liquidity to other participants. Banks *expecting to receive* liquidity from a critical participant encountering an operational disruption may not be able to access their funds in time. This results in uncertainty; and as they may also be concerned as to whether they are going to have enough liquidity by the end of the day to execute all of their payments, they will probably delay the initiation of their own payment transactions (Figure 1). A negative spiral is generated, which could ultimately result in a perceivable slow-down in payments. This is one of the reasons why it is necessary to identify systemically important payment participants. Using the methodologies described in this paper, it is possible to trace the position and relative importance of a system participant within the network, which could contribute to increasing the effectiveness of oversight. Additionally, based on the indicators applied, the central bank can determine whether it is required, in its capacity as the overseer of financial infrastructures, to take action to maintain the smooth operation of payment systems.

[4] The Hungarian equivalent of real time gross settlement systems.
[5] No netting means that a netting effect will not occur, i.e. the financing role of incoming items will not be taken into account.
[6] See Section 4.3 for more details.

Figure 1
Contagion effect in the event of an operational disruption to an RTGS participant



Source: Author's compilation.

This paper starts with a review of the relevant literature. Section 3 provides a description of the data considered, the time horizon, and the methodology used. Section 4 examines the general network properties of the Hungarian RTGS. Section 5 identifies systemically important participants. Finally, Section 6 provides a summary of the key messages and conclusions of the paper.

2 Overview of the literature

The network properties of RTGS have been addressed by a number of authors. Countless authors have sought to explore the network of money markets, with particular regard to that of payment systems. Notably, Soramäki et al. (2014) explored the network properties of the South Korean RTGS in 2014. Using Craig and von Peter's model,[7] they identified the core and periphery banks. Then they applied another approach called *SinkRank* – previously developed by Soramäki – to locate systemically important participants. The SinkRank indicator models the movement of liquidity in the system. The faster a given participant receives a unit of liquidity, the higher its SinkRank value will be. So higher SinkRank value is assumed to represent higher "importance" for the participant. However, the authors found that neither the core-periphery model, nor the SinkRank can perfectly capture the property of the given system participant, that is, whether it has enough liquidity to continue the execution of payments and withstand any liquidity shocks during the day. To assess the payment capacity of a bank and to ensure that its liquidity position at any specific point in time can be monitored more accurately, the authors developed a new dynamic liquidity indicator, PS-LI,[8] which enables real time oversight (Soramäki et al., 2014).

RTGS systems tend to have a hierarchical core–periphery structure. Of particular note is the work of León et al. (2014), who examined the network of the Colombian RTGS and identified systemically important participants using a combination of Craig and von Peter's *core–periphery* methodology and LSI,[9] an enhanced version of the HITS algorithm[10] that builds on authority and hub centralities. Their analysis relied on transaction data for the unsecured interbank market and the repo market. They found the network of the Colombian RTGS to be of low density, i.e. that there was a far lower number of links connecting individual nodes than what could be implied by the number of nodes. Additionally, the system was found to be inhomogeneous, with a small number of strongly connected participants being large contributors to system turnover and the spread of liquidity, as opposed to the majority of participants, which were weakly connected and as such they qualified as peripheral participants, or *"minor contributors"*. The system is *"hierarchical"*, arranged into a core–periphery structure. The network is "ultra-small",[11] characterised by the small world[12] property. On one hand, this is a positive feature since the short distances within the network greatly support the flow of liquidity in the system, while it could also have a negative effect in the event of a contagion (e.g. when a bank encounters an operational disruption) (León et al., 2014).

The Hungarian literature also incorporates a large number of papers pertaining to network theory, focusing partly on the analysis of unsecured interbank money markets, and partly on the analysis of the RTGS. Among Hungarian authors, of particular note are Berlinger et al. (2011), who examined the evolution of the network of the unsecured interbank forint market in the period between December 2002 and March 2009. They found that in the first half of the period, network properties remained stable, but from 2006–2007 onwards, major changes could be observed in some of the indicators: *"borrower concentration increased, average closeness and average degree dropped, while the size of the network core also shrank"*. By contrast, "*before October 2008 general market indicators (turnover, interest rate, etc.) provided virtually no indication of change. That is, credit institutions had already perceived the increasing credit risk before the crisis, and had become more*

[7] Core–periphery model. Craig–von Peter (2010), in: Soramäki et al. (2014).

[8] **P**ayment **S**ystem **L**iquidity **I**ndicator

[9] Liquidity Spreading Index, discussed in detail in Section 5.1.

[10] Clustering procedure (**H**yperlink-**I**nduced **T**opic **S**earch), see Sections 3.2 and 5.1 for details.

[11] *"ultra small networks (...) in which the average minimal number of links required to connect any two financial institutions (i.e. the mean geodesic distance) is particularly low (i.e. ~2)"* (León et al., 2014).

[12] *"In networks exhibiting the »small world« property, the average shortest path between vertices is low relative to the size of the network"* (Banai et al., 2013).

selective as to which borrowers they would lend to" (Berlinger et al., 2011). A similar assessment was carried out by Berlinger and Daróczi (Berlinger–Daróczi, 2015). With specific regard to Hungarian payment systems, the work of Lublóy (2006) is of particular note, who examined the network topology of the Hungarian RTGS based on turnover data for June 2005. She found that there were no material changes in the most important centrality indices between individual days. Additionally, she found a mere 30% of all links to be constant, which, on the other hand, were used for the execution of 90% of all payment orders. In terms of specific days, the strongest or most important links would not necessarily be the same, but they would be "dominated" by the same small number of banks. Consequently, there was no meaningful change in the composition of the most central participants in June 2005. The Hungarian RTGS can be characterised by the presence of multiple liquidity centres. The participants with the strongest tendency towards contagion were not the ones with the largest total assets, but participants actively involved in the USD/HUF FX swap market either directly or indirectly (Lublóy, 2006).

Some authors analysed the FX swap market by means of network theory. While the previously mentioned papers primarily focused on the network properties of RTGS systems and unsecured interbank markets, the analysis by Banai et al. (2013) concentrated on the FX swap market. This is also what makes their paper particularly special, since both Hungarian and international literature on finance had offered network research addressing the two aforementioned areas, whereas no network approach had previously been used to analyse the FX swap market. The authors used data for the period between 2005 and 2012 to observe the properties and network characteristics of the FX swap market. They found that *"since the second half of 2010, banks in the network periphery have gradually become disconnected"*, and that *"foreign participants are more selective of their counterparties than domestic ones, and the contrast has only become stronger since 2009"* (Banai et al., 2013).

Based on conventional network theory indicators, Banai et al. (2014) developed a proprietary indicator for the identification of systemically important participants. They specifically propose an idea for identifying systemically important participants. Their goal was to create a tool that enabled systemically important participants to be identified efficiently. Based on the currently available tools of network theory, they developed the *ACI*,[13] the operational efficiency of which they tested using FX swap market data. They found that under adverse market circumstances (when bid–ask spreads increased and liquidity became scarce), the ACI values of top participants dropped significantly. By contrast, during the intense period of the crisis, the ACI values of foreign participants increased considerably compared to domestic banks, which had not been typical in the pre-crisis period at all. Presumably, the foreign banks present in the region were making a positive contribution to the stability of the financial system. Subsequently, the difference between the ACI values of domestic and foreign banks readjusted to the levels seen before the crisis (Banai et al., 2014).

These examples show that network research with a financial focus has a wide range of literature both in Hungary and worldwide. Given the steady development in the methodology of network analysis, the number of such papers is expected to grow in the near future, which will hopefully support a more accurate understanding of the increasingly complex network of money markets.

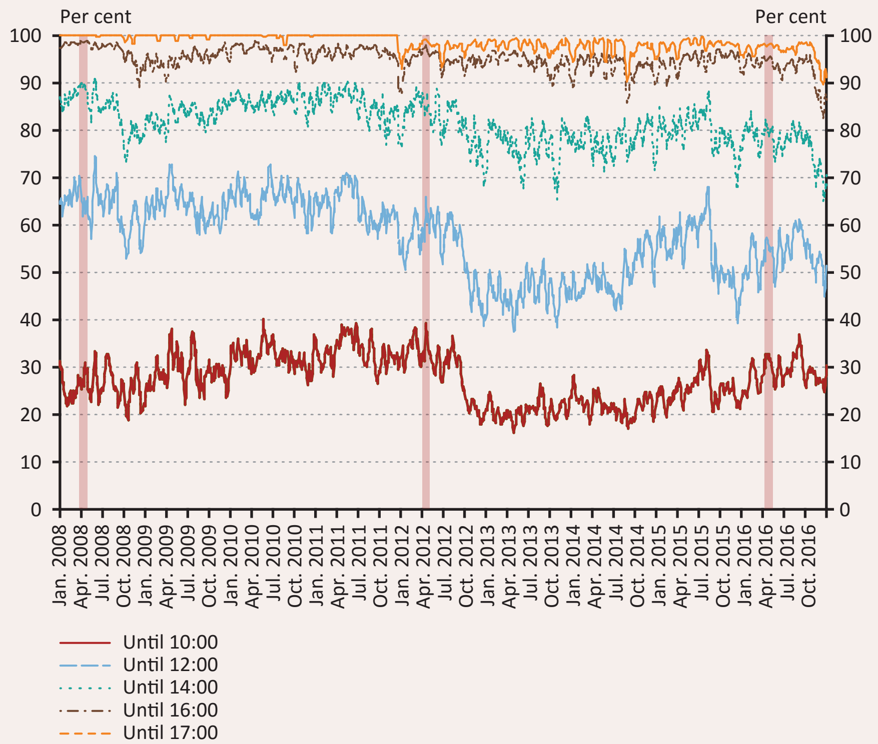
[13] Aggregated Centrality Index

3 Data used, methodology description

3.1 DATA SPECIFICATION, TIME HORIZON

One of the objectives of this paper is to explore the long-term changes in the network characteristics of the Hungarian RTGS, which was carried out using the three time windows April 2008, April 2012 and April 2016. In part, the analysis aimed to assess whether the network properties of the Hungarian RTGS had changed over the long term and if so, to what extent. To this end, we chose the same month in 2008, 2012 and 2016. In all three years, we sought to select the "most neutral" month which was free of any extreme economic events that would be a shock to payment systems, was free of extraordinary seasonal effects in turnover (which is typical in the last months of the year as the holidays are approaching), and did not contain any bank holidays that would distort e.g. the number of business days. Regarding the timing of transactions we did not experience any abnormalities in the chosen months (there were no sudden intraday shifts to later or earlier hours). (Figure 2) We insisted on a single month in each year because the assessment of an entire year would have presumably involved a number of other effects, whereas a comparison of the same month in different years eliminates the variations resulting from the seasonality of payments during the year.

Figure 2
Timing of turnover in VIBER
(what portion of total daily turnover is completed until a specific point in time, 2008 – 2016)



Source: Author's compilation based on MNB data. We used light red to indicate April months.

We used transaction-level data of VIBER turnover to conduct the analysis. For the analysis, we used the network derived from the transaction-level turnover data of the Hungarian RTGS operated by the MNB, taking into account all transaction types that can be submitted into the system,[14] because we focus on payments liquidity in general. Since we wish to capture the aggregated network properties of the RTGS, we had to consider all transaction types. We considered daily gross turnovers, i.e. the amount transferred by Bank "A" to Bank "B" (based on transaction value) on one business day. Next, we removed the turnovers of smaller value (those below HUF 1 billion, which are less relevant in terms of the "movement" of payment liquidity at systemic level,[15] but could distort the final outcomes), then aggregated the turnovers for the given month (monthly sum). Thus, the network links are weighted and the weight of each link is derived from the value of the turnover executed through it. As a starting point, we used this gross, month-specific, directed and weighted turnover matrix and adjusted it where necessary.

The other main objective of our analysis is the identification of systemically important participants. We are primarily interested in finding out which participants are the most important ones in the group of commercial banks, Hungarian branches and credit institutions. Therefore, to avoid any distortions, we disregarded institutions engaged in the operation of the payment system (which are more of a technical nature) and other special participants[16] such as MNB, KELER, Hungarian State Treasury, Hungarian Post, and CLS.[17] For the purpose of our analysis, we considered at the transaction level the related turnovers of the retail payment system (ICS[18]), operated by GIRO Zrt., which means that the time window of April 2016 also includes the sub-network of the ICS in addition to the network of the Hungarian RTGS. Between 2008 and 2016, the number of participants in the payment system also changed; thus, following the aforementioned changes we analysed the payment networks of 30 participants for April 2008, 31 for April 2012, and 34 for April 2016.

3.2 METHODOLOGY

To identify participants that play a systemically important role in the redistribution of liquidity, we used four approaches based on network theory. To identify systemically important participants, we applied four methodologies that are covered widely in literature, namely: the LSI *(Liquidity Spreading Index)* based on the HITS algorithm, *Conway*'s model capturing the relation of eigenvector and betweenness, diffusion centrality, and the model exploring the effect of combining nodes (*"kpset"* algorithm).[19]

The HITS algorithm allows participants of the payment system to be grouped according to their relative importance in terms of the transmission of liquidity within the system. HITS is a search algorithm primarily for the evaluation of internet webpages to determine whether a specific page had a tendency to refer to other webpages (i.e. had high "hub" centrality), or conversely, the page in question was referenced by a large number of other pages (i.e. had high "authority" centrality). Good hubs (pages with high *hub* centrality) do not contain a large amount of data themselves, but *collect* countless references, *"pointing to"* pages which, with high

[14] The key transaction types in the Hungarian RTGS are as follows: **MT103 (customer message)**: payments initiated and/or received by customers of direct and indirect VIBER participants. **MT202 (interbank item)**: payments ordered by direct or indirect VIBER participants, when the beneficiary is a direct or indirect VIBER participant as well. **CBACT**: central bank transfers, manually entered items (i.e. extraordinary transactions received by the MNB e.g. on paper or by fax, and are therefore entered into the system manually). **EXTACT**: bankcard settlement (VISACARD and MASTCARD), placement of deposits, cash items (CASH). **TPACT**: includes the transactions executed in the RTGS on a DvP basis (SECURITY, REPO) related to the cash leg of securities clearing transactions, and the items required for the settlement and collection of multiple same-day clearing cycles in the ICS (IG2CCOLL).

[15] They account for a mere 1-3% of the overall turnover of the Hungarian RTGS.

[16] This means that we ignored the participants detailed here on both the debit and credit sides.

[17] For the purpose of our analysis, we also ignored the related turnovers of Borgun, Euronet, O. F. Sz. Zrt. and Wirecard.

[18] The ICS (Interbank Clearing System) is a gross payment system operated on a batched basis by GIRO Zrt., and is used primarily to clear small-value credit transfers, collection orders and direct debit orders (e.g. utility bills), and payment transactions associated with other official transfer orders. The ICS operates two clearing modules: overnight clearing (InterGiro1, IG1), and multiple same-day clearing cycles (InterGiro2, IG2). The latter has been available to customers and credit institutions since July 2012, and initially cleared credit transfers in 5 cycles per day, which increased to 10 cycles per day as of 7 September 2015 (Bodnár et al., 2015).

[19] For more details on the latter two, see An et al., 2016.

authority scores, act as main sources of information.[20] Owing to the ease of interpretation it affords, the HITS algorithm is a popular tool in network analysis, and although it is primarily used in information technology, it is also instrumental in generating useful results for networks of payment systems.

The algorithm itself generates two scores for each node: *hub centrality* and *authority centrality*. Let us denote a certain node as v, its hub centrality as $h(v)$ and its authority centrality as $a(v)$. Initially, we set $h(v)= a(v)=1$ for all nodes and we also know that $v \rightarrow y$ meaning there is an existing link between nodes v and y.

$$h(v) \leftarrow \sum_{v \rightarrow y} a(y)$$

$$a(v) \leftarrow \sum_{y \rightarrow v} h(y)$$

Equation (1) indicates the hub score for v which equals the sum of authority scores of all the nodes v points to. If v points to nodes with high authority scores then v's hub score also increases. Equation (2) works the exact opposite way. It indicates v's authority score which equals the sum of hub scores of all the nodes pointing to v. This means that if v is linked to by good hubs, its authority score will be higher. Now the above equations are updated based on the recomputed hub scores, generating new authority scores and this iteration continues. Then we should convert equation (1) into a matrix-vector format. Let $\vec{h}$ and $\vec{a}$ denote the vectors of all hub and all authority scores respectively. Let A denote the adjacency matrix of the network. If a cell of $A_{i,j}$ equals 1 then there is indeed a link existing between nodes i and j, or 0 otherwise. Now we can rewrite the above equations the following way:

$$\vec{h} \leftarrow A\vec{a}$$

$$\vec{a} \leftarrow A^T\vec{h}$$

Where A^T refers to the transposed version of A. Combining these equations we can rewrite them:

$$\vec{h} \leftarrow AA^T\vec{h}$$

$$\vec{a} \leftarrow A^T A\vec{a}$$

Now we introduce the eigenvalue into the system (let's denote the eigenvalue of AA^T as λ_h and the eigenvalue of $A^T A$ as λ_a) and we are changing the symbol „$\leftarrow$" to „=". Thus, we get the equation for eigenvectors of AA^T and $A^T A$, so that we could finally define the vectors of hub and authority scores.

$$\vec{h} = \frac{1}{\lambda_h} AA^T\vec{h}$$

$$\vec{a} = \frac{1}{\lambda_a} A^T A\vec{a}$$

So the procedure is: following the calculation of AA^T and $A^T A$ we compute their eigenvectors to form the vector of hub scores $\vec{h}$ and authority scores $\vec{a}$. (Manning et. al., 2008)

In terms of payments, this means that if a financial institution is a major liquidity *provider*, it should rather be regarded as a participant having *hub centrality*, whereas if it *receives* a great amount of liquidity then it is rather a participant having *high authority* (i.e. a *liquidity "sink"*). On this basis, any institution connected to the central bank or other important *hub* participants will be a good *authority* and any system participant that contributes to spreading liquidity may be treated as a good *hub* to a certain degree (León et al., 2014). Using

[20] Source: Website of the UCINET software package for the analysis of social network data. Website: http://www.analytictech.com/ucinet/help/hs4200.htm

the method affords a relatively accurate understanding of the position and behaviour of specific participants within the system. It also helps us answering the question, to what extent does a certain participant actually contribute to the transmission of payment liquidity?

The applied algorithm assigned similar authority and hub scores to each bank in the system; participants having high authority and hub scores can be considered as key players in terms of spreading payment liquidity. We calculated authority and hub scores using the *"authority_score"* and *"hub_score"* functions of the R package called *"igraph"*.[21] Based on the results of the algorithm, we can define which participants play an important role in the transmission of payment liquidity; and thus ultimately which participants comprise the network core and which ones should rather be considered as peripheral. For this purpose, we examine the value of hub and authority scores for each participant and also the relationship of these scores. System participants with low scores for both authority and hub centrality may be considered as peripheral. Participants with equally high authority and hub scores will be the *critical* banks that play a key role in the transmission of payment liquidity (León et al., 2014).

Based on the Liquidity Spreading Index, participants in the RTGS can be grouped into two clusters. We created the groups using the *Liquidity Spreading Index (LSI)* introduced by León et al. (2014), which builds on authority and hub scores. For a given system participant i, the LSI is calculated as follows:

$$LSI_i = \frac{\left(\dfrac{autoritási\ ceralitás_i}{\sum_{i=1}^{n} autoritási\ centralitás_i} \cdot \dfrac{hub\ centralitás_i}{\sum_{i=1}^{n} hub\ centralitás_i} \right)}{\sum_{i=1}^{n} \left(\dfrac{autoritási\ centralitás_i}{\sum_{i=1}^{n} autoritási\ centralitás_i} \cdot \dfrac{hub\ centralitás_i}{\sum_{i=1}^{n} hub\ centralitás_i} \right)}$$

Calculated for all system participants, the LSI will take the value of 1:

$$LSI = \sum_{i=1}^{n} LSI_i = 1$$

León argues that banks with the greatest contribution to the LSI will be the ones that are particularly important in terms of transmitting payment liquidity.

Applying Conway's procedure we used the relationship of two classical centrality indices (betweenness and eigenvector centrality) to find the systemically important participants. (Conway, 2009). To this end, we will first provide a brief overview of these two network indicators. Betweenness measures the extent to which a given node within a network can be considered a *"bottleneck"* in terms of the circulation of payment liquidity within a day. Using betweenness to find critical actors can be helpful. The index itself refers to *"the number of shortest paths that include a given vertex".* (Banai et al., 2013) Let us say we want to establish the shortest link between two nodes. In order to connect these, the link has to go through vertex "X". Betweenness basically measures the number of such links existing in the system that contain our vertex "X". The *"betweenness"* function of an R-package called *"igraph"* was used to calculate the index which works based on the algorithm suggested by Brandes (2001).[22] In the case of a vertex *v*, betweenness is calculated as follows:

$$\sum_{i \neq j, i \neq v, j \neq v} \frac{g_{ij}(v)}{g_{ij}}$$

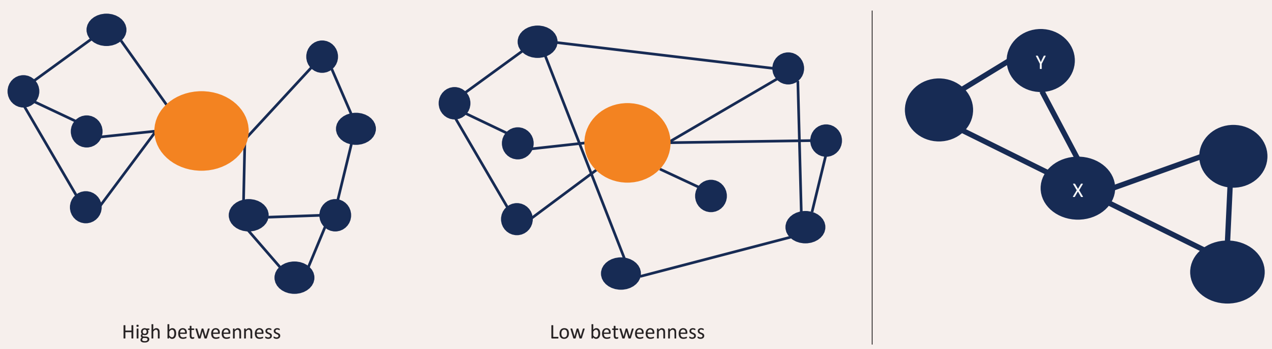
[21] For more details, see Csárdi et al. (2006).

[22] For further information about the code applied, see Csárdi et. al. (2006).

- where i and j are randomly chosen nodes within the graph (i sender, j receiver)
- $g_{ij}=g_{ji}$ is the number of shortest paths between nodes i and j
- $g_{ij}(v)$ is the number of shortest paths between nodes i and j which contain vertex v

High values indicate that a given node can reach others within a short distance or a given node lies on many shortest paths linking others in the system. Betweenness affords a more accurate understanding of which system participant can be considered as systemically important in terms of payment liquidity and it also helps identify the system participants for which it is critically important to meet their payment obligations without any disruptions. Although in an RTGS, any system participant can submit payment items to any other participant, operational issues encountered by such bottlenecks of high betweenness could pose a risk to the *circulation of liquidity in the system*. This may have a number of consequences: when the liquidity available is insufficient for the execution of payments in the case of system participants with high betweenness, they may use their credit facilities for a longer period within the day, accumulate a higher number and value of queued items, or worse, a gridlock may emerge. Hence the liquidity shortage of individual participants does not only affect the turnover of the RTGS, but may also have an impact on the execution of transactions cleared in the small-value (retail) payment system (ICS[23]), and may ultimately be felt even by the end users. Consequently, a participant with high betweenness may be systemically important regarding payment dynamics and the efficient redistribution of aggregated payment liquidity. That is why it is important to evaluate the results of betweenness (Figure 3). However, caution is warranted regarding these results, because it is possible that a high betweenness value is assigned to participants positioned at the periphery of the network. That is, their significance may be limited e.g. to the connection between two completely separated islands, which are peripheral anyway.

Figure 3
High and low betweenness values (schematic representation on the left); betweenness in relation to nodes X and Y (schematic representation on the right)



Note:In the representation on the right, X has higher betweenness because compared to Y, it needs to be traversed by a greater number of shortest paths connecting node pairs. Author's compilation.
Source: Based on Tomson (2013) and Eaton (2013).

[23] In the ICS, transactions are cleared and settled separately. The ICS "only" clears payments (it determines the payment position of each bank with the rest), whereas settlement (actual financial execution) is a responsibility of the MNB in its capacity as a settlement bank (Luspay et al., 2014). To execute payments, in both the RTGS and the ICS participants use the same liquidity, comprised of their available account balances and the intraday credit lines provided against their security portfolios pledged to the MNB. In this way, when a bank has insufficient liquidity on its payment account in the RTGS, its items submitted through the ICS will also not be executed.

Eigenvector centrality[24] focuses on the role of a given node within the overall network, providing a more accurate picture compared to degree centrality. In network analyses, eigenvector centrality[25] is a preferred indicator, which – compared to the rest of the network indicators – has the huge advantage that it focuses on the global role of a given node considering the *entire graph* and relies less on the local properties. The indicator is used to identify the "most central" participants within the network. Higher values may indicate a "more central" property of the participant concerned, i.e. that the given system participant is connected either to a large number of other nodes, or primarily to central participants, or both (León et al., 2014). Lower values indicate a more peripheral position of the node in the graph. In this way, the indicator may provide a more accurate understanding compared to degree, which is only concerned with the number of links to and from the given node. A participant with a high degree will not necessarily be assigned a high eigenvector centrality indicator and vice versa: a node with a high eigenvector score will not necessarily be of a high degree – in this case, it may only have a few counterparties, but will generate high turnover with them. To calculate eigenvector, we used the "evcent" function of the aforementioned R-package called "igraph".[26] In general, *"let's define a node's centrality so that it is proportionate to the sum of its neighbours' centralities depending on a proportion factor* $c = \frac{1}{\lambda}$ *so we get:"*

$$v_i = c \sum_j A_{ij}^T v_j$$

- where A indicates the adjacency matrix,
- i and j are random nodes within a network (i sender, j receiver)
- c indicates a proportion factor

"Rewriting the above equation using matrix operations we get:

$$A^T v = \lambda v,$$

so the vector v including the centralities of the nodes is actually one of the eigenvectors of A^T *with* λ *eigenvalue"* (Kiss, 2012).

Based on the relationship of betweenness and eigenvector centrality, inferences may be made about systemically important participants. According to Conway, the relationship of betweenness and eigenvector centrality can be approximated using a linear model, which means that every non-linear, extreme outlier may be considered as a key "actor".[27] Accordingly, we applied a linear model between the two variables. The R code we used was the following:

```
el=read.csv("input.csv", header = TRUE, sep=",")
g2=graph.data.frame(el)

cent <- data.frame(bet=betweenness(g2),eig=evcent(g2)$vector)
res  <- lm(eig~bet,data=cent)$residuals
cent <- transform(cent,res=res)

p <- ggplot(cent,aes(x=bet,
                     y=eig,
                     label=rownames(cent),
                     colour=res,
                     size=abs(res)))+
                     xlab("Betweenness Centrality")+
                     ylab("Eigenvector Centrality")

p+geom_text()+ geom_smooth(method = "lm", se = FALSE)
```

[24] Partially based on the following website: Franceschet (2014).

[25] Some internet search engines also use this indicator. It enables them to "score" the relative importance of a given webpage (e.g. according to the number of searches for the page, the number of clicks, etc.). See Bryan–Leise (2006).

[26] For further information about the code applied, see Csárdi et. al. (2006).

[27] For more information about the code applied, see Csárdi et. al. (2006) and Conway (2009).

Although linearity between the two variables is not necessarily perfect, Conway holds that the method may point to the interesting participants in the system. Displaying the line derived from the linear model based on the relationship of betwenness and eigenvector centrality, the focus should be centred on the participants situated far from this benchmark reference line (i.e. the nodes ending up with high residual values).

Apart from the identification of systemically important participants, it is also important to see which participants may be the most affected by the spill-over effect of the liquidity risk resulting from operational incidents. Network theories based on diffusion models may be instrumental in cases where we want to know, for example, the *speed* at which a virus, a contagion, *a unit of information*, or an operational disruption at a participant in an RTGS could cause damage to the system. This is measured using *diffusion centrality*, which may also be construed as the *probability* of (liquidity) risk spilling over calculated for a given node. This indicator is also useful because conventional centrality indices are not necessarily capable of capturing the diffusion properties of a given node (Kang, 2012).

Diffusion centrality is a tool to measure the speed at which the liquidity risk resulting from an operational disruption at a specific participant in the Hungarian RTGS can spread, i.e. cause interruptions in payments within a certain timeframe. To use diffusion centrality, we used the *"diffusion"* algorithm of the R package called *"keyplayer"* developed by Weihua An and Yu-Hsin Liu (An et al., 2016). The description of the package defines diffusion centrality as the speed at which a given node has the *ability* to disseminate information across the network. The authors relied on the formula developed by Banerjee et al. (2013), where the value of diffusion centrality is derived as the sum of rows in the following matrix:

$$S = \sum_{t=1}^{T} p^t$$

- where P indicates a probability matrix
- $t = 1 \ldots T$ refers to the number of iterations
- matrix S measures the aggregated tendency for diffusion

So P indicates the probability matrix, and $P_{i,j}$ measures the probability of reaching node j from node i. According to Banerjee's original suggestion, $P = q \times g$ where q is the probability of transmission among nodes and g is the adjacency matrix. For the sake of simplicity, the package *"keyplayer"* asks the user to input the probability matrix right at the beginning. We specified the probabilities in proportion to monthly gross turnovers. Thus, the larger the turnover executed between Participants "A" and "B", presumably the higher the probability that an operational disruption of Participant "A" will have a major impact on Participant "B", which relies on the payments to be received from Participant "A" regarding the execution of its payments. For these reasons, we used a weighted and directed adjacency matrix as our input. The components of the matrix S measure the aggregated tendency of reaching node j from node i through a set number of iterations, designated by T. The T value is a positive integer which can be interpreted as the elapsed time, i.e. the amount of time allowed for the dissemination of information (or the spread of liquidity risk resulting from an operational disruption) between two nodes. This could be a day, a week, a month or even 2 months; what matters is the amount of information passing through within a certain time frame. The interpretation of T always goes hand-in-hand with the input matrix used in the algorithm.[28] Suppose, for instance, that a message may take 3 paths from a given node, which corresponds to having 3 probabilities, with T = 1. A sum of these probabilities will provide the diffusion centrality of a given node (in this case, its possible value will be between 0 and 3). This is what the matrix S registers and the sum of this matrix's rows implies the ultimate importance of the given node

[28] Since the matrix covers one month, T = 1 will correspond to one month elapsed, T = 2 to two months elapsed, etc. However, the pattern of participants' daily turnovers in the payment system does not particularly differ from the patterns of monthly turnovers (suppose participant "A" sends lots of payment transactions to participant "B" in a month, then chances are high that some turnover will also be generated only on one randomly chosen business day within this month, considering these two nodes), hence parameter T may also be construed as the unit of *days* elapsed. This simplification greatly facilitates the interpretation of results.

for disseminating information. This value cannot tell *why* a particular node turned out to have high *diffusion capacity*: either because the given node has a large number of linkages or because it dispatched messages only via high-probability paths. Instead, it rather implies an aggregated strength, which has to do with the *ability* of a given node *to spread risk*. For each of our three time windows, we specified diffusion centralities for each node in the network. We assigned three values to parameter T (T=1, T=2, T=3; i.e. 1, 2 and 3 days elapsed, respectively). Using the diffusion centralities derived for individual T=1, T=2, T=3 units of time, we calculated growth rates,[29] which we then compared to the outputs provided by LSI, separately designating each node according to its status of being critical or peripheral.

Due to the complex interrelations among banks, it is worth observing certain participants combined together as a group, rather than treating them independently, in isolation. This will afford an understanding of the *combined impact* of several system participants. The methods discussed previously primarily focused on individual nodes. However, in today's advanced world of finance, owing to the interdependencies between individual credit institutions, investigating the influence of certain *bank groups* may also be critical. From an overseer perspective, it is imperative not to treat specific institutions independently in isolation, and instead it might be better to investigate several system participants combined into groups, because assessing these interrelations can be critical in analysing contagions. Thus, it may be appropriate to treat a *group of properly selected nodes* as one separate vertex within the network. It is plausible that the three most central nodes together constitute a group that no longer qualifies as particularly central, or conversely, a system participant that was previously *thought to be weak* and *assumed* to be peripheral under conventional methods of network theory, may even *see its role within the network appreciate significantly*. Consequently, the artificial combination of certain nodes may create groups within the network which can already be of risk to the overall system (e.g. in the course of an acquisition or a merger). This scenario is addressed by the *"kpset"* function of the R package *"keyplayer"* developed by Weihua An and Yu-Hsin Liu (An et al., 2016), which basically works on the basis of a slightly modified version of the greedy algorithm suggested by Borgatti (2006). The idea is as follows:

Step 1. Select an initial set of nodes C. The residual set is denoted as R.

Step 2. Update set C.

1. Let's choose a node in set C. Swap it with a node in R (loop 1). Make the swap if it improves the score of the resulting C. The number of iterations is defined by the number of nodes in R.
2. Repeat loop 1 for each node in C sequentially (loop 2). The number of iterations in loop 2 is defined by the number of nodes in C.
3. Stop if (1) the change in C's centrality score is smaller than a specified threshold or (2) if the process reaches a specified number of iterations.

Step 3. Return the final set C and its centrality score.

In their model, groups are selected through the optimisation of various centrality indicators. We opted for diffusion centrality, which is the indicator that can best capture the spread of liquidity risk resulting from a temporary operational disruption. The algorithm enables pre-setting the number of participants to be included in each group. For our analysis, we set groups of 3 and 5 institutions. Once that input has been provided, the model optimises iteratively until it finds the final cluster, respectively comprising 3 and 5 nodes, which ultimately has the highest diffusion centrality.

Section 4, which provides a general description of the network of the Hungarian RTGS, uses other concepts of network theory which are discussed in that Section.

[29] The formula used: ((diff. centr.$_{T=3}$ / diff. centr.$_{T=2}$) + (diff. centr.$_{T=2}$ / diff. centr.$_{T=1}$)) / 2

4 Network characteristics of the Hungarian RTGS

Table 1
Comparison of the network properties of RTGS systems
(averages, including standard deviations where possible)

Network properties	BOK-Wire+ (South Korea)	LVTS (Canada)	TOP (Netherlands)	Fedwire (USA)	VIBER (Hungary)	VIBER (Hungary)	VIBER (Hungary)
Period	2013 August	2004 April - 2008 December	2005 June - 2006 May	2005	2008 April	2012 April	2016 April
Turnover (transaction value)	190 trillion KRW	25.4 trillion CAD (year)	584 million EUR	1.3 trillion USD	80 111 billion HUF*	62 219 billion HUF*	64 068 billion HUF*
Turnover (transaction volume)	11 672	4.4 million (year)	21 400	345 000	60 456	84 485	8 686 521**
Number of nodes	122 ± 5.9	14	155	5 086 ± 123	30	31	34
Number of edges	2 871 ± 471	N/A	1 182	76 614 ± 6 151	412	357	396
Connectivity (%)	18.1 ± 2.5	69.2 ± 3.3	7	0.3 ± 0.01	47.36	38.39	35.29
Degree (average)	45.4 ± 6.9	N/A	9	15.2 ± 0.8	7.85 ± 5.50	7.17 ± 5.32	9.05 ± 7.56
Maximum in-degree	84 ± 8	N/A	N/A	2 097 ± 115	20	20	28
Maximum out-degree	86 ± 10	N/A	N/A	1 922 ± 121	19	20	32
Reciprocity (%)	58 ± 6.0	89.3 ± 2.5	63	21.5 ± 0.03	42.3	42.7	39.2
Characteristic path length	1.85 ± 0.05	1.31 ± 0.03	~2.3	2.62 ± 0.02	1,59	1,66	1,69
Average eccentricity	2.9 ± 0.1	1.84 ± 0.07	~3.3	4.67 ± 0.33	2.47 ± 0.50	2.5 ± 0.5	2.97 ± 0.3
Average diameter	3.8 ± 0.4	2.01 ± 0.07	N/A	6.6 ± 0.5	3	3	4
Clustering coefficient (%)	51.3 ± 1.7	84.3 ± 1.5	38	53.0 ± 1	54.1	49.7	46.1

Source: Soramäki et al. (2014) and MNB data.
** Excluding the related turnovers of the MNB, KELER, the Hungarian State Treasury, the Hungarian post, and other participants detailed in Section 3.1.*
*** Including the number of transactions resulting from the turnover of the retail payment system.*

In the following, an overview is provided of the network properties of the Hungarian RTGS based on network theory, examining the main changes that occurred to the network structure over the long run.

Network density of the Hungarian RTGS decreased over the long term. Connectivity (density) is examined over the entire network.[30] A network will be fully connected (dense) when each of its nodes is connected to one another through a link. In such a graph, none of the nodes in the system is inaccessible, and all of the nodes are interconnected. In a disconnected graph however, there may be nodes in the system that are not connected to others. The density of the Hungarian RTGS decreased by 12 percentage points between 2008 and 2016 (Table 1). This means that a smaller proportion of all potential links between network nodes was actually used in April 2016 (35% on average) compared to the previous 47%. In other words: the number of active links connecting individual nodes is smaller than what could otherwise be expected based on the number of nodes. This may be explained by the fact that the shares of many participants have been purchased throughout the examined time interval (e.g. by means of acquisition) or their system membership terminated, decreasing the number of active links. Another possible reason for the softening could be the presence of several system participants that used the Hungarian RTGS on only one or two business days in the examined time windows (examples include Bank 29 in April 2012, or Banks 38 and 39 in April 2016[31]). Such participants are relatively distant from the centre of the network and are only loosely connected to the core through just one or two links, making them systemically less relevant (Figure 8, see below). Although only slightly, the number of system participants also increased between 2008 and 2016, which may also have contributed to lower density by increasing the number of potential links.

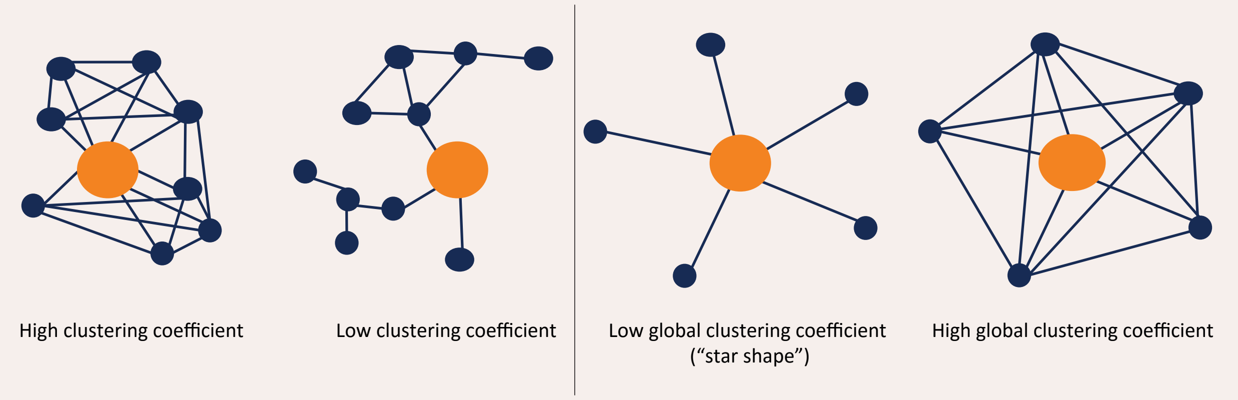
Based on international comparison, the network of the Hungarian RTGS is relatively dense (i.e. a significant portion of the potential interbank linkages are in fact active), which on one hand enables risks to be diversified, however, in terms of diffusing contagion, this property is much less ideal. Although the density of the Hungarian system declined between 2008 and 2016, it is still high compared to other systems' values, exceeding the data for South Korea, the Netherlands and the US. This is not necessarily a disadvantage; it is a widely held view among network researchers that a dense network enables the risk of individual failure to be diversified. However, systemic risk could also increase significantly as the connectivity of specific nodes within the network becomes stronger, since the removal of whole groups from the network (instead of single nodes) may result in a less predictable and less stable system (when a large number of nodes "drop out" simultaneously from a relatively dense network) (Schweitzer et al., 2009). We further explore this phenomenon later in Section 5.4. One possible reason for the high density of the Hungarian RTGS on an international level is that it is much smaller compared to other systems (the number of its nodes varied between 30 and 34). Regarding these values, the Hungarian network is closest to the Canadian system with its 14 nodes, whereas in all the other systems a far higher number of participants (>100) operated in the periods considered (Table 1). Hence, the low number of nodes can be associated with high density. Furthermore, compared to the other systems, the Hungarian RTGS is characterised by a lower characteristic path length (on average, it takes 1.6-1.7 steps to move from one node to another), generally lower average eccentricity (the *maximum* number of steps required to move from one node to another in the system), and the average diameter of the graph is low. Due to the smaller dimensions, even the most strongly connected system participant has a relatively low degree. In 2016, a system participant received transactions from a *maximum* of 28 other system participants, and submitted transactions to 32 on a daily basis; these values are considerably lower compared to the systems of both South Korea and the US. Nevertheless, the number of possible connections increases at a rate of the size squared (Banai et al., 2015). Since the network of the Hungarian RTGS is dense, an operational disruption at a given participant may affect several system participants within the graph directly, which makes this property less ideal in terms of contagion.

[30] *With formula:* $\frac{\textit{number of active links between nodes}}{\textit{number of all potencial links between nodes}}$

[31] The numbers indicate the anonymous reference numbers of the participants in the payment system.

The clustering coefficient measures the tendency for "cliquishness" between the immediate neighbours of a given node, i.e. the probability that the direct counterparties of a given participant will transact with one another. The clustering coefficient measures the extent to which the immediate neighbours of a given node may be clustered. It shows how strongly connected the counterparties of a given node are, measuring the active links of all potential links between the neighbours of a given node. In other words, it specifies the probability of the neighbours of a given node being connected to one another (Figure 4) (Banai et al., 2013, p. 17). Using the analogy of social networks, if I have X number of friends and those friends are also friends with one another, then I will have a high clustering coefficient.

Figure 4
Difference between nodes with high and low clustering coefficients (left pane); global clustering coefficient (right pane)



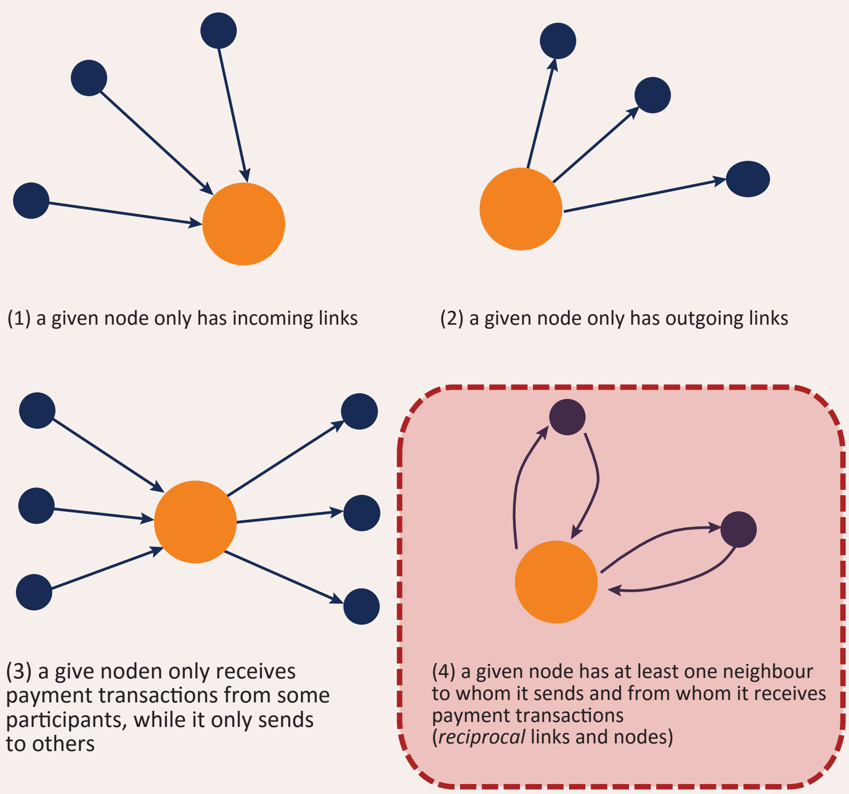
Source: Left pane: author's compilation. Source: Tompson (2013). Right pane: author's compilation.

In the interval considered, apart from a slight decrease, there was no meaningful change in the global clustering coefficient for the network of the Hungarian RTGS, which points to the robustness of the system.[32] The *global* clustering coefficient of a network is derived as the average of the coefficients of the nodes it contains. An aggregated clustering coefficient of 0 indicates that the network does not contain any clusters, representing a *"star"* formation where a central participant is connected to a large number of nodes, which are not connected to one another (Figure 4, right pane). An aggregated indicator of 1 represents a single interconnected group where each node is connected to all other nodes. So the probability that two immediate neighbours of a given participant are *also* connected to each other is higher than what would be expected in the case of a random network (León et al., 2014). In other words, at the global level the clustering coefficient measures the tendency for "cliquishness". Networks with high clustering coefficients may be considered robust, because they can absorb random shocks.[33] In respect of the time windows considered, the clustering of the Hungarian RTGS network declined only slightly (by 8 percentage points), and its level is similar to that in other payment systems considered (46-53% in the observed period, see Table 1). This means that for any randomly selected node in the system, approximately half of the potential linkages between its neighbours were in fact active. Consequently, nodes (and their immediate neighbours) are mostly connected to one another, which is a property to be expected of an RTGS.

[32] This paragraph is partially based upon Annenberg Learner's website and Xrci (2014).
[33] Stam's (?) website.

There is virtually no link in the system the removal of which would cause a permanent breakdown in the circulation of payments between the two participants originally connected by this link (and would thus prevent liquidity from being rechannelled at the system level). What happens if a link connecting nodes "A" and "B" is removed from the system? Will this permanently terminate the connection between the two nodes (in other words: will this prevent liquidity from being rechannelled), or will there be an alternative path (e.g. through a third node "C") that enables "A" to resume transactions with "B"?[34] This is another way to measure the robustness of the network.[35] The value obtained was 1.21% for April 2008, 2.8% for April 2012, and 2.27% for April 2016. Hence, the share of links in the entire graph the removal of which would cause a permanent breakdown in the circulation of payments between the nodes originally connected by them (and would thus prevent liquidity from being rechannelled at systemic level) is very low. Since an RTGS enables every participant to submit payment orders to all other participants, the drop-out of a single link will not necessarily terminate the connection permanently; there will always be an alternative path for the two nodes concerned to bypass the original link and transmit liquidity to each other indirectly. The low values confirm the robustness of the network.

Figure 5
Possible payment scenarios between participants in the Hungarian RTGS



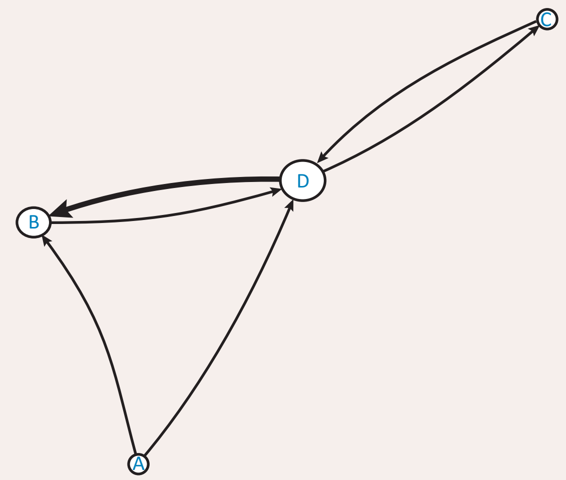
Source: Author's compilation. Case 4 represents the property of reciprocity.

[34] A possible practical interpretation is as follows: suppose Bank "B" needs intraday funds urgently, because it seeks to take a secured loan from the central bank. In the default case, it would expect funds from Bank "A", but Bank "A" is prevented due a communication error from submitting payments to Bank "B". In this case, Bank "B" can contact a third system participant, "C", which in turn will be able to submit payments to "B", ultimately enabling "B" to finance its secured loan.

[35] We calculated this using the results of the "fs" *("fraction of shortcuts in the graph")* output of the MatLab function "erange.m" in the *Brain Connectivity Toolbox.*

Reciprocity shows how stable certain business circles are within a system. In respect of a specific node, reciprocity shows the portion of the links connected to it that may be considered *bi-directional*, i.e. each party of the same edge *both receives and submits payments* to the other[36] (Figure 5). Reciprocity provides answers to questions such as how a given participant in the Hungarian RTGS is related to its immediate neighbours, i.e. how *constant* specific business circles are. Do business relations tend to be fixed or variable? The example in Figure 6 shows that node "D" is directly connected to each of the nodes "A", "B" and "C". If "D" both received payments from and submitted payments to each of its nodes, this would represent 100% reciprocity from the perspective of node "D". However, in our example, "D" submits and receives payments *simultaneously* through links to only two nodes, "B" and "C". This amounts to four directed links, two in each direction, while "D" only receives transactions from "A", without submitting any payments to it. Therefore, the reciprocity of "D" is derived as the ratio of the number of reciprocal links to the number of all links in the system: 4 / 6 = 0.666, i.e. 67 per cent.

Figure 6
Reciprocity – an example



Source: Output generated using the BOF-PSS2 simulator.

It is rare for a participant to act only as a *"liquidity sink"* or as a *liquidity provider* in a system. Between 2008 and 2016, reciprocity did not change significantly, varying between 39% and 43% on an aggregate level. That is, from the perspective of any specific node, close to one-half of all links with the system participants connected to it are reciprocal, another indication of the robustness of the overall network, and of its stability over time.[37] An even higher rate of reciprocity is observed for central participants, averaging between 76% and 78% in all three time windows considered, as opposed to the readings of 36-39% for the periphery (Table 2, for further information on the central-periphery clustering, see Section 5.1). Therefore, participants selected from the centre of the network are more likely to include fixed counterparties, in their case the probability of establishing active *bi-directional* payment connections will also be higher compared to peripheral nodes. That is, compared to marginal participants, they have a greater proportion of immediate neighbours with which they *both receive and submit payments* to each other. In general, there is a minimal presence of "free riders" in the system, so the statement made by Lublóy that it is rare for a node to *act only as a "liquidity sink" or only as a liquidity provider* in respect of a given counterparty[38] still stands after a decade. The high reciprocity observed at the centre of the network may be attributable to the presence of preferred business relationships, and to

[36] Source: Hanneman et al. (2005)

[37] If the data included the turnovers of the MNB, KELER, the Hungarian State Treasury, the Hungarian post, and other participants detailed in Section 3.1, the value of reciprocity would likely be higher.

[38] *"In general, none of the banks can act as a "liquidity sink" (receive large amounts of payments without sending large amounts of payments) or as "liquidity treasure island" (send large amounts of payments without receiving large amounts of payments) – not even in the short run."* (Lublóy, 2006, pp. 20–21.).

the fact that participants engaged in similar business activities are also likely to be strongly connected, e.g. banks playing an active role in the FX swap market will presumably trade with one another frequently and in large volumes, which could also lead to high reciprocity (Lublóy, 2006; Soramäki, 2014).

Table 2
Reciprocity values by system participant (April 2008, April 2012, April 2016)

Bank name	Comment	Reciprocity (2008 April)
Bank 1	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	83.23%
Bank 2	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	78.90%
Bank 3	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	74.26%
Bank 4	Critical system participant in terms of the transmission of payment liquidity in 2008 (based on the LSI). Moved to the periphery in 2012 and 2016.	75.54%
Average reciprocity (critical participants)		**77.98%**
Average reciprocity (peripheral participants)		**36.79%**
Average reciprocity (the whole graph)		**42.28%**

Bank name	Comment	Reciprocity (2012 April)
Bank 1	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	79.97%
Bank 2	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	75.22%
Bank 3	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	80.19%
Average reciprocity (critical participants)		**78.46%**
Average reciprocity (peripheral participants)		**38.92%**
Average reciprocity (the whole graph)		**42.74%**

Bank name	Comment	Reciprocity (2016 April)
Bank 1	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	77.13%
Bank 2	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	80.46%
Bank 3	Critical system participant in terms of the transmission of payment liquidity in all examined 3 time windows (based on the LSI).	71.16%
Average reciprocity (critical participants)		**76.25%**
Average reciprocity (peripheral participants)		**35.61%**
Average reciprocity (the whole graph)		**39.19%**

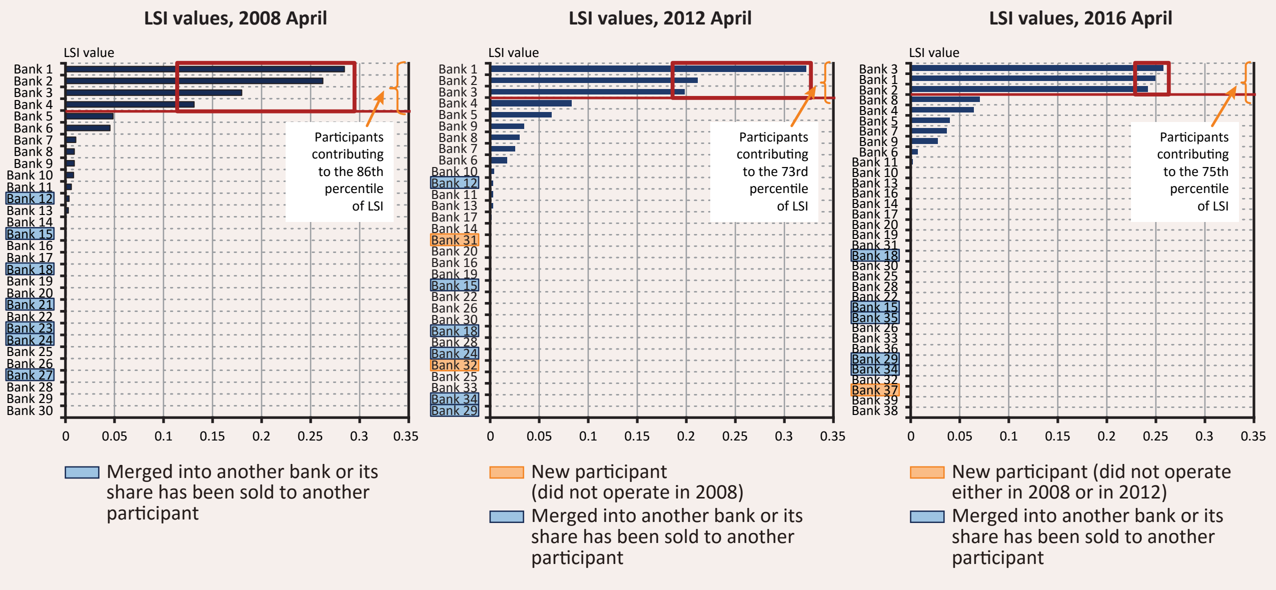
Source: Author's compilation based on MNB data, generated using the BOF-PSS2 simulator. Regarding the LSI-based central-periphery clustering, see Section 5.1 later.

5 Identification of systemically important participants

5.1 LSI – ANALYSING THE TRANSMISSION OF PAYMENT LIQUIDITY

Transaction-level data of the Hungarian RTGS suggest that no single participant in the system could be considered as "central" by itself. Based on the LSI, two distinct clusters emerge. One is the group of system participants which are less significant in regards to the transmission of liquidity. They are peripheral banks for which the R algorithm has generated very low authority and hub scores, and consequently, low LSI values. It is also possible to distinguish a cluster of banks that plays an important role considering the redistribution of liquidity. This includes a small group of three (for 2008: four) participants with the highest authority and hub scores. These players also qualify as the participants with the highest turnovers. Together, they generated more than one-half (51-60%) of the total turnover in the months considered, contributing to some 75-85% of the total LSI. In general, there is no single actor that could be considered as "central", instead there are more participants in the network that play key roles in terms of the redistribution of liquidity (Figure 7).

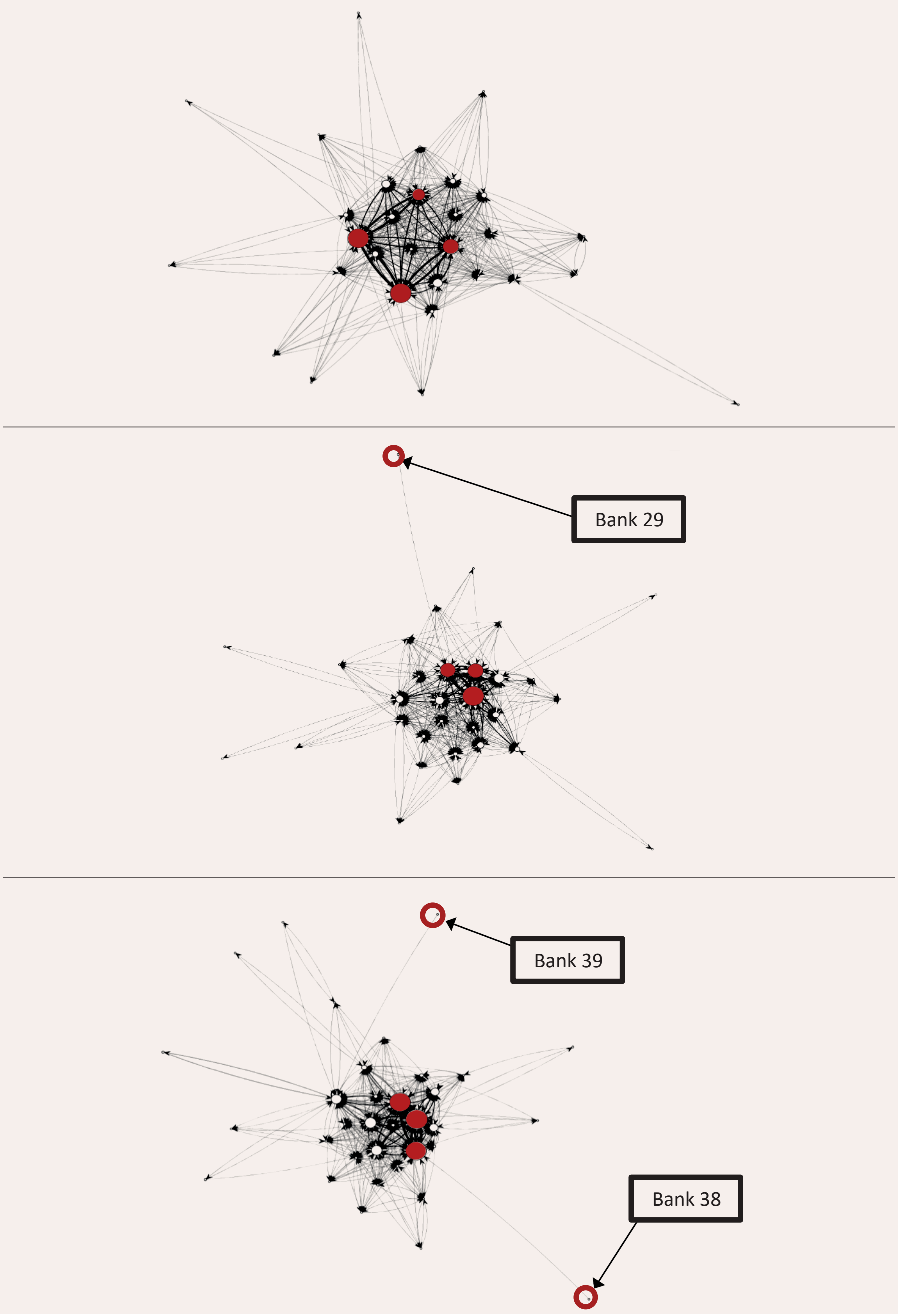
Figure 7
LSI values at the level of system participants (April 2008, April 2012, April 2016)



Source: Author's compilation based on MNB data. The related calculations were carried out in R, using the "igraph" package.

Between 2008 and 2016, no meaningful difference is found in the group of central participants. By 2016 the number of main spreaders had dropped slightly, corresponding to a minimal increase in concentration: while in April 2008 the core consisted of 4 participants, there were only 3 core participants in April 2016 and their relative ranking also changed slightly. Apparently, in 2008 each of the most important system participants had high but varying LSI values, as if four financial centres had been operating at that time, each with a different characteristic in terms of spreading liquidity. By 2012, peripheral participants appear to have been increasingly disconnected from the core, accompanied by a certain concentration within the core itself: Bank 1 had an extremely high LSI, followed by Banks 2 and 3, somewhat lagging behind, but with similarly high LSI scores. Between 2012 and 2016 the advantage of Bank 1 in spreading liquidity virtually evaporated; in the 3rd time window each of the top three participants achieved similar LSIs and became more closely positioned to one another. Other than the above, no meaningful change can be observed concerning the central participants, and the group of three banks with the highest turnovers which also play a crucial role in terms of transmitting liquidity essentially remained the same (Bank 1, Bank 2 and Bank 3) (Figure 7).

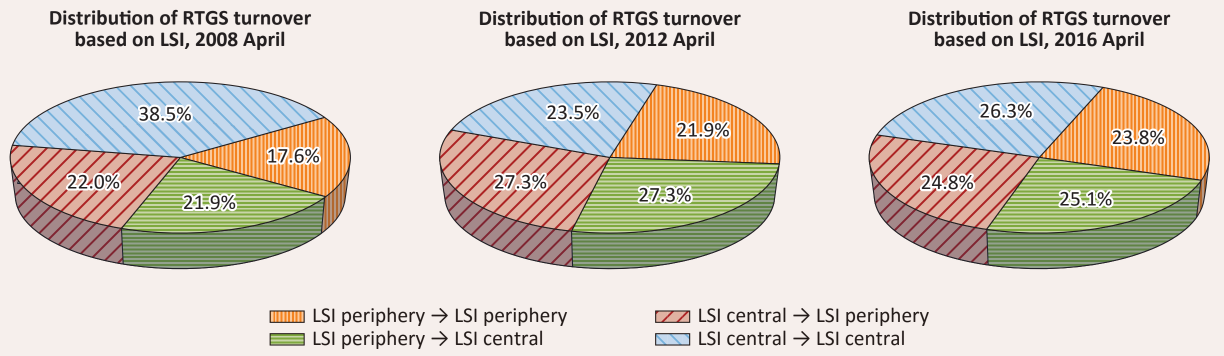
Figure 8
Network structure of the Hungarian RTGS (April 2008–2012–2016)



Note: The nodes marked in red qualify as main spreaders based on the LSI, and those marked in white belong to the periphery. The diameter of each node is proportional with its credit and debit turnover, while the thickness of each link represents the corresponding gross turnover. The graph's display is based on the output of the BOF-PSS2 simulator, the Fruchterman–Reingold algorithm has been applied.

The prominent role of systemically important participants can also be captured based on their shares in total turnover. The significance of participants belonging to the core based on their LSIs is also apparent from the fact that some 25-40% of the total turnover is generated amongst them. Figure 8 also shows that system participants positioned at the centre of the network are connected through a higher number and thicker links compared to the periphery.[39] About 20-25% of the payments generated by them are submitted to peripheral participants, and similar volume is observed in the opposite direction (periphery → main spreaders). To sum up, participants qualified as systemically important in the redistribution of liquidity based on their LSIs account for some four-fifths of the total turnover of the Hungarian RTGS (also taking into account the turnovers generated with the periphery). The remaining 15-25% of the total turnover is generated among peripheral banks (Figure 9).

Figure 9
Distribution of turnover in the Hungarian RTGS system by LSI-based clustering
(April 2008, April 2012, April 2016)



Source: Author's compilation based on MNB data.

The changes taking place at the level of participants during the period under review (the termination or establishment of direct membership of certain participants – that is, entering or exiting the network) primarily affected the *periphery* of the graph. The participants comprising the core of the RTGS remained essentially the same. We have previously noted that there was only a slight increase in concentration. In the period between 2008 and 2016, certain banks were acquired by or merged with other participants (e.g. participants 12, 15, 18, 21, 23, 27, 29, 34 and 35), Bank 12 had its direct membership terminated, whereas new participants entered the network (participants 31, 32, 37 and 38; see Figure 7). It is important to note that in reality a far greater number of changes occurred; however, as daily turnovers below HUF 1 billion are disregarded, the remaining movements of system participants are not relevant to our analysis. The point is that each of the above changes affected the periphery of the network. On those grounds, the network (particularly its core) is found to be stable and robust.

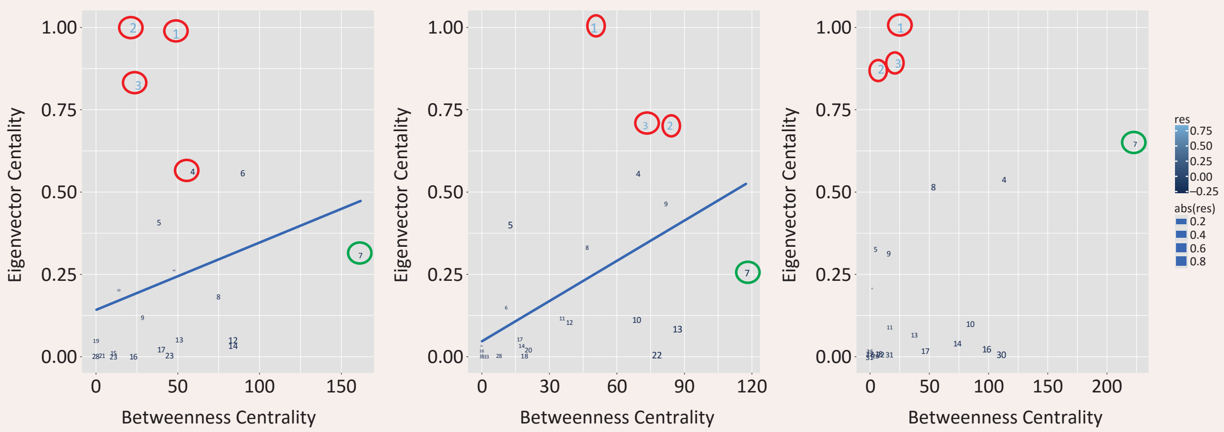
5.2 BETWEENNESS AND EIGENVECTOR CENTRALITY – THE CONWAY METHOD

The Conway analysis also shows that no single participant in the system could be considered as "central" by itself, instead there are several participants of similar importance. There is one particular actor who should be highlighted, due to its high betweenness it can be considered the *"bottleneck"* of the system in terms of payments. The Conway method produced similar results to those of the LSI algorithm. Participants with the highest model residuals – situated furthest from the reference line – are all crucial actors based on their LSIs regarding all 3 time windows (Figure 10, Table 3). Thus, there is no single prominent participant, and instead several system participants of similar importance operate in the Hungarian RTGS. Participant 7 is of special importance: it has a particularly high betweenness, i.e. it is located on a great number of shortest paths linking

[39] Just like in Japan, where *"Financial institutions situated in the middle of the network structure hold more links than those institutions on the periphery of the network."* Inaoka (2004), cited by Lublóy (2006).

nodes in the network. This is probably owing to the fact that it transacts with a very high number of banks, submitting payments to an average 14 participants on any given business day in April 2008, 15 participants in April 2012 and 26 in April 2016, whereas an individual participant typically transacts with "only" 7-9 other participants on a daily basis, on average (Figure 10). We also realised that there is a 99% correlation coefficient between the turnover generated by participants and their eigenvector centrality. (However, obvious causality does not necessarily exist, and the correlation may be determined by a – probably unknown – third factor. For the purpose of this paper, this is not addressed in greater detail.) The point is that the ranking of individual nodes by eigenvector centrality largely corresponds to their ranking by RTGS turnover.

Figure 10
Relationship of betweenness and eigenvector centrality for specific days
(1 April 2008, 12 April 2012, 28 April 2016)



Source: Based on MNB data. R output. For the code applied, see Conway (2009). The size of each node is proportionate to the residual values of the model. The red circles indicate systemically important participants based on their LSIs. The colour and intensity of each reference number shows the two possible extremes of the residual: light blue refers to high eigenvector centrality, whereas dark blue refers to high betweenness. Participant 7, which has the highest betweenness, can be found on the right in each chart (highlighted in green).

Table 3
Residuals of the top 6 players based on the linear model between 2 indices: betweenness and eigenvector centrality, also including the share of LSI

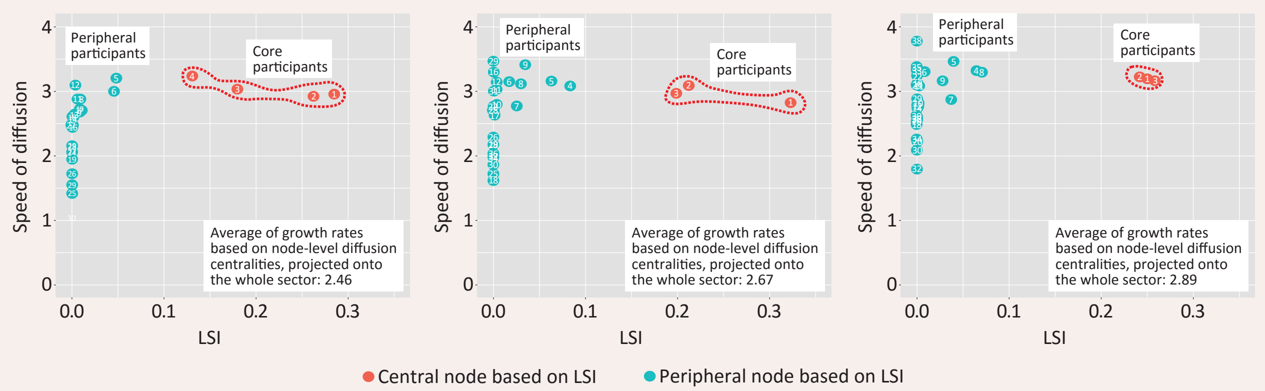
April 2008	Residuals (abs.)	Contribution to LSI (%)
Bank 2	0.81	26%
Bank 1	0.74	28%
Bank 3	0.63	18%
Bank 4	0.30	13%
Bank 14	0.28	0.1%
Bank 12	0.26	0.4%
April 2012	**Residuals (abs.)**	**Contribution to LSI (%)**
Bank 1	0.74	32%
Bank 22	0.36	0.0003%
Bank 3	0.36	20%
Bank 13	0.32	0.3%
Bank 2	0.31	21%
Bank 5	0.29	6%
April 2016	**Residuals (abs.)**	**Contribution to LSI (%)**
Bank 1	0.80	25%
Bank 2	0.69	24%
Bank 3	0.69	26%
Bank 30	0.32	0.001%
Bank 16	0.28	0.023%
Bank 8	0.27	7%

Source: Based on MNB data.

5.3 CONTAGION ANALYSIS BASED ON DIFFUSION CENTRALITY

Previously, we mostly relied on indicators capturing static network properties. We applied a variety of methods to identify central participants that are systemically important. In the following, a contagion analysis is carried out, which relies on diffusion centrality. The final results are illustrated in Figure 11.

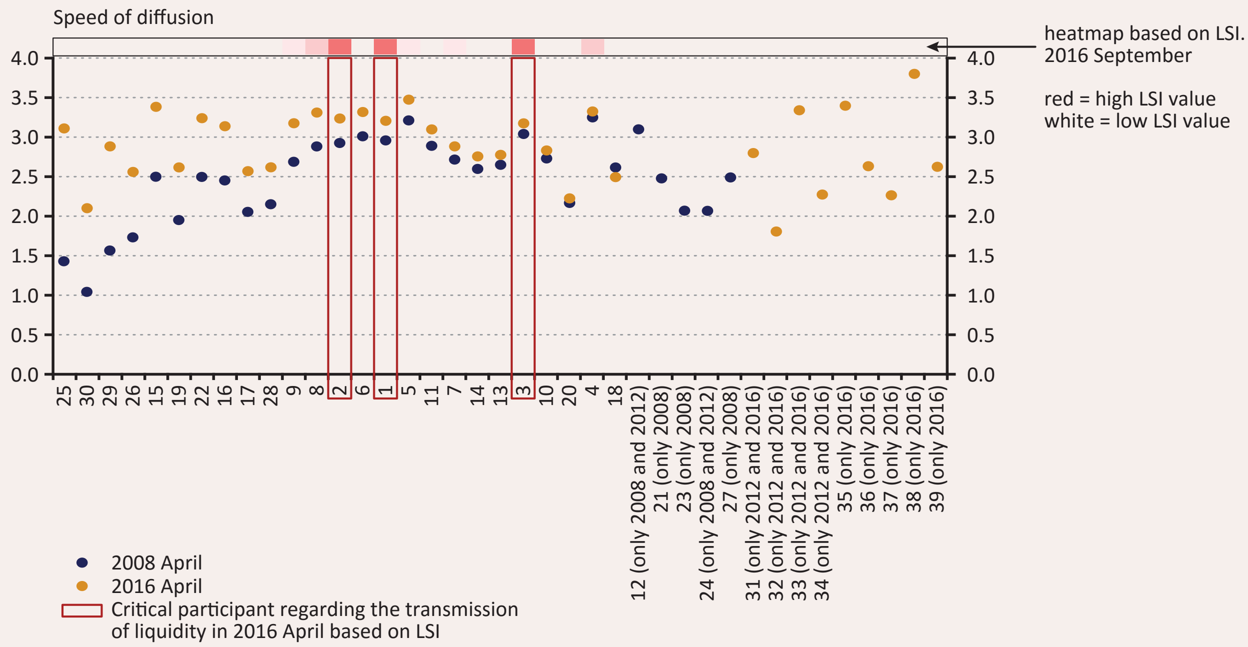
Figure 11
Relationship of diffusion growth and LSI scores
(April 2008, April 2012, April 2016)



Source: MNB data. R output. The numbers in circles indicate the anonymous reference numbers of the participants in the payment system.

The speed of diffusion increased for the majority of critical and peripheral participants, indicating an increase in contagion risk over the long term both at individual and aggregated level. All participants qualified as critical based on their LSIs can be considered risky in terms of diffusion, and it is also notable here how close the core actors have become following 2008, as if they had formed one single money centre. Conversely, although marginal on an LSI basis, certain participants had very high diffusions. These latter are system participants for which an operational disruption could primarily emerge as a *local problem* (with operational incidents mainly causing difficulties for their immediate neighbours), while the significance of this is negligible for the overall network. One example is participant 12 in April 2008. It is ranked in the middle of the grid based on its LSI (with a mere 0.36% contribution to the total LSI), which makes it peripheral. So an operational disruption in its case would not result in a systemic problem and would, at most, cause interruptions for immediately adjacent participants with which it transacts on a daily basis, given its property as the third largest risk spreader in the average of 3 days (3 units of time) elapsed. Similar properties are found in case of participants 29 (April 2012) and 38 (April 2016), both with LSI contributions converging to zero. Ranked higher on an LSI basis (and therefore important for the transmission of liquidity) but still peripheral, of particular note are participants 5 and 6 (April 2008) with a combined LSI contribution of close to 10%, and participants 4, 5, 6, 8 and 9 (April 2012 and 2016), with combined LSI contributions of 23% in April 2012, and 21% in April 2016. In their case, the impact of the spill-over of liquidity risk resulting from a potential operational disruption is relatively large in the average of 3 units of time, so the risk of potential contagion may be high. Considering their position as relatively important participants for the transmission of liquidity, a potential operational disruption in their case could cause significant risks *both locally and systemically*. It is also apparent that the diffusion centrality positions of most participants increased between 2008 and 2016, which means that for several participants, the risk of contagion may have become higher, with a greater speed of spreading liquidity risk. The change is also substantial at the systemic level: between 2008 and 2016, the speed of diffusion increased by approximately 18% (Figures 11, 12).

Figure 12
Diffusion speed of liquidity risk at the level of individual banks
(April 2008, April 2016)



Source: Author's compilation based on MNB data. The figure represents the averages derived from the increments of diffusion centrality values obtained for parameters T=1, T=2 and T=3, for April 2008 and April 2016. The participants qualified as systemically important on an LSI basis in April 2016 are highlighted in red, and a heat map, generated on the basis of the LSI scores for April 2016, is shown in the upper end of the chart.

5.4 SELECTING CENTRAL PARTICIPANTS BY COMBINING NODES IN THE NETWORK

The simultaneous drop-out of 3 or 5 system participants could carry higher risk than operational disruptions encountered individually by critical participants. However, each artificially selected group needs at least one critical participant that will ultimately amplify the contagion effect of its group, for all three time windows. Observing April 2008 data we can conclude the following. When participants 1, 29 and 30 are treated as a group (assuming their simultaneous drop-out following a hypothetical merger), the diffusion of liquidity risk resulting from its operational disruption – calculated over 3 units of time[40] – will reach a level (2.96) that exceeds the values measured *individually* for participants 1, 29 and 30 (2.95, 1.56 and 1.04, respectively). When participants 2, 29 and 30 are selected into a group, the diffusion of liquidity risk associated with this combined group will again exceed the values measured individually for each participant. Things look somewhat different if we modify the allowed number of participants that can be clustered; however, the results obtained using a 5-participant model will overall be similar to the previous model. Additionally, whether the model allows 3 or 5 participants, the artificially selected group will in both cases include at least one system participant that qualified as critical based on at least one of the previously detailed methodologies. On this basis, system participants 1 and 2 for April 2008 and April 2012 could be highlighted (they are also among the top 3 players generating the highest turnover in the RTGS). The rest of the participants which were included in the artificially created groups were originally peripheral based on the previous methods; so this basically means that their roles in the network have appreciated due to the groupings. For April 2016, we obtained similarly high contagion values due to the *forced* combination of certain nodes into a group; additionally, in groups of both 3 and 5, the high contagion power was primarily attributable to participant 2 (Table 4).

[40] Based on the input matrix, this is one month, but could also be one day for greater ease of interpretation.

Table 4
Diffusion centralities by bank for each iteration (T = 1, T = 2, T = 3), also indicating artificially selected groups of participants considered as central based on the *kpset* algorithm
(April 2008)

Bank name	diffusion centrality (T=1)	diffusion centrality (T=2)	diffusion centrality (T=3)	growth of diffusion centrality (T = 1; T = 2; T = 3)
Bank 4	2.09	8.00	21.28	3.24
Bank 5	1.29	4.83	12.97	3.21
Bank 12	0.38	1.35	3.59	3.09
Bank 3	2.80	9.60	25.39	3.04
Bank 6	1.42	4.77	12.62	3.00
Bank 1 + Bank 25 + Bank 28 + Bank 29 + Bank 30	2.78	9.84	23.60	2.97
Bank 1 + Bank 29 + Bank 30	3.54	11.74	30.60	2.96
Bank 1	3.71	12.17	32.00	2.95
Bank 2 + Bank 29 + Bank 30	3.55	11.46	30.44	2.944
Bank 2 + Bank 27 + Bank 28 + Bank 29 + Bank 30	2.46	8.41	20.59	2.937
Bank 2	3.67	11.65	31.05	2.92
Bank 11	0.55	1.76	4.50	2.89
Bank 8	0.70	2.23	5.76	2.88
Bank 10	0.77	2.27	5.69	2.73
Bank 7	0.89	2.59	6.49	2.71
Bank 1 + Bank 27 + Bank 28 + Bank 29 + Bank 30	2.88	8.99	20.21	2.69
Bank 9	0.78	2.26	5.61	2.68
Bank 13	0.48	1.37	3.37	2.65
Bank 18	0.05	0.14	0.34	2.61
Bank 14	0.27	0.75	1.84	2.59
Bank 15	0.11	0.27	0.65	2.49
Bank 22	0.01	0.02	0.05	2.49
Bank 27	0.00	0.00	0.00	2.49
Bank 21	0.01	0.02	0.04	2.48
Bank 16	0.06	0.16	0.38	2.45
Bank 20	0.04	0.08	0.17	2.16
Bank 28	0.01	0.03	0.06	2.15
Bank 23	0.01	0.02	0.04	2.07
Bank 24	0.01	0.02	0.03	2.06
Bank 17	0.09	0.17	0.36	2.05
Bank 19	0.07	0.14	0.26	1.95
Bank 26	0.00	0.01	0.01	1.73
Bank 29	0.00	0.01	0.01	1.56
Bank 25	0.01	0.01	0.02	1.42
Bank 30	0.00	0.00	0.00	1.04

Source: Author's compilation based on MNB data and R output. Values in red font colour refer to those system participants for which the kpset algorithm produced the available optimum at the indicated T parameter. In the case of the combined groups, the red squares indicate the core actors based on the LSI.

Table 4 (continued from previous page)
Diffusion centralities by bank for each iteration (T = 1, T = 2, T = 3), also indicating artificially selected groups of participants considered as central based on the *kpset* algorithm
(April 2012)

Bank name	diffusion centrality (T=1)	diffusion centrality (T=2)	diffusion centrality (T=3)	growth of diffusion centrality (T = 1; T = 2; T = 3)
Bank 29	0,00	0,00	0,00	3,47
Bank 9	1,00	4,19	10,96	3,41
Bank 16	0,03	0,13	0,37	3,30
Bank 5	1,54	5,66	15,00	3,16
Bank 6	0,81	2,99	7,87	3,15
Bank 12	0,36	1,31	3,47	3,15
Bank 2 + Bank 18 + Bank 19 + Bank 28 + Bank 29	2,78	10,34	26,51	3,14
Bank 8	1,11	4,00	10,50	3,12
Bank 2 + Bank 29 + Bank 32	2,91	10,61	27,26	3,11
Bank 4	1,80	6,38	16,88	3,09
Bank 2	3,00	10,76	27,77	3,09
Bank 11	0,37	1,28	3,35	3,03
Bank 31	0,09	0,32	0,84	3,00
Bank 3	3,05	10,22	26,45	2,97
Bank 1	4,40	13,14	35,14	2,83
Bank 1 + Bank 19 + Bank 28	4,11	12,35	32,52	2,82
Bank 10	0,50	1,50	3,89	2,80
Bank 13	0,44	1,35	3,43	2,79
Bank 7	1,25	3,76	9,55	2,78
Bank 22	0,02	0,04	0,11	2,77
Bank 20	0,08	0,24	0,59	2,72
Bank 24	0,00	0,01	0,03	2,72
Bank 14	0,22	0,62	1,57	2,68
Bank 17	0,28	0,80	1,96	2,64
Bank 1 + Bank 18 + Bank 19 + Bank 28 + Bank 29	2,99	8,19	18,31	2,49
Bank 26	0,02	0,05	0,11	2,29
Bank 28	0,01	0,03	0,07	2,18
Bank 19	0,04	0,09	0,20	2,18
Bank 15	0,04	0,08	0,17	2,04
Bank 33	0,00	0,01	0,02	2,04
Bank 32	0,01	0,01	0,02	2,01
Bank 34	0,00	0,00	0,01	1,98
Bank 30	0,03	0,05	0,10	1,88
Bank 25	0,01	0,01	0,02	1,73
Bank 18	0,02	0,03	0,05	1,63

Source: Author's compilation based on MNB data and R output. Values in red font colour refer to those system participants for which the kpset algorithm produced the available optimum at the indicated T parameter. In the case of the combined groups, the red squares indicate the core actors based on the LSI.

Table 4 (continued from previous page)
Diffusion centralities by bank for each iteration (T = 1, T = 2, T = 3), also indicating artificially selected groups of participants considered as central based on the *kpset* algorithm
(April 2016)

Bank name	diffusion centrality (T=1)	diffusion centrality (T=2)	diffusion centrality (T=3)	growth of diffusion centrality (T = 1; T = 2; T = 3)
Bank 38	0,00	0,01	0,02	3,79
Bank 5	1,24	4,96	14,47	3,47
Bank 35	0,01	0,04	0,12	3,39
Bank 15	0,02	0,07	0,20	3,38
Bank 33	0,01	0,03	0,08	3,34
Bank 4	1,74	6,56	18,87	3,33
Bank 6	0,59	2,21	6,36	3,31
Bank 8	1,84	6,89	19,68	3,30
Bank 22	0,02	0,06	0,18	3,24
Bank 2 + Bank 19 + Bank 37 + Bank 38 + Bank 39	3,41	12,40	35,10	3,24
Bank 2	3,54	12,77	36,36	3,23
Bank 2 + Bank 19 + Bank 38	3,51	12,67	35,93	3,23
Bank 1	3,64	13,00	36,88	3,20
Bank 9	1,21	4,26	12,00	3,17
Bank 3	3,78	13,12	37,54	3,17
Bank 16	0,12	0,42	1,18	3,13
Bank 25	0,02	0,08	0,23	3,10
Bank 11	0,35	1,18	3,30	3,10
Bank 29	0,00	0,00	0,01	2,88
Bank 7	1,87	5,76	15,45	2,88
Bank 10	0,38	1,13	3,02	2,82
Bank 31	0,05	0,15	0,40	2,80
Bank 13	0,30	0,87	2,29	2,77
Bank 14	0,14	0,39	1,03	2,75
Bank 36	0,00	0,01	0,02	2,63
Bank 28	0,03	0,09	0,21	2,62
Bank 19	0,10	0,29	0,67	2,61
Bank 39	0,00	0,00	0,00	2,61
Bank 17	0,14	0,36	0,90	2,57
Bank 26	0,02	0,05	0,13	2,56
Bank 18	0,05	0,12	0,29	2,49
Bank 34	0,00	0,01	0,01	2,27
Bank 37	0,00	0,01	0,01	2,26
Bank 20	0,16	0,34	0,79	2,22
Bank 30	0,08	0,16	0,36	2,09
Bank 32	0,00	0,00	0,01	1,80

Source: Author's compilation based on MNB data and R output. Values in red font colour refer to those system participants for which the kpset algorithm produced the available optimum at the indicated T parameter. In the case of the combined groups, the red squares indicate the core actors based on the LSI.

5.5 SUMMARY – IDENTIFYING SYSTEMICALLY IMPORTANT PARTICIPANTS USING SPECIFIC METHODS

In the Hungarian RTGS, there is no one single central participant, instead there are several systemically important participants. We have produced a summary table that shows the most important participants based on various methods. (Table 5). It clearly presents that there is no one single participant, instead there are multiple, similarly important actors in the network. Also, different participants are indicated as "critical" depending on which model is applied. Obviously, there are partial overlaps between the individual results. It is important to note that it is not necessarily the participants with the highest shares of turnover that may be considered "critical". For example, participant 7 featured the highest betweenness score in all three periods, meaning it lies on many of the shortest paths linking pairs of nodes in the system. The Hungarian RTGS has a hierarchical structure which can be typically clustered into 2 subsegments: core and periphery. The participants comprising the core essentially remained the same, with strong links to each other. The speed of diffusion increased for the majority of critical and peripheral participants, indicating an increase in contagion risk over the long term both at the level of individual banks and at the aggregated level. Among certain system participants, the degree of interrelations and financial interdependencies is also relevant (see the "grouping effect" columns). E.g. participant 2 was included in the artificially selected groups in all three time windows, whereas in April 2008 and 2012, participant 1 had very high contagion power in the new combined group. Some participants had their direct membership in the Hungarian RTGS terminated between the time windows considered, and at the same time new banks also entered the system. The changes[41] taking place at the level of participants during the period under review primarily affected the periphery of the graph, which is consistent with the findings of Lublóy (2006), i.e. the group of dominant and central participants remains relatively constant over the longer term.

[41] Entries to and exits from the Hungarian RTGS at the level of individual participants.

Table 5
Systemically important participants (April 2008, April 2012, April 2016)

2008 April	contribution to LSI (%)	share in turnover	LSI output	Conway method	Speed of diffusion (average based on T=1, T=2, T=3)	Rank	Group effect (3 particpant model)	Group effect (5 participant model)	Comment
Bank 1	28,46%	18%	central	high residual	2,95	6.	! + 29 + 30	! + 25+ 28 + 29 + 30 OR + 27 + 28 + 29 + 30	In case of an operational disruption it will certainly cause problems on systemic level (high turnover, grouping effect)
Bank 2	26,22%	18%	central	high residual	2,92	7.	! + 29 + 30	! + 27+ 28 + 29 + 30	In case of an operational disruption it will certainly cause problems on systemic level (high turnover, grouping effect)
Bank 3	17,98%	14%	central	high residual	3,04	4.			In case of an operational disruption it will certainly cause problems on systemic level (high turnover)
Bank 4	13,09%	10%	central		3,24	! 1.			In case of an operational disruption it will certainly cause problems on systemic level (high turnover, high diffusion)
Bank 5	4,81%	6%	peripheral		3,21	! 2.			It could cause problems on systemic level (high diffusion)
Bank 6	4,54%	7%	peripheral		3,00	! 5.			It could cause problems on systemic level (high diffusion)
Bank 7	1,00%	4%	peripheral	hith betweenness !	2,71	11.			It could cause problems locally (high betweenness)
Bank 12	0,36%	2%	peripheral		3,09	! 3.			It could cause problems locally (exceptionally high diffusion)
2012 April	**contribution to LSI (%)**	**share in turnover**	**LSI output**	**Conway method**	**Speed of diffusion (average based on T=1,**	**Rank**	**Group effect (3 particpant model)**	**Group effect (5 participant model)**	**Comment**
Bank 1	32,27%	21%	central	high residual	2,83	13.	! + 19 + 28	! + 18 + 19 + 28 + 29	In case of an operational disruption it will certainly cause problems on systemic level (high turnover, grouping effect)
Bank 2	21,19%	15%	central		3,09	9.	! + 29 + 32	! + 18 + 19 + 28 + 29	In case of an operational disruption it will certainly cause problems on systemic level (high turnover, grouping effect)
Bank 3	19,85%	15%	central		2,97	12.			In case of an operational disruption it will certainly cause problems (high turnover)
Bank 4	8,29%	9%	peripheral		3,09	! 8.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 5	6,24%	8%	peripheral		3,16	! 4.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 6	1,72%	4%	peripheral		3,15	! 5.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 7	2,51%	6%	peripheral	high betweenness !	2,78	16.			It could cause problems locally (high betweenness)
Bank 8	3,01%	5%	peripheral		3,12	! 7.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 9	3,42%	5%	peripheral		3,41	! 2.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 29	0,00%	0%	peripheral		3,47	! 1.	! + 2 + 32	! + 2 + 18 + 19 + 28	It could cause problems locally (group effect, exceptionally high diffusion)
2016 April	**contribution to LSI (%)**	**share in turnover**	**LSI output**	**Conway method**	**Speed of diffusion (average based on T=1, T=2, T=3)**	**Rank**	**Group effect (3 particpant model)**	**Group effect (5 participant model)**	**Comment**
Bank 1	24,97%	17%	central	high residual	3,20	11.			In case of an operational disruption it will certainly cause problems (high turnover)
Bank 2	24,17%	16%	central	high residual	3,23	10.	! + 19 + 38	! + 19 + 37 + 38 + 39	In case of an operational disruption it will certainly cause problems (high turnover, grouping effect)
Bank 3	25,77%	18%	central	high residual	3,17	13.			In case of an operational disruption it will certainly cause problems (high turnover)
Bank 4	6,43%	8%	peripheral		3,33	! 6.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 5	3,94%	6%	peripheral		3,47	! 2.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 6	0,76%	3%	peripheral		3,31	! 7.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 7	3,68%	9%	peripheral	high betweenness !	2,88	18.			It could cause problems locally (high betweenness)
Bank 8	7,02%	9%	peripheral		3,30	! 8.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 9	2,76%	6%	peripheral		3,17	! 12.			In case of an operational disruption it *could* cause problems on systemic level (high diffusion)
Bank 38	0,00%	0%	peripheral		3,79	! 1.	! + 2 + 19	! + 2 + 19 + 37 + 39	It could cause problems locally (grouping effect, exceptionally high diffusion)

Source: Author's compilation. In the diffusion speed column: the colours approximating red on the colour scale indicate higher values, while those approximating white indicate lower values. Red exclamation marks indicate that the system participant is ranked high according to the methodology applied and thus can be considered important.

6 Summary

In this paper, we investigated the Hungarian RTGS (VIBER) by means of network theory. First, we examined the network characteristics of the system. We observed whether these properties have changed over the long term (comparing the time windows of April 2008, April 2012, and Aprils 2016), and if so, to what extent. Second, we identified systemically important participants using various network theory methodologies. We hope that our paper will contribute to increasing the effectiveness of carrying out the central bank's oversight functions.

By international standards, the network of the Hungarian RTGS is relatively dense, which enables risks to be diversified on the one hand, although the same property is less ideal in terms of the diffusion of contagions. The level of the global clustering coefficient for the network of the Hungarian RTGS is similar to that in other payment systems considered (46-53% in the observed period), which means that for any randomly selected participant, approximately one-half of the potential linkages between its neighbours were in fact active. Consequently, banks (and their immediate "neighbours") are mostly connected to one another, which is a property to be expected of an RTGS system. In the periods considered, apart from a slight decrease, the indicator has not shown any material changes which points to the robustness of the system.

Another way to measure the robustness of a network is to determine whether the drop-out of a single link would permanently terminate payments between the two nodes originally connected by it, or there would be an alternative path for these two nodes to bypass the defaulted link and resume communications with each other. The value obtained for April 2008 was 1.21%, which basically means that there was not a single link the removal of which would have terminated communications between the two banks originally connected by it and would therefore have posed a systemic risk in terms of rechannelling payment liquidity. The same figure was 2.8% for April 2012, and 2.27% for April 2016. These results also confirm the robustness of the network.

It is rare for a participant to act only as a "liquidity sink" or only as a liquidity provider in the system. A higher rate of reciprocity is observed for the "core" participants that play an important role in the transmission of liquidity, averaging between 76% and 78% in all three time windows considered, as opposed to the lower readings of 36-39% for the periphery. Therefore, participants randomly selected from the centre of the network are more likely to include fixed counterparties, and in their case the probability of the establishment of active *bi-directional* payment connections will also be higher compared to peripheral banks. Between 2008 and 2016, aggregated reciprocity did not change significantly, and varied between 39% and 43% on an aggregate level, which also points to the stability of the overall network.

Based on the LSI indicator, two distinct clusters emerge: the first is the group of participants that play a key role in the *transmission of liquidity* within the system, and the other is the cluster of peripheral participants. The financial centre within the network of the Hungarian RTGS consists of several elements rather than a single element. Between 2008 and 2016, no significant difference was found in the group of central participants. The banks comprising the core of the RTGS essentially remained the same, with only minor variations regarding their LSI-based rankings. Accordingly, the core of the network can be considered stable. Participants qualified as systemically important in the redistribution of liquidity based on their LSIs, account for some four-fifths of the total turnover of the Hungarian RTGS (also taking into account the turnovers generated with the periphery)

The remaining one-fifth of the total turnover of the RTGS is generated by peripheral banks. We also observed that the changes taking place at the level of participants during the period under review (that is, entering or exiting the network) primarily affected the periphery of the network.

The Conway analysis also proved that no single participant in the system could be considered as "central" by itself, instead there are several participants of similar importance. Specifically, participant 7 could be highlighted, which, due to its high betweenness, can be considered as the *"bottleneck"* of the system in terms of payments regarding all three time windows. In other words, it lies on many of the shortest paths linking a large number of bank pairs in the system. This is explained by fact that it transacts with a very high number of system participants, submitting payments to an average 14 participants on any given business days in April 2008, 15 participants in April 2012 and 26 in April 2016, whereas an individual participant typically transacts with "only" 7-9 other participants on a daily basis, on average. So these features makes this a "bottleneck" node within the network and thus it deserves close attention as a result.

The speed of diffusion increased for the majority of critical and peripheral participants, indicating an increase in contagion risk over the long term at the level of individual banks. The growth is also substantial at the systemic level: between 2008 and 2016, the diffusion of liquidity risk increased by some 18% in the average of all nodes.

The risk of combined contagion of certain participants could be particularly high. From an overseer perspective, it is important not to treat specific institutions independently in isolation, but, as far as possible, to investigate several system participants combined into groups, because the level of complex financial interrelations among them may be absolutely critical when exploring systemic contagions. We found that the simultaneous drop-out of 3 participants could already carry higher risk than operational disruptions individually encountered by critical banks. This could mean that a participant that was previously *assumed* to be marginal may even see its role within the network appreciate significantly. However, each artificially selected group needs at least one systemically important participant that will ultimately amplify the contagion effect of the group, for all three time windows considered. Therefore, otherwise holding a dominant position in the transmission of liquidity, participant 2 was included in the artificially selected groups (of both 3 and 5 participants) in all three time windows, whereas regarding the time windows of 2008 and 2012, participant 1 had very high contagion power.

As we have seen, the network of the Hungarian RTGS is rather concentrated, with 3 or 4 participants accounting for some 75-85% of the total LSI. For that reason, useful enhancements could be made to the findings of this analysis by examining the network of the payment system and systemically important participants on a *subset excluding* those 3 or 4 participants. Also, it might be wise to further include other markets into the scope of such analysis, e.g. the network of future / derivative products, etc.

The results of each indicator showed that there were no significant changes regarding the network properties across the 3 time windows, confirming the robustness of the Hungarian RTGS and its stability over time, which is presumably attributable to the fact that the structure of the sector has not changed significantly. The methods described in this paper enable the identification of the risky groups in the system, contributing to more effective daily oversight and ultimately to the maintenance of financial stability, which is one of the main tasks of the central bank.[42]

[42] In the case of the Magyar Nemzeti Bank: *"Pursuant to Act CXXXIX of 2013 on the Magyar Nemzeti Bank, the primary objective of Hungary's central bank is to achieve and maintain price stability. One of the main responsibilities of the Magyar Nemzeti Bank (MNB) as set forth in the Act on the Magyar Nemzeti Bank is to promote the smooth execution of payments and to facilitate the reliable and efficient functioning of the payment and settlement systems. The smooth execution of payments and the reliable and efficient operation of payment and settlement systems are crucial for the execution of real economic and financial transactions."* (MNB, 2016).

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