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Topology of the Hungarian
large-value transfer system

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Topology of the Hungarian large-value transfer system
(A valós idejű bruttó elszámolási rendszer [VIBER] topológiája)

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Abstract

The paper deals with the *topology of the Hungarian large-value transfer system*, known as VIBER. The paper is generally descriptive in nature, the goal of the research being the assessment of the payment topology. A graph theoretical framework is applied; the graph representation allows a system-wide assessment of high-value payments. By taking interdependences between institutions into account, seven centrality indices are defined. The different measures of centrality focus on different aspects of the payment topology. The goal of applying graph theoretical methods is twofold. *Firstly*, the paper aims to analyse the *permanency of the network over time*. This is achieved by depicting the centrality measures, examining the correlation coefficients of the centrality indices across days, drawing empirical distributions and defining matrices of the strongest linkages. It is shown that the structure of the payments was permanent in June 2005; ad hoc relationships did not dominate the topology of the payments. The most central institutions were the same; the key players did not vary across days. One interesting feature of the topology was that only 30 per cent of the existing linkages were permanent linkages, although nearly 90 per cent of the payment orders were sent or received through these linkages. The Hungarian payment system can be characterised as a structure with multiple liquidity centres. *Secondly*, according to certain network criteria *institutions most capable of generating contagion* were identified. The fact that a liquidity crisis could arise if funds are not transferred to counterparties, although the counterparties might expect it, was taken into account. A well-defined group of institutions was identified; the illiquidity of these institutions could cause the most serious disruption of the payment system. Surprisingly, the institutions most capable of generating contagion were not the largest Hungarian banks measured by asset size. Rather they were directly or indirectly active players of the USD/HUF FX swap market.

JEL: G21, L10, L14.
Keywords: real time gross settlement, large-value transfer system, structure, network, topology, centrality indices.

Összefoglaló

A tanulmányban a hazai valós idejű bruttó elszámolási rendszer, a VIBER topológiájának leíró jellegű elemzésére kerül sor. A kutatás célja a bankok közötti fizetések hálójának statisztikai és gráfelméleti módszerekkel történő vizsgálata. A tanulmányban gráfelméleti alapokra építve hét központiság index kerül definiálásra és kiszámításra. Az egyes központiság indexek a fizetési rendszer topológiájának különböző aspektusait világítják meg. A gráfelméleti megközelítés célja kettős. A társadalmi kapcsolati hálózatok elemzésének módszertana egyrészt lehetővé teszi a tranzakciók révén összekapcsolt háló időbeli állandóságának mérését. Ennek eszközét jelentik az egyes központiság indexek grafikus megjelenítése, a központiság indexek napok közötti korrelációjának meghatározása, a bilaterális kapcsolatok stabilitásának és a rajtuk menő forgalomnak a vizsgálata, valamint a legerősebb kapcsolatok mátrixának megszerkesztése. 2005 júniusában a VIBER strukturális jellemzői időben stabilak. A központi szereplők köre időben állandó, az ad hoc kapcsolatok nem dominálják a topológiát. A topológia egyik érdekes vonása, hogy ugyan csak a kapcsolatok 30%-a állandó, viszont ezen bonyolódik a fizetési forgalom közel 90%-a. A háló vizuális megjelenítése azt jelzi, hogy a hazai fizetési rendszer struktúrája egy több likviditási központtal rendelkező struktúra. Emellett, a gráfelméleti megközelítés lehetővé teszi a rendszerkockázati szempontból kulcsfontosságú szerepet betöltő intézmények beazonosítását is. A kulcsfontosságú szerepet betöltő intézményi kör meghatározása során abból indultunk ki, hogy likviditási válság akkor alakulhat ki, amikor egy bank nem küldi el a fizetési tételeit, holott a partnerbankok számítanak a bejövő tételek finanszírozó szerepére. A kulcsfontosságú szerepet betöltő intézmények csoportja egyértelműen definiálható, a hálón lebonyolított forgalom ezen intézmények technikai vagy tényleges fizetésképtelensége esetén sérülne a legjobban. A rendszer stabilitása szempontjából kulcsfontosságú bankok nem a mérlegfőösszeg szerinti legnagyobb intézmények, hanem akár közvetlen, akár közvetett, módon az USD–HUF FX-swappiac aktív szereplői.

1. Introduction

Payment and settlement systems provide the technical infrastructure through which banking and securities market transactions are settled. The stable and safe functioning of interbank payment systems is crucial for the *financial stability* of the whole system. This is also reflected in the Act LVIII of 2001 on the MNB[1], in which the development of the payment and settlement systems and monitoring their activities in order to achieve sound and efficient operation and smooth money circulation are listed as basic tasks of the MNB. (Act LVIII of 2001 on … [2001], 4. § (5).)

In Hungary, as in many other countries, two interbank settlement systems operate side by side. The *Interbank Clearing System*, which is operated by Giro Zrt., only accepts batched orders provided that coverage of the transaction was ensured in advance. Giro Zrt. specialises in handling and clearing large volumes of low value commercial and private payment orders. In the Interbank Clearing System clearing takes place on a gross basis, but not in real time. Payment orders are not transmitted promptly; the transfers are cleared after the business day, between 5 p.m. and 2 a.m. The IBI (Interbank Indebtedness) matrix comprises the single credit and debit balances of the institutions. These are booked after the overnight processing on the current accounts of the institutions.

VIBER (Valós Idejű Bruttó Elszámolási Rendszer) is a real time gross settlement system in which the moments of clearing and settlement are not separated in time; booking is managed item by item continuously and in real time. In VIBER the processing of payment orders and their final settlement takes place continuously, while the participants concerned are notified in real time. VIBER is operated by the MNB and is designed to handle the payment and settlement of high value, urgent interbank transactions, which occur in relatively small numbers.[2] In real time gross settlement systems each settlement takes place by examining whether the bank has provided sufficient liquidity. If so, the payment orders are settled immediately. In Hungary the liquidity of direct participants normally consists of the positive balance available on the accounts of participants and the intraday credit line, which can be obtained from the central bank by providing collateral (in the form of securities). However, real-time gross settlement systems are costly for member banks, in the sense that explicit (interest rates or fees) or implicit (opportunity cost of posting collateral) charges for intraday liquidity management are in place.[3]

The turnover of the two interbank settlement systems was 24.7 times the projected GDP data. In 2004 the systems operated by the MNB handled roughly 90 per cent of the value of payment transactions. (Report on Financial Stability… [2005].)

In the Interbank Clearing System and VIBER payment orders are settled after cover checking; banks do not have open positions against each other resulting from payment and settlement. In this way the credit risk is totally eliminated. However, as a consequence of the profit maximizing policy of commercial banks *liquidity risk* could emerge in VIBER. In developed countries during a business day commercial banks settle transactions exceeding multiple (even several hundred) times their average account balances. Given the high turnover/balance ratio it could happen that a bank is not able to provide funds for its transactions for a little while as it has exhausted its current account. This situation can easily occur if one of the counterparties has lagged behind with an agreed money transfer on which amount the bank counted. This kind of liquidity risk stems from the incentives of system participants to free ride on the liquidity of other participants. However, a delay in settlement, while reducing the sender's liquidity costs, increases both delay costs and the receiver's liquidity costs, as the latter needs to finance its outgoing payments using other means. This creates a dead-weight loss at system level. The liquidity risk of the real time systems is reduced by the credit line provided in return for collateral and by automatic resolution of gridlocks.

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[1] MNB stands for Magyar Nemzeti Bank, the central bank of Hungary, hereinafter MNB.

[2] The Interbank Clearing System and VIBER complement each other harmoniously. There is no mandatory value limit or other criterion for channelling turnover between VIBER and the Interbank Clearing System. However, the pricing policy is developed to encourage the declared aim of the payment and settlement systems.

[3] The paper does not aim to compare different kinds of payment systems from the point of view of efficiency, costs or risks. For eleven separate studies on payment and settlement systems conducted using simulation techniques see Leinonen (2005). The study of Koponen and Soramäki (2005) examines, for example, the efficiency of four pre-selected payment systems from the standpoint of liquidity needs and settlement delay, while Leinonen and Soramäki (2005b) focus on settlement speed, liquidity usage, risk and cost components, as well as gridlock issues and optimisation possibilities.

It is widely accepted in the literature that payment systems could serve as an intermediary and under certain circumstances can transmit problems from one institution to other institutions. Assuming abnormal market conditions, unsettled payments of one or a couple of participants may become contagious and may eventually impede the effective functioning of the payment system or even the financial system at large. Thus, in the context of payment systems systemic risk could occur. According to Leinonen and Soramäki (2005a) systemic risk refers to the risk that the failure of one participant in a system to meet its required obligation could cause other participants to be unable to meet theirs. The cost of a systemic disturbance can be high. The chain reaction may expand into an overall systemic crisis and can jeopardise the operation of the entire financial system and ultimately the real economy. Leinonen and Soramäki argue that, as a consequence of the efforts to reduce risk in the interbank payment systems, the likelihood of a chain reaction caused by exposures in these systems seems currently to be relatively low. This is supported by the studies of Kuusaari (1996), Bech et al. (2002), Northcott (2002) and Blåvarg and Nimander (2002) focusing on the Finnish, Danish, Canadian and Swedish interbank payment systems. However, Blåvarg and Nimander point out that systemic risk comes mainly from foreign exchange exposures.

In this paper a graph theoretical framework is applied. The aim of the application of centrality measures is twofold. Firstly, the paper aims to analyse *the permanency of the network over time*.[4] Is the structure of the payments invariable over a longer time horizon? Or do ad hoc relationships dominate the topology of the payments? Are the most central institutions the same or do the key players vary across days? Do randomly selected days describe the topology properly? Secondly, according to certain network criteria *institutions most capable of generating contagion* are determined. Which institutions could cause the most serious contagion effects if they became illiquid or insolvent? Can we find a well-defined group of institutions whose illiquidity or insolvency could generate under certain circumstances severe domino effects? Are the most important participants in the payment system those institutions that we would expect from the point of view that they are the largest banks by asset size or have the most extended retail or corporate client base?

This paper assessing the topology of the Hungarian large-value payment system is of a descriptive nature. It is organised as follows. Section 2 highlights the methodological background of investigating the topology of the Hungarian large-value system. In Section 3 the data used and some descriptive statistics of the Hungarian payment orders are provided. Section 4 deals with the permanency of the payment structure over time. Seven centrality indices are defined and on the basis of the centrality measures the invariability of the payment topology is assessed. Different measures of centrality focus on different aspects of the payment topology. By examining the permanency of relations over time the constancy of exact linkages and the similarity of the strongest linkages are taken into account. The visualization of the topology (Section 5) of the Hungarian payment system provides important insights into the underlying structure. In Section 6 the institutions most capable of generating contagion are determined. From the point of view of financial stability not all the centrality measures are relevant. A liquidity crisis could arise if funds are not transferred to institutions, even though the institutions might have expected it. The systemically important institutions are determined on the basis of this assumption. Section 7 provides a conclusion and highlights the area for further research.

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[4] The permanency of the network corresponds to the stability of the underlying network structure. However, in network theory the stability of the network refers to the tolerance of the network in relation to random failures and attacks. (See, for example, Barabási et al. [2000] and Barabási [2002].) To avoid confusion, the word permanency or invariability is used.

2. Methodology

The *stability and robustness of the network* could be interpreted by finding out whether the number of interlinkages – degree distribution – follows a power law, by measuring the clustering coefficient of the network and by determining the average shortest path between any two vertices in the network. Barabási et al. (1999), (2000) and Barabási (2002) argue that the structure of the network influences the stability, the dynamic behaviour and the fragility of the underlying system. According to the classical analytical framework, one key feature of networks is the connectivity distribution $P(k)$, giving the probability that a node in the network is connected to k other nodes. Barabási et al. (1999) demonstrated that the existing empirical and theoretical results indicate that complex networks can be divided into two major classes based on their connectivity distribution. The first class of networks is characterised by a connectivity distribution that peaks at an average k and decays exponentially for large k. The most investigated examples of such *exponential networks* are the random graph model of Erdos and Rényi and the small-world model of Watts and Strogatz, both leading to a fairly homogeneous network, in which each node has approximately the same number of links, k. The connectivity distribution of exponential networks follows normal distribution, most of the nodes dispose of the average number of links, while only a limited number or even none of the nodes have only a few or lots of links. In contrast, results on large networks indicate that many systems belong to a class of inhomogeneous networks, called *scale-free networks*, for which $P(k)$ decays as a power law, free of a characteristic scale. The connectivity distribution follows a Pareto distribution, that is, many nodes have few links and a few nodes have many links. Whereas the probability that a node has a very large number of connections is practically prohibited in exponential networks, highly connected nodes are statistically significant in scale-free networks. Barabási, Albert and Jeong (2000) found that scale-free networks display a surprisingly high degree of tolerance against random failures, a property not shared by their exponential counterparts. The exponential network is more fragile, in the case of malfunctioning of its nodes (which could also be banks) the network can break easily into many isolated fragments, which can reduce the efficiency of the network dramatically. The scale-free networks are more resistant; from these networks we can eliminate a large number of nodes randomly and the network will not fall into fragments. However, the error tolerance comes at the expense of attack survivability. The diameter of scale-free networks increases rapidly and they break into many isolated fragments when the most connected nodes are targeted. The network theoretical framework provides an ideal tool to assess not only the structure of the payment system, but also the relationship between the topology of the system and its stability consequences.

A few recent papers *describe the actual topologies* observed in the financial system, building on the theory of complex networks. Boss et al. (2003) provide an empirical analysis of the network structure of the Austrian interbank market. The authors find that there are very few banks with many interbank linkages, whereas there are many with only a few links. The clustering coefficient of the network is low and the average shortest path length is relatively short. This network is found to be robust against the random breakdown of links, for example the default of single institutions due to external shocks. In was also shown that the interbank network shows a community structure that exactly mirrors the regional and sectoral organisation of the Austrian banking system. Inaoka et al. (2004) analyse the network structure of financial transactions, using the logged data of financial transactions through the Current Account of the Bank of Japan. The authors show that the network of financial transactions between financial institutions possesses a fractal structure. Moreover, it was found that financial institutions situated in the middle of the network structure hold more links than those institutions on the periphery of the network, implying that the formed structure is a result of the pursuit of efficiency rather than stability. The paper of Soramäki et al. (2006) describes the network topology of the interbank payments transferred between commercial banks over the Fedwire Funds Service in the United States. The authors find that the network is compact, despite low connectivity. It is also shown that the network includes a tightly connected core of money-centre banks to which all other banks connect. The degree distribution is scale-free over a substantial range. Soramäki et al. also proved that the properties of the network changed considerably in the immediate aftermath of the attacks of 11 September 2001.

Unfortunately, the theory of complex networks cannot be used in the case of the Hungarian payment system, as the number of participants is too small. Instead, a *graph theoretical framework* is applied, a method widely used in social network analysis. Graph theory has a wide range of applications. In addition to social network analysis graph theory is often employed in the fields of natural or engineering sciences. In finance the application of graph theory, similarly to network theory, has recently emerged. Graph representation allows a system-wide assessment of the financial linkages between

different kinds of institutions since it takes the interdependences into account.[5] Müller (2006) assesses contagion in the Swiss interbank market using data on bilateral bank exposures and credit lines. In the paper – based on a graph theoretical framework – banks that are, according to certain network criteria, systemically relevant are identified. In addition to the assessment of the network topology of the interbank market, by means of simulations the vulnerability and fragility of the interbank market are also captured and the spill-over effects of a bank failure on the liquidity and solvency of other banks are measured. The main findings are that the structure of the interbank market has a considerable impact on its resilience against spill-over effects; centralised markets are more prone to contagion than homogenous ones.

By carrying out a graph theoretical analysis of the payment data of VIBER, financial institutions that are, on the basis of their relations to other banks, *systemically relevant* could be identified. It is not sure that the largest banks (measured either by asset size or tier 1 capital) are the most important institutions in the payment system. According to Müller (2006) the systemic importance of an institution could be measured by several *network criteria*. The standard concept from graph theory states that vertices can be ranked on the basis of their centrality (Watkins and Wilson [1990], Faust and Wasserman [1994]). In the context of the payment system, a central vertex is an institution that has the following characteristics:

(1) The institution has settled payment orders with many other institutions.

(2) The institution has settled large amounts of payment orders.

(3) The illiquidity of the institution would directly or indirectly affect numerous banks or, on the contrary, the institution can be affected – directly or indirectly – by the illiquidity of many other banks.

(4) The counterparties of the institution are themselves important banks.

(5) The institution lies on numerous potential contagion paths.

Based on these characteristics the systemic relevance of a bank can be measured by several *centrality indices*. Different measures capture different aspects of systemic relevance. A bank can be considered as systemically important if it is an institution that is the most capable of generating contagion, it is the one that could transmit and exaggerate the initial shock, or it is the one that could suffer from the shock and thus intermediates the initial shock to the real side of the economy.[6] Following Müller (2006) and Hanneman and Riddle (2005) the topology of the payment structure is examined using seven centrality indices:

(1) In- and outdegree centrality indices show the number of linkages.

(2) Valued in- and outdegree centrality indices refer to the size of the settlement position of a financial institution.

(3) In- and out-proximity centrality indices reflect the distance from all other financial institutions.

(4) Rank centrality indices – defined either on the basis of outgoing or ingoing payment orders – consider an institution as important if it has many relations with other important institutions. These counterparties again are only important if they have themselves many relations with other important institutions and so on.

(5) Betweenness centrality defines the position of an institution in the network.

The centrality measures will be discussed in detail in the context of the permanency of the payment topology (Section 4).

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[5] In the rest of the paper the terminology of graph and network are used as synonyms. In the literature network analysis corresponds to the interpretation of graph theoretical relations on real data.

[6] Section 6 will discuss these issues in detail.

3. Data used

The data are obtained from the Hungarian large-value transfer system, known as VIBER. VIBER is managed by the MNB and operated on the basis of Hungarian legislation. In VIBER payments are denominated in Hungarian forints. The VIBER statistics contain every transaction of the 36 VIBER participants on a bilateral basis. In addition to the 29 commercial banks – in November 2005 the banking sector comprised 35 institutions – the MNB, the Central Securities Clearing and Depositary (the Hungarian CSD, hereinafter KELER), the Hungarian State Treasury (MÁK), the Hungarian Development Bank (MFB), the Hungarian Export Import Bank, the Hungarian Post and one savings co-operative (HBW Express) are also members of VIBER.

In VIBER there are four different types of payments. A payment order is considered as *customer payment* if its original sender or beneficiary or both are customers having an account with a direct or indirect VIBER participant.[7] *Bank-to-bank items* are payments ordered by direct or indirect VIBER participants, where beneficiaries are also direct or indirect VIBER participants. The third type of transaction is related to the settlement of the cash leg of securities transactions. KELER manages the securities accounts, but VIBER performs cash settlement for securities transactions of banks. *Delivery versus payment transactions* are settled in real time, item by item. Such DVP transactions include T+2 and T+3 day multi-net settlement, settlement of fixed-price auctions and free-market transactions of the Budapest Stock Exchange, OTC transactions, primary market transactions, repo transactions and settlement of derivative exchange transactions. The fourth type of transactions is *manual account transfers by the central bank*, using the CAS workstation. The CAS is the central accounting system of VIBER, which settles payment orders finally and irrevocably. The MNB uses the CAS to bring to book the second interbank indebted matrix, bankcard settlements, cash deposits and withdrawals at the MNB cash desk and at the cash desks of Regional Directorates, some part of deposit placements with the central bank, transfers due to corrections and prepayment of central bank credits. For a more detailed description of the payment orders settled in VIBER see VIBER System Description, Version 3.3. (VIBER System… [2005].)

Figure 1, Figure 2 and Table 1 show some descriptive statistics of VIBER. The transactions were classified into four groups; the items were designated as a bank to bank payment (B2B), customer payment (CUS), settlement transaction related to securities (SEC) or item booked manually in CAS (CAS). Figure 1 demonstrates the daily turnover of VIBER in 2005.[8]

Figure 2 presents the daily number of transaction settled in the Hungarian real time gross settlement system in 2005 for each transaction type. Table 1 shows the minimum, the average and the maximum of the daily turnover and the number of transactions settled in VIBER during the business days of 2005.

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[7] *Direct VIBER participants* are institutions that keep a current account or HUF account with the MNB and send and receive payment orders using their own interface. *Indirect VIBER participants*, also called correspondent credit institutions, are correspondent clients of direct VIBER participants.

[8] The extremely low volumes of payment orders are exclusively related to national holidays in the USA, UK or to those Saturdays which were working days in Hungary, but not abroad.

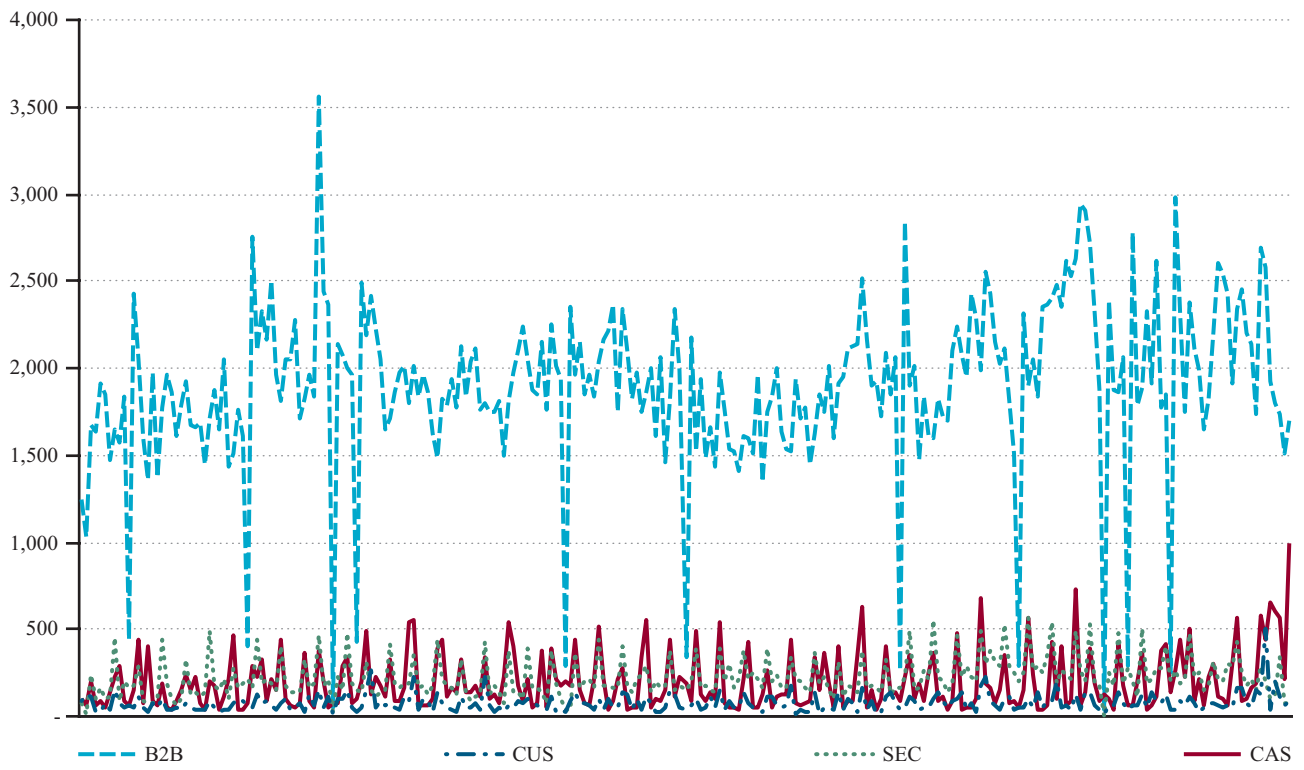**Figure 1**

Daily turnover of VIBER in 2005 (billion HUF)
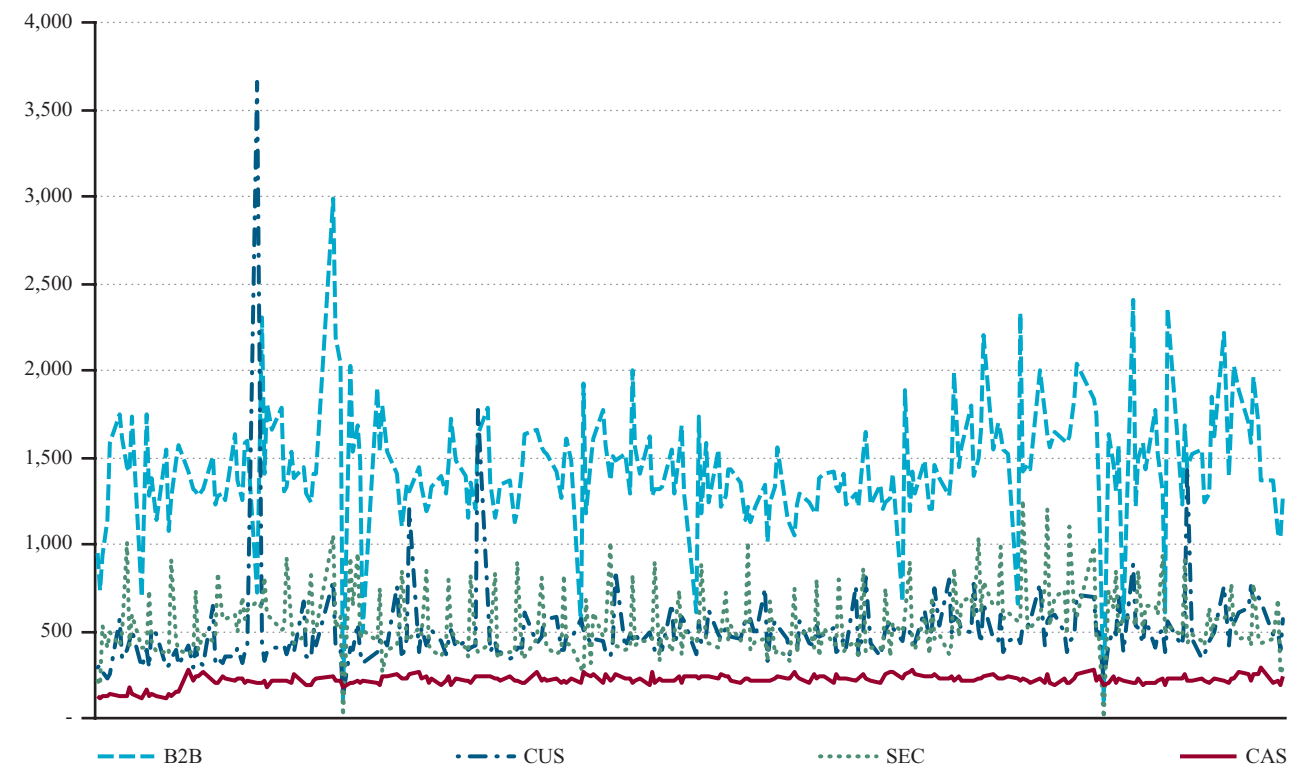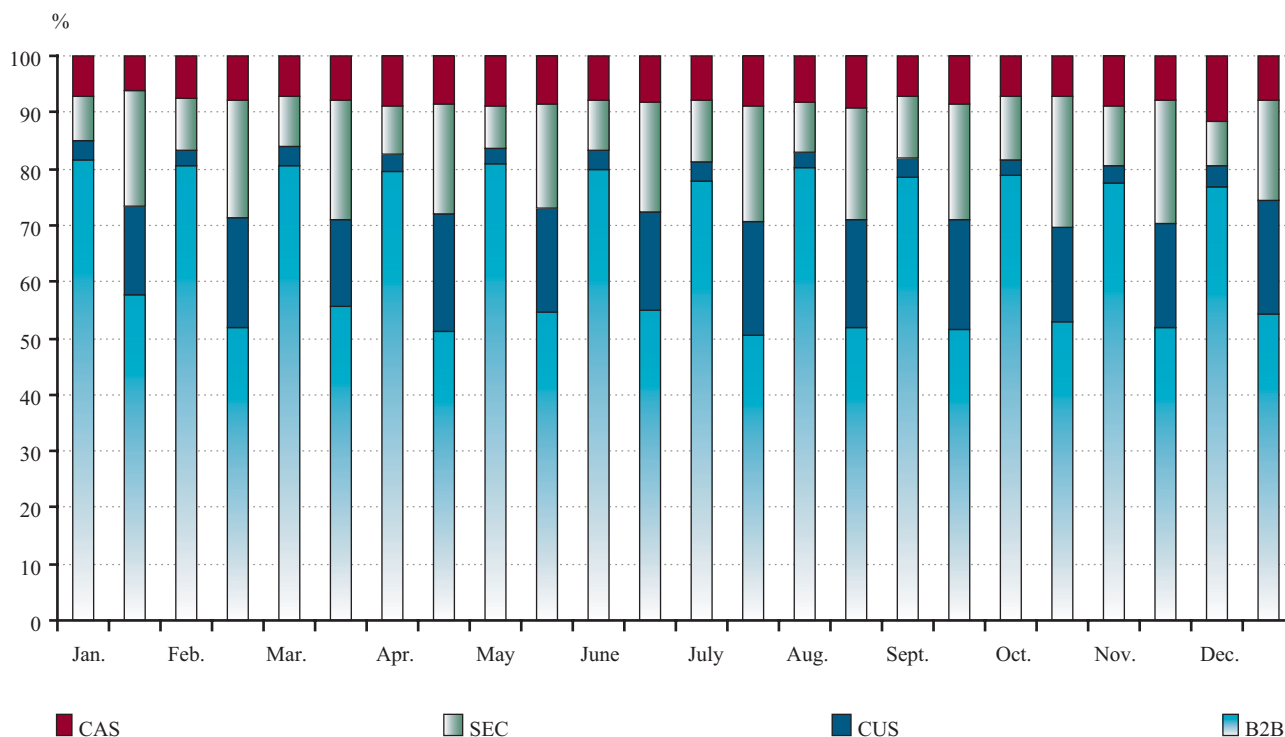

Figure 2

Daily number of transactions in VIBER in 2005

Table 1

Descriptive statistics of VIBER

		Minimum	Average	Maximum
Daily turnover (billion HUF)	B2B	38.95	1896.60	3554.14
	CUS	16.21	77.57	509.15
	SEC	0.12	222.27	563.52
	CAS	33.63	197.67	997.32
Daily number of transactions	B2B	96	1433.03	2987
	CUS	122	496.22	3652
	SEC	5	545.54	1250
	CAS	118	218.05	286

Figure 3 represents the proportion of the four different types of payments on a monthly basis. The first column of each month is based on the turnover data; the second column is based on the number of transactions. The percentage share of the turnover of the bank to bank items totalled 79.22% in yearly average, while, looking at the number of transactions, its share accounted for 54.24%. The respective figures are 3.34% and 20.30% for the payments initiated by customers, and 9.28% and 17.58% for the payment orders related to securities settlement. Thus, as also shown in Table 1, the bank to bank items are of higher value than the sample average, while customer payments and transactions related to securities are of lower value than the sample average.

Figure 3

Proportion of the turnover and the number of transactions of the four different types of payments in 2005

The VIBER statistics contain daily item by item payment data of the VIBER participants. For analytical purposes the bilaterally measured incoming and outgoing payments are written in a matrix form, presented in Figure 4.

Matrix of bilateral payments

Matrix P	Participating institutions						$\Sigma_j^N p_{ij}$
	1	2	3…	j	…N		
1							
2							
3							
…							
i				p_{ij}			i_i
…							
N							
$\Sigma_i^N p_{ij}$				o_j			

In the case of N participants we arrive at an asymmetric matrix of $N \times N$. The p_{ij} element of matrix P represents the daily cumulative incoming payment of participant i from participant j. Summing across row i gives the total incoming payments of participant i, that is, i_i represents the volume of transactions providing liquidity for participant i on a certain day. Summing down column j gives bank j's total outgoing payments, that is, o_j represents the transactions requiring the liquidity of participant j.

The matrix of bilateral payments can be constructed for each working day. For the sake of simplicity the *time horizon* of the analysis is the month of June 2005. The analysed month was selected randomly from the year 2005. The one month period can be considered as a short time horizon and thus the conclusions of the paper should be interpreted in the light of this caveat. In June no special event occurred; there was neither an idiosyncratic nor a macroeconomic type of shock that could have affected the payment system. In June the daily turnover and the daily number of transactions were typical for the year 2005 (see Figures 1 and 2). The proportion of the four different types of payments (measured either in the turnover or in the number of transactions) was just around the average (see Figure 3). Thus, in June 2005 the payment system can be characterised by normal market conditions.

4. The permanency of the payment topology

The unique data set used in this paper allows the graph representation of the incoming and outgoing payments. In the graph of bilateral payments, nodes represent VIBER participants and edges illustrate payments. The *graph* constructed on the basis of the data stemming from VIBER is *weighted and directed*. The weights of the edges equals the size of the daily cumulative payments, while the directions of the edges illustrate the course of the payments.

The invariability of the payment topology is assessed in different ways. The *first method* is related to the *centrality indices*. Centrality indices measure different dimensions of the structure of a network. The centrality indices listed in Section 2 are calculated for each day of the month of June 2005.[9] The similarity of the indices across days is measured by the following tools:

– By visualizing the centrality indices we can see whether those institutions that had high (low) centrality on one day tend to have high (low) centrality on the following days as well.

– Correlation of centralities across days.

The centrality indices describe different dimensions of the underlying network topology. However, the indices cannot reveal whether the existing linkages between banks vary across days or not. To overcome this problem the invariability of the underlying network topology is assessed by taking the *permanency of exact linkages* into account. This is done by means of drawing two empirical distributions. The first distribution shows how many links existed on a certain number of days (e.g. 1, 2, 3 or 22 days) out of the maximum 22 days. The second distribution highlights the distribution of the turnover of payments on the linkages that existed on a certain number of days (1 to 22 days).

As a third method of discovering the invariability of the payment topology *the similarity of the strongest linkages* is examined. I address the question whether the linkages with the highest daily turnover from day to day are the same or not. By means of matrices it is examined how similar are the strongest 5, 10 and 20 linkages of one day to the strongest 5, 10 and 20 linkages of other days.

4.1. CENTRALITY INDICES

4.1.1. Degree centrality

The position of an institution in the network can be characterised by the number of linkages it has to other institutions, that is, by the number of counterparties in the large-value transfer system. As in the payment context the direction of linkages is also crucial, we have to distinguish between *indegree and outdegree centrality*. Indegree shows the number of incoming edges (Equation 1). An institution has high indegree if it received payments from many other banks. Outdegree shows the number of outgoing edges (Equation 2). An institution has high outdegree, if it sent payments to many other banks. In- and outdegree centrality is defined formally as:

$$0 \le d_{in}\,(p_i) = \frac{\sum_{j=1}^{n}(a_j,a_i)}{(n-1)} \le 1$$

(Eq. 1)

$$0 \le d_{out}\,(p_i) = \frac{\sum_{j=1}^{n}(a_i,a_j)}{(n-1)} \le 1$$

(Eq. 2)

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[9] Rank centrality regards an institution as important if it has many relations to other important institutions. These counterparties again are only important if they have themselves many relations to other important institutions, and so on. In mathematical terms this means that in the case of n institutions there are n linear equations with n unknowns. The rank centrality of an institution can be determined by solving this system of linear equations. To do so, the n x n matrix of the payment transactions should be inverted. Unfortunately, the 36 x 36 matrix of bilateral payments is not invertible, and thus the rank centrality indices of the institutions can not be determined. Hereafter the rank centrality index is excluded from the analysis.

where p_i represents participant i, n represents the number of participants in the payment system, which is now 36, and a stands for the elements of the adjacency matrix. In an adjacency matrix in the intersection of row i and column j the element equals 1 if there is a direct relation between participant i and participant j, and 0 otherwise. More precisely, as the matrix is not symmetric, the element in the intersection equals 1 if participant i has received payments from participant j. The centrality measure is standardised by the maximum number of possible linkages. The measure can also be expressed in a percentage form. If the indegree centrality of a node is 0.8, it means that the node took advantage of 80% of its potential relations.

Based on the data of June 2005, Figure 5 shows the *indegree centrality* of VIBER participants. Institutions with the highest *indegree* are either the largest Hungarian banks measured by asset size or banks that are medium-sized but active in the foreign exchange swap market.[10] Figure 6 shows the *outdegree centrality* of VIBER participants. Looking at Figure 5 and Figure 6, we can see that, regardless of one VIBER participant, institutions with the highest outdegree are the same as institutions with the highest indegree.[11] The correlation between the participants' in- and outdegree across days is 0.8014 on average.

Figure 5

Indegree centrality
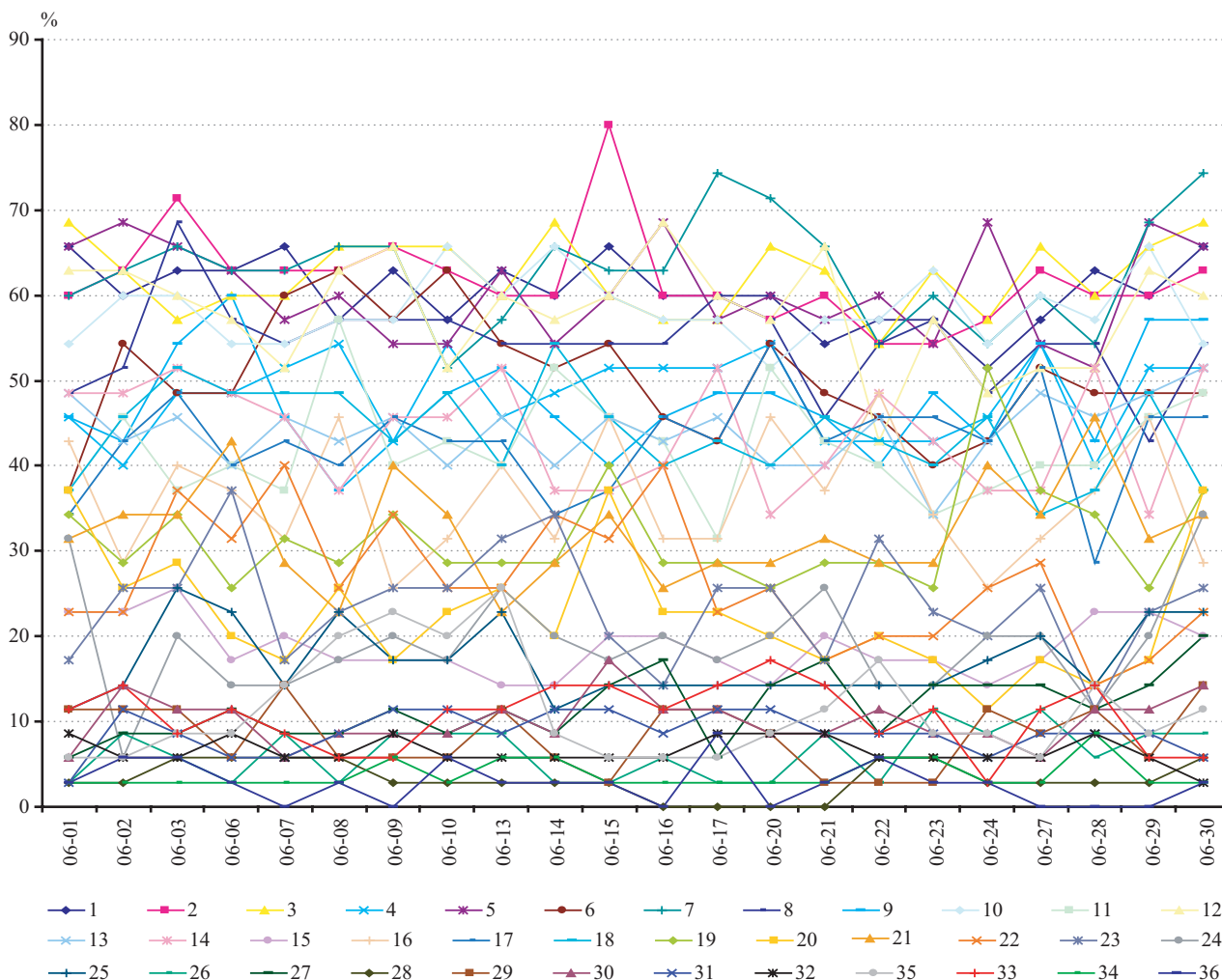
[10] As individual bank data cannot be published, the banks were coded and they obtained a number according to their systemic importance (see Section 5). To the systemically most relevant bank code 1 was designated, to the second most relevant bank code 2 was given, and so on.

[11] The institution with the outstandingly high outdegree (institution No. 15) is the Hungarian Post, which can be explained by the cheque system. In Hungary customers can send money to beneficiaries (e.g. the electricity works) indicated on the cheque through post offices. The customer gives the cash value written on the cheque to the Post and later on the Post transfers this money to the beneficiaries, whose account is managed in most cases by one of the banks participating in VIBER.

As demonstrated by Figures 5 and 6, institutions more or less vary in their in- and outdegree. The institutions have most of the time high, middle or low degree centrality. Thus, by picturing the value of the degree centralities the payment topology seems more or less permanent. Those institutions that had high (low) degree on one day tended to have high (low) degree on the following days as well.

The standard deviation of the number of incoming edges of the institutions ranges from 0.55 to 2.55, while the standard deviation of the number of outgoing edges of the institutions varies from 0.39 to 2.8. However, the number of incoming edges of a given bank can vary significantly, in a couple of cases the maximum range of the incoming edges (the difference between the maximum and minimum of the incoming edges) is 9. The range of the outgoing edges is 11.

The invariability of the degree centralities can be also captured by means of correlations. As shown in Table 2 the average of the correlations of indegrees across all pairs of days (e.g. the average of the 0.9380 correlation of indegrees of the 1st of June and the 2nd of June, the 0.9463 correlation of indegrees of the 1st of June and the 3rd of June, etc.) is 0.9473. The maximum of the correlation coefficients is 0.9784 and its minimum is 0.9097. The respective figures for outdegree centrality are also shown in Table 2.
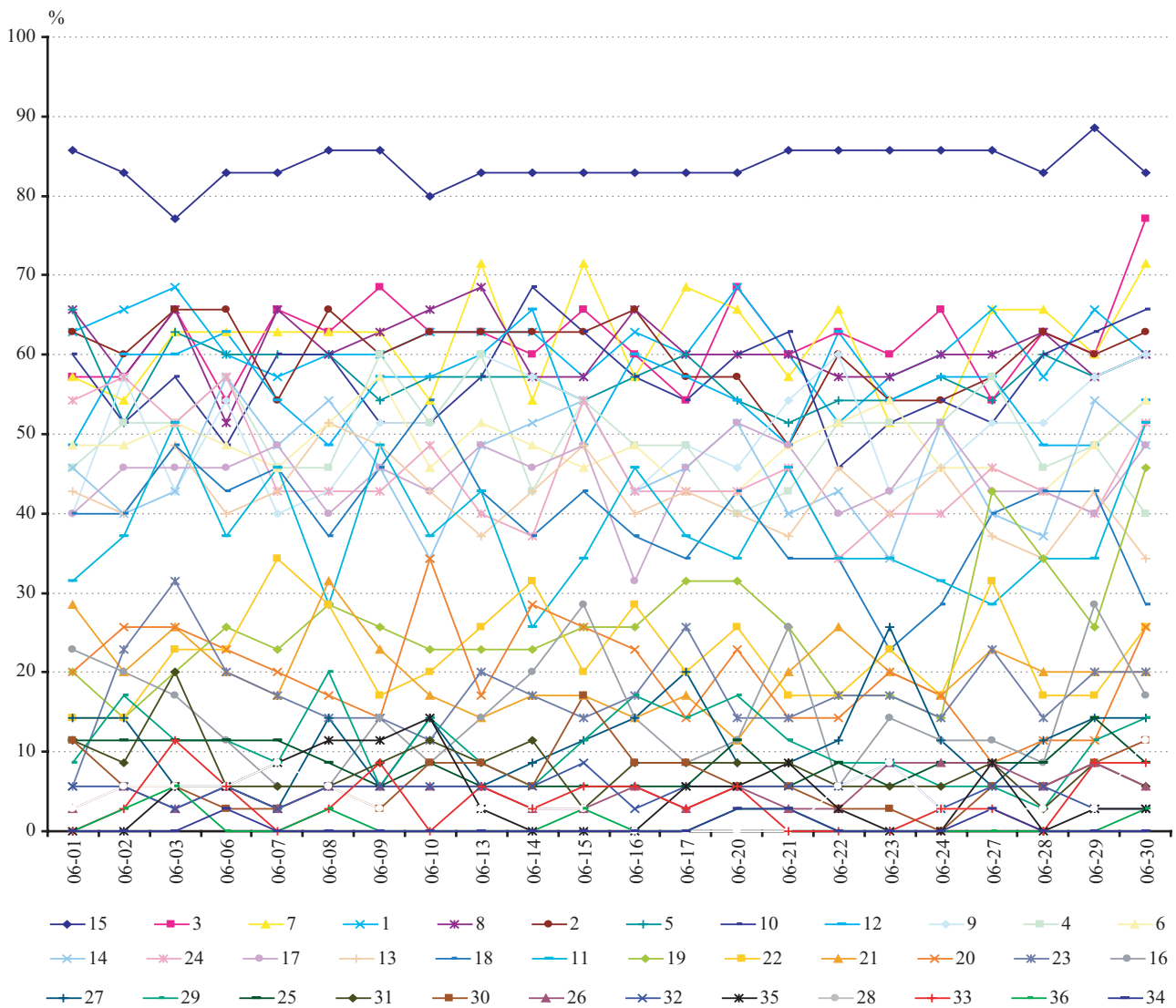
Figure 6

Outdegree centrality

Table 2

Correlation coefficients

	Indegree	Outdegree	Valued indegree	Valued outdegree	In-proximity centrality	Out-proximity centrality	Betweenness centrality
Average	0.9473	0.9595	0.9582	0.9611	0.8694	0.8348	0.7959
Maximum	0.9784	0.9819	0.9946	0.9936	0.9732	0.9878	0.9414
Minimum	0.9097	0.9261	0.9039	0.8918	0.6850	0.6229	0.5592

4.1.2. Valued degree centrality

The permanency of the structure means not only that VIBER participants have more or less the same number of counter-parties in the payment system, but that they send or receive more or less the same amounts of payments. In graph theoretical terms this means that the payment linkages of an institution have similar weights across days. The *valued indegree centrality* equals the proportion of participant *i's* incoming payments to total incoming payments. Similarly, *valued outdegree centrality* refers to the proportion of participant *i's* outgoing payments to total outgoing payments. Formally:

$$0 \leq Valued\_d_{in}(p_i) = \frac{\sum_{j=1}^{n} w(p_j, p_i)}{\sum_{j=1}^{n} \sum_{k=1}^{n} w(p_j, p_i)} \leq 1 \qquad \text{(Eq. 3)}$$

$$0 \leq Valued\_d_{out}(p_i) = \frac{\sum_{j=1}^{n} w(p_i, p_j)}{\sum_{j=1}^{n} \sum_{k=1}^{n} w(p_i, p_j)} \leq 1 \qquad \text{(Eq. 4)}$$

Expressing valued in- and outdegree centrality as a percentage, the index shows the market share of participant *i* in the payment system in relation to transactions providing and requiring liquidity.

Figure 7 demonstrates the *valued indegree centrality* of VIBER participants. The institution with the highest valued indegree centrality accounts for 20.37% of all incoming payments on average, the second most dominant actor has a market share of 14.98%, while the third most important participant possesses 14.23% of the market. In the second line we can find three other banks with an average market share of 8.72%, 6.74% and 6.24%. The high market share of the above mentioned institutions are surprising at first sight. With the exception of one bank which is among the largest Hungarian banks measured by asset size, the banks are definitely not the largest Hungarian banks. Banks with the highest valued indegree centrality are the 7th, 11th, 12th, 19th and the 21st in the ranking of banks according to asset size.[12]

However, previously it could have been expected (as it was expected), that the largest Hungarian banks would have the highest valued indegree centrality. The dominance of the medium and small-sized banks in the Hungarian payment system can be explained by the active role of the banks in the FX swap market. The banks themselves could also be active in the FX swap market, or they are members of large international banking groups active in the USD/HUF FX swap market, or they are correspondent banks of institutions such as JP Morgan or Morgan Stanley which are active in the USD/HUF FX swap market. Thus a large proportion of the transactions settled in VIBER is related to FX swaps. From another database it is known that the FX swap market is fairly concentrated and dominated by a couple of institutions, namely by the banks with the highest valued indegree centrality. Taking this into account, it is no longer surprising why medium and small-sized banks can play such an important role in the Hungarian large-value transfer system.[13]

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[12] By virtue of Figure 7 there is one participant (No. 16) in the system whose market share indicates a significant weekly cyclicity. This participant is the Hungarian State Treasury. Each Wednesday the proportion of the State Treasury's incoming payments to total incoming payments increases notably. This increment is related to the weekly discount T-bill auction settlements.

[13] For an overview of various patterns in the behaviour of non-resident participants in the FX swap market and the functions of the FX swaps (not enough liquid markets of discount treasury bills and government securities with maturity of less than 1 year, the hedged FX swaps enjoying priority over unsecured interbank deposit transactions, intra-year yield speculation, etc.) see the Developments in the structure of … [2005].

Figure 7

Valued indegree centrality
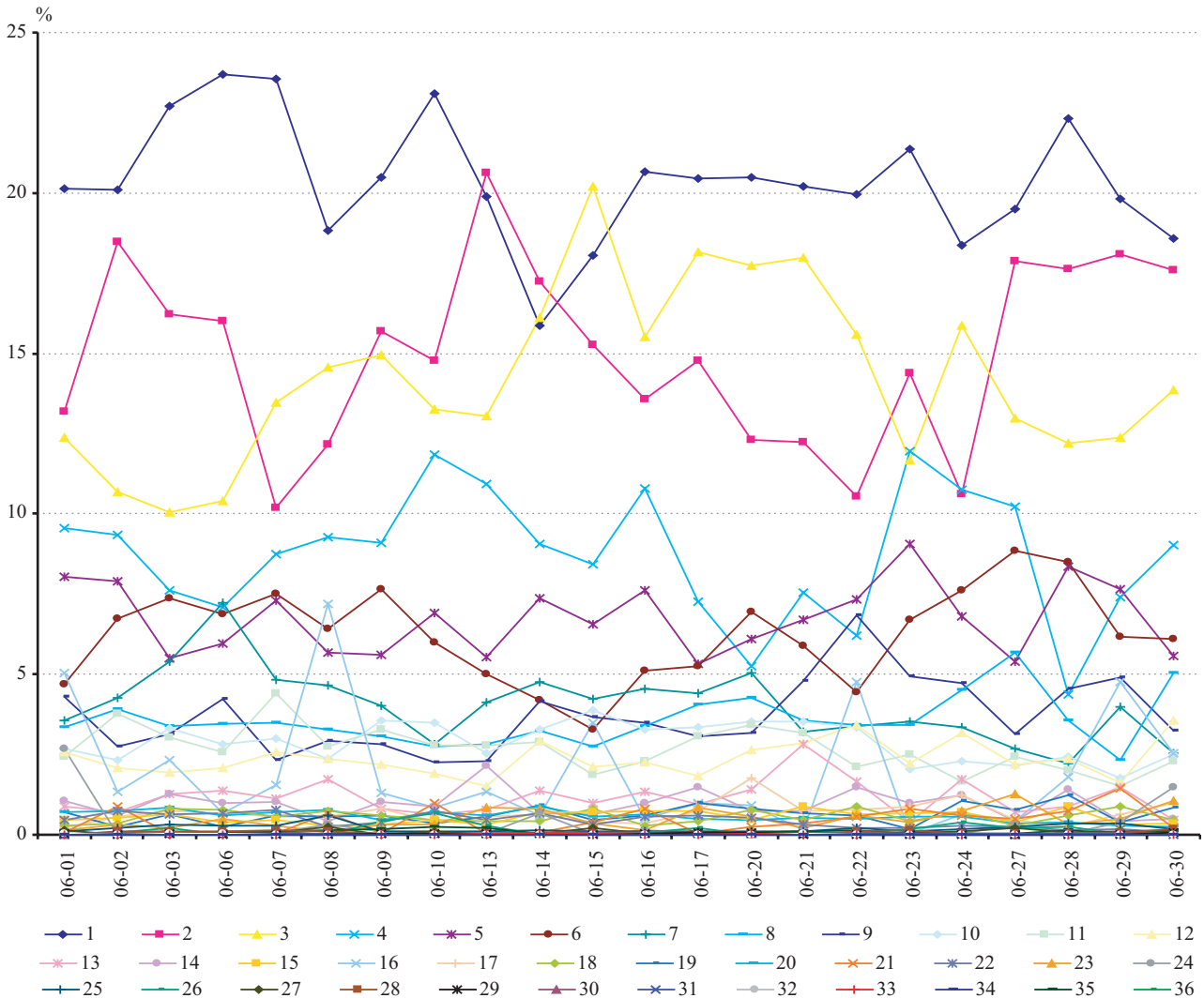
The correlation between indegree centrality and valued indegree centrality is moderate, namely 0.6492 on average across days. That is, institutions receiving ingoing payments from many (a few) counterparties are definitely not the same as institutions with a significant (negligible) amount of ingoing payments. The mean correlation coefficients between the various centrality measures are summarised in Table 3.

Table 3

Correlation coefficients between the various centrality indices

	Indegree	Outdegree	Valued indegree	Valued outdegree	In-proximity proximity	Out-proximity proximity	Betweenness
Indegree	1	0.8014	0.6492	0.6448	0.9441	0.6673	0.6535
Outdegree		1	0.5623	0.5714	0.7661	0.8192	0.7627
Valued indegree			1	0.9908	0.5890	0.4140	0.3970
Valued outdegree				1	0.5856	0.4157	0.4060
In-proximity					1	0.7069	0.6151
Out-proximity						1	0.6020
Betweeness							1

The *valued outdegree centrality* of VIBER participants is illustrated in Figure 8. Again, there are three participants – the same as in the previous case – with significantly higher valued outdegree centrality. The institution with the highest market share accounts for 20.43% of all outgoing payments on average. The second most significant actor has a market share of 15.25%, while the third most important participant possesses 15.40% of the market. In the second line we can again find the same three banks as in the case of valued indegree centrality, with a market share of outgoing payments of 8.67%, 6.70% and 6.25% on average. Again, these banks are either active in the FX swap market, or belong to an international banking group that is active in the FX swap market, or are simply correspondent institutions of active USD/HUF FX swap traders.

Figure 8

Valued outdegree centrality
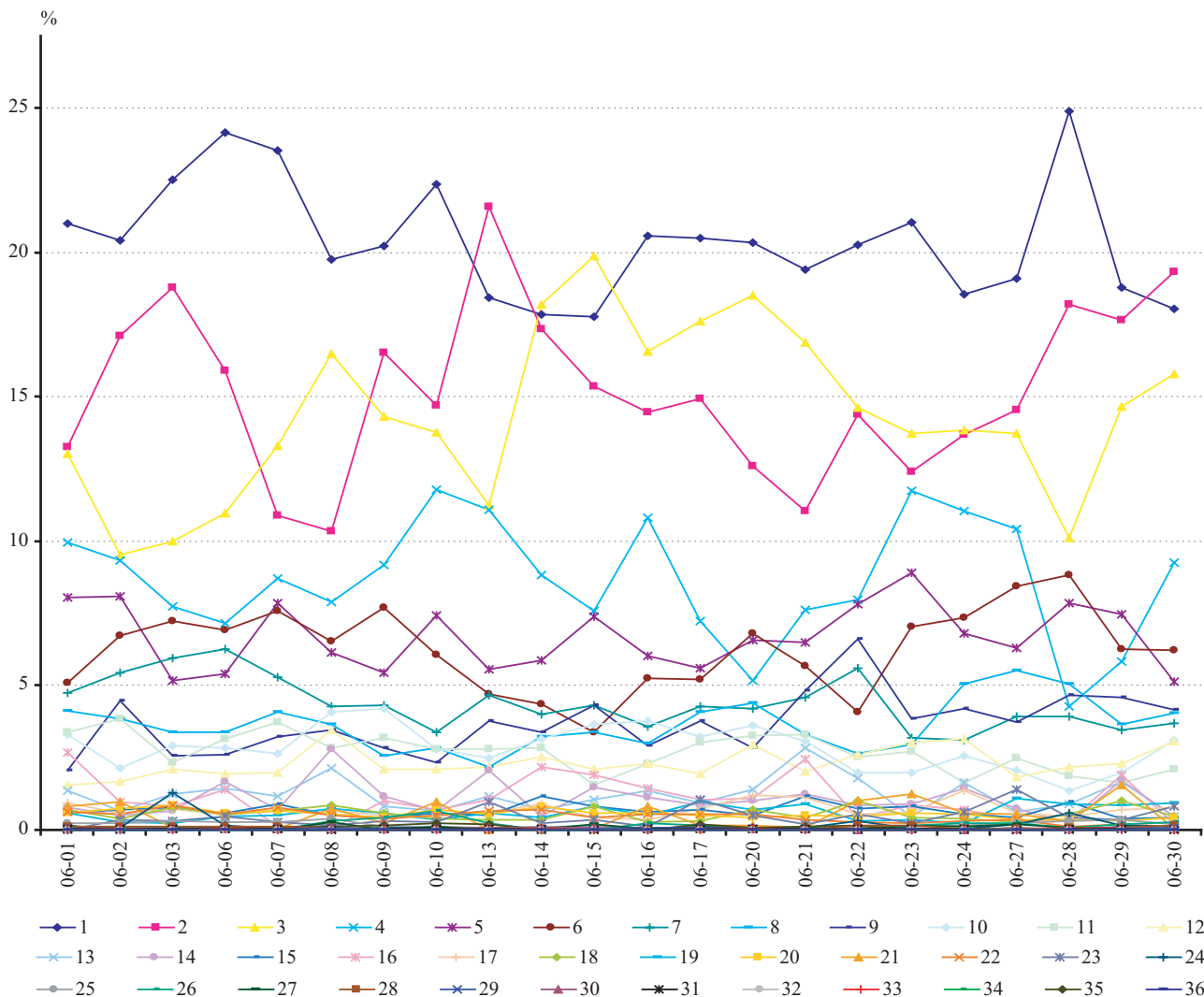
As demonstrated by Table 3 the correlation between outdegree centrality and valued outdegree centrality is moderate, 0.5714 on average across days. That is, institutions sending payments to many (a few) counterparties are definitely not the same as institutions with a significant (negligible) amount of outgoing payments.[14] The average correlation coefficient of valued indegree and valued outdegree centrality is remarkably high, 0.9908. That is, institutions receiving a significant volume of payments are also sending a significant amount of payments. This, however, is not surprising. VIBER is a large-value transfer system; banks send and receive payments through their interfaces. 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 a "liquidity

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[14] We should consider the case of the Hungarian Post. The Post had the highest outdegree, as it sent nearly all of the participants' payments. However, the amounts of payments are low; concerning the valued outdegree criteria the Post is only the 17th most significant institution.

treasure island" (send large amounts of payments without receiving large amounts of payments) – not even in the short run. Large outgoing payments have to be financed somehow, which implies large payment inflows.

If the permanency of the structure is tackled through the visualization of valued in- and outdegree centrality, the structure seems fairly stable. On the basis of Figures 7 and 8 we can see that institutions with a high (low) percentage of the total incoming or outgoing payments on one day tend to posses high (low) market shares of the incoming or outgoing payments on the following days. The respective correlation coefficients are also high; the relevant figures are presented in Table 2.

4.1.3. Proximity centrality

Another feature of the permanent structure of the payment system is that the proximity of the institutions to all other institutions does not vary significantly across days.

To be able to define more complex properties of node positions and the structure of a network as a whole the definition of geodesic distance is needed. *Geodesic distance (d)* is the minimum number of linkages that are required to reach node *j* from node *i*. In contrast with degree centrality measures, which only take the immediate ties an actor has into account, measures based on geodesic distance also take direct and indirect relations into account. However, the line values are disregarded.[15]

According to the *proximity centrality index*, a systemically relevant bank is characterised by two facts. First, it has a large influence domain, that is, the number of institutions that are directly or indirectly linked to the bank is high. Second, the average distance from all banks in the influence domain is small. Proximity centrality takes only those institutions into consideration that are directly or indirectly connected. *In-proximity centrality* is defined on the basis of direct or indirect incoming linkages. The index takes only those institutions into account which, directly or indirectly, send payment orders to bank *i*. The group of institutions defined on this way is called the influence domain of bank *i*. *Out-proximity centrality* is based on direct or indirect outgoing linkages. The index takes only those institutions into account to which bank *i* sends payment orders directly or indirectly.

Proximity centrality takes not only the number of institutions in the influence domain into account, but also the average distance from all other institutions in the influence domain. Thus, the index is defined as the ratio of the fraction of institutions in the influence domain of participant *i* and the average distance of the institutions in the influence domain from participant *i*. The index based on incoming and outgoing relations can be written formally as:

$$0 \le p_{in}(p_i) = \frac{I_i/(n-1)}{\sum_{j=1}^{n} d(p_j, p_i)/I_i} \le 1$$

(Eq. 5)

$$0 \le p_{out}(p_i) = \frac{I_i/(n-1)}{\sum_{j=1}^{n} d(p_i, p_j)/I_i} \le 1$$

(Eq. 6)

where I_i stands for the number of institutions in the influence domain of participant *i*. The proximity centrality of a participant was set to zero if there was no institution in its influence domain.

The *influence domain* – defined on the basis of both incoming and outgoing relations – of the VIBER participants is most of the times high and in a couple of cases zero. If an institution is linked to the network it has high influence domain. The influence domain does not vary across banks and days. Thus, according to the influence domain criteria the payment topology seems to be permanent.[16] The generally high influence domain of the participants is not surprising. It can be

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[15] One commonly used measure would be *closeness centrality*. As closeness is inversely related to distance, the closeness of participant *i* equals the reciprocal of the sum of geodesic distances from bank *i* to each actor *j*, where *i≠j*. The centrality measure should be normed by the theoretically most central actor, that is, by (n–1). Closeness centrality, however, can only be calculated for strongly connected networks. If in the directed graph there is at least one institution that is not reachable from an institution, the distance between these institutions would be infinite. Since in the payment system not all the institutions are strongly connected, the index of closeness centrality cannot be used. Instead, proximity centrality is calculated.

[16] However, based on the measure of influence domain the institutions cannot be differentiated as there is no variance across banks.

related to the small and rather centralised payment system. Namely, in a small and centralised system most of the institutions have a link to one institution with high degree centralities.

In the Hungarian payment system the average *distance* between two participants is 1.88. The maximum distance, that is, the diameter of the payment system is 4. On average, in 31.88% of the potential relations there are direct relations between two participants and in 8.02% of the cases there are no relations at all, either direct or indirect ones.

As demonstrated by Table 3 in-proximity centrality correlates the strongest with indegree centrality; the mean correlation coefficient is 0.9441. The out-proximity centrality correlates the strongest with outdegree centrality; the mean correlation coefficient being 0.8192. The correlation between the proximity centrality and the respective valued degree centrality measures is moderate or even week. The correlation coefficient between the in-proximity centrality and valued indegree centrality is 0.5890 on average, while the coefficient between the out-proximity and valued outdegree centrality is 0.4157 on average. In Section 6 this issue will be discussed in detail.

In comparison with other centrality measures the institutions differ less in their proximity centralities. (The corresponding figures of in- and out-proximity centralities are not shown.) However, we can still identify institutions that have most of the time high, middle or low centralities. The descriptive statistics of the correlation coefficients of the daily values of proximity centralities are presented in Table 2. As demonstrated by the table the corresponding figures are lower than in the previous cases, although the correlation is still high.[17] Based on the high average correlation of proximity centralities across days, the position of VIBER participants in the network seems more or less stable over time.

4.1.4. Betweenness centrality

The seventh centrality measure that serves to analyse the permanency of the payment topology is the betweenness centrality. According to the *betweenness centrality* the structure is invariable if an institution lies on the same number of potential contagion paths across days, that is, it connects the same number of institutions with each other.

In the graph theoretical literature betweenness centrality is defined as

$$0 \leq b\,(p_i) = \sum_{j<k} \frac{g_{jk}\,(p_i)}{g_{jk}} \leq 1 \tag{Eq. 7}$$

where g_{jk} is the total number of shortest paths between node j and k, and $g_{jk}(p_i)$ is the number of shortest paths between node j and k through i (i, j and k should be distinct). Thus, the betweenness of participant i is the sum of the proportion of all geodesics linking participant j and participant k which pass through participant i. The betweenness centrality of participant i basically measures the sum of probabilities across all possible pairs of participants that the shortest path between participant j and k will pass through participant i. Accordingly, the values of betweenness centralities can be expressed in percentage terms.

Betweenness is a measure of the number of times a participant occurs on a geodesic. The measure – similarly to proximity centrality – disregards the line values; however, it takes direct and indirect linkages into account. If the participant is situated on all geodesics, the index reaches its maximum. If the participant is not situated between any two nodes, the index equals zero.

Betweenness centrality should be analysed carefully. As we have seen previously, in more than 30% of the potential relations there are direct relations between two participants, that is, there are no participants "between" the others. In this

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[17] The strong, but (in comparison with the previous indices) lower correlation can be partly explained by the "passive" banks. Let us suppose that an institution does not send payment orders to VIBER participants regularly, but only to a couple of institutions on a few days. In most cases the influence domain is zero and the average distance from all other banks is infinite. In this case the proximity centrality was considered as zero. However, if one of the "passive" institutions sends a payment to an "active" VIBER participant, the number of institutions in the influence domain increases; through the active VIBER participant the institution can reach indirectly many other participants. At the same time, the average distance from all other institutions decreases, and overall the proximity centrality increases significantly.

case it can easily happen that institutions having links to institutions on the periphery become more central, as they are the ones being between the others and the institutions on the periphery.[18] Secondly, if a new link appears the between-ness of the participants can change drastically.

There are five institutions that have a betweenness centrality higher than 5% on average. (The corresponding figure of betweenness centrality is also not demonstrated.) However, even in the case of the institution with the highest between-ness centrality the average probability that the institution lies on the shortest path between any two participants is 11.37%, which is fairly low. As mentioned previously, this is due to the fact that a high proportion of connections can be made in the network without the need of any intermediary; hence there cannot be a lot of "betweenness." As shown in Table 3, betweenness centrality correlates the strongest with indegree centrality (0.6535) and with outdegree centrality (0.7627).

The average correlation of the daily values of betweenness centralities is 0.7959, which is still high, though slightly lower than in the case of previously defined indices. This can be explained by the higher sensitivity of the measure to a new link. The maximum and the minimum of the correlation coefficient are also shown in Table 2. The higher range and stan-dard deviation of betweenness centrality are also in line with the sensitivity of the index to small changes in the network topology. In summary, on the basis of the betweenness centrality the structure of the network seems more variable than on the basis of the previously defined indices. However, the mean correlation of betweenness centralities across all pairs of days is high. That is, the structure is a more variable, but still stable.

4.2. PERMANENCY OF EXACT RELATIONS OVER TIME

One drawback of the analysed centrality measures is that they are not able to take into account *the permanency of exact linkages*. Do the existing linkages between banks vary across days and do the institutions send payment orders to some banks on one day and to others on the next? Or are the bilateral relations constant? The permanency of relations over time is shown in Figure 9. Note that only those linkages were taken into account where at least one payment order was sent or received during the month of June 2005. In 486 out of 1260 cases (38.57%) no payment orders were sent between the institutions on any of the days. These links were disregarded.

Figure 9

Permanency of relations over time

Existing links over time between pairs of banks
(in number of days)

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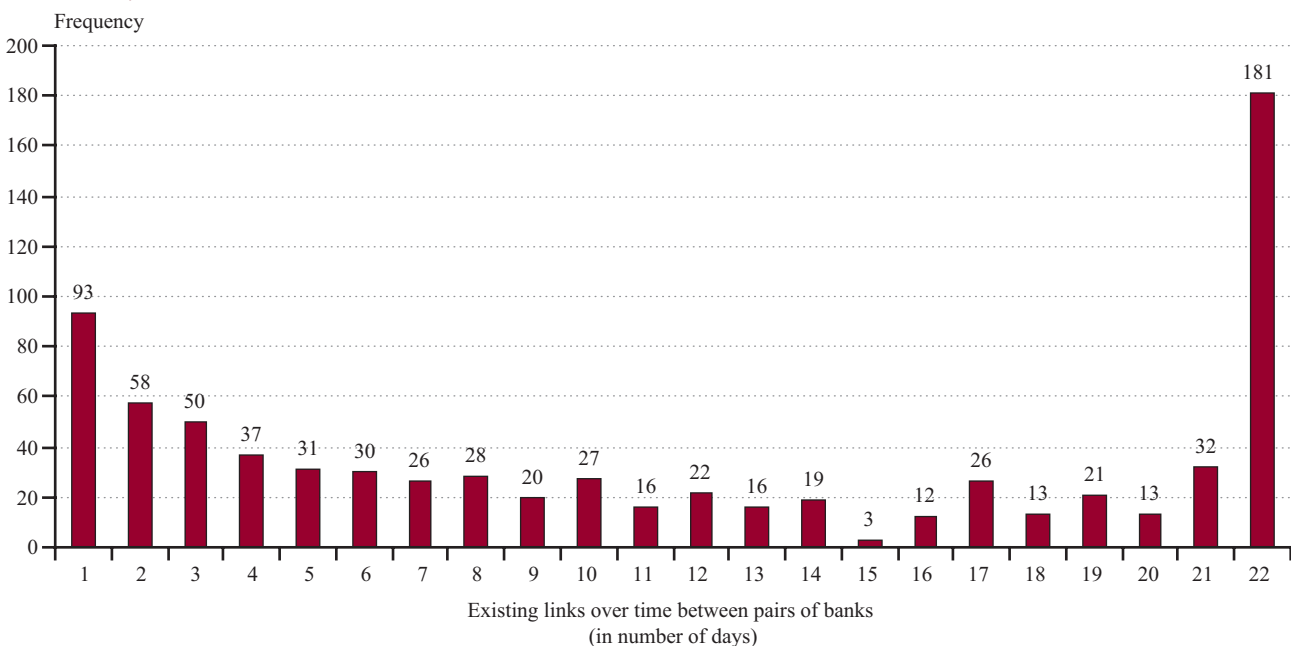
[18] This can be easily seen on the orgnet homepage (http://www.orgnet.com/sna.html). The example of the homepage shows that the actor Heather has the highest betweenness centrality as it links two actors of the periphery to the other actors in the network.

The *x* axis represents the number of days on which a link existed between two institutions. The maximum number of days on which an exact link could exist is 22, as in June 2005 the number of working days was 22. The *y* axis represents the frequency of the links. Thus, for example, there were 27 pairs of institutions that had linkages to each other on 10 days out of the maximum 22. The U-shaped form of the distribution presented in Figure 9 is remarkable. There are many ad-hoc linkages and many fairly constant relations. Taking only those 774 linkages into account where at least one payment order was sent during the month of June, around 20% of the pairs of institutions have ad hoc relations, that is, they have linkages on less than 10% of the days. On the other hand, *around 30% of the pairs of institutions have permanent relations as they have linkages to each other on more than 90% of the days*.

Figure 10 depicts one interesting feature of the permanency of the payment linkages. Namely, 83.42% of the payment orders of June were sent or received through linkages that existed on each day. 88.38% of the turnover was realised through linkages which were present in more than 90% of the days.

Figure 10

Turnover of the ad hoc/permanent linkages
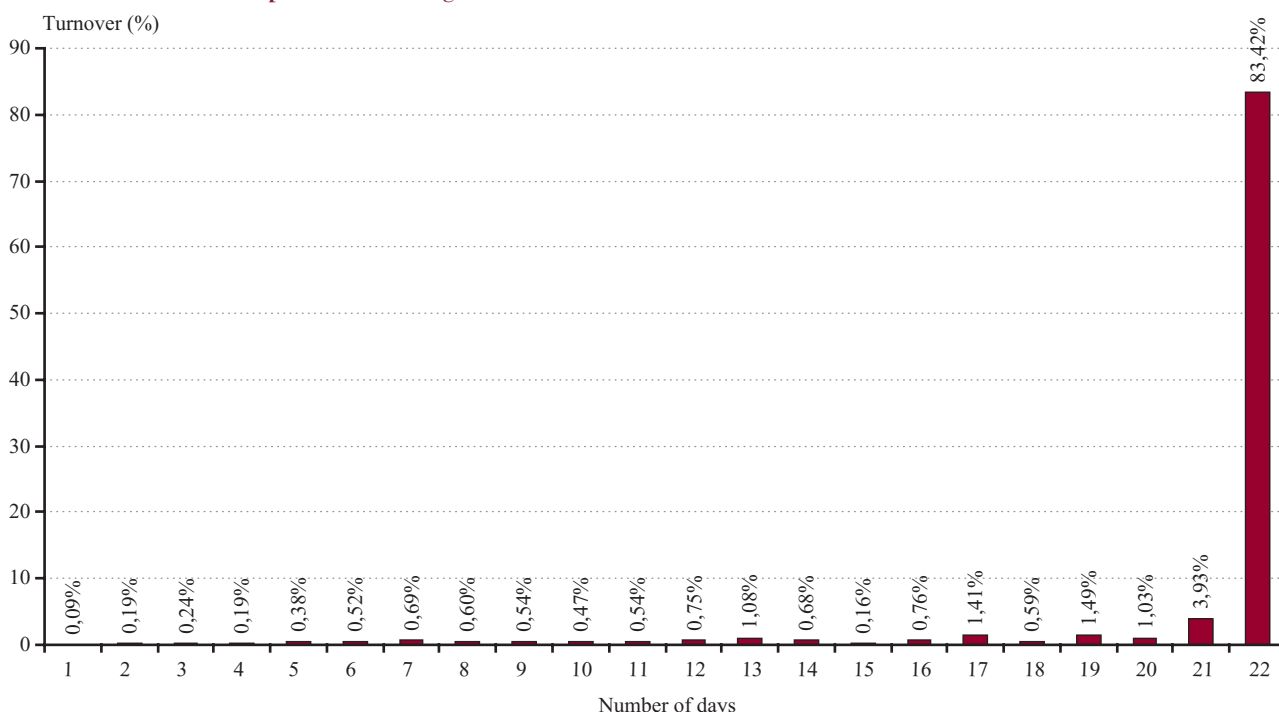
Based on Figures 9 and 10 we can conclude that there are many linkages among banks which existed only on a couple of days. There are nearly 200 relations (out of 774) through which payment orders were sent only on one, two or three days out of the potential 22 days. More than 50% of the linkages (400 out of 774) existed on less than half of the days (on less than 11 days). However, the turnover realised through these *weak linkages* is extremely low. 0.53% of the turnover is related to the linkages that existed on one, two or three days. The turnover realised through the linkages that existed on less than half of the days does not reach 4% of the total turnover. In the light of Table 1 it is a reasonable assumption that these weak linkages are dominated by customer payments. At the same time, 83.42% of the payment orders of June were sent or received through linkages that existed on each day. Moreover, nearly 90% of the turnover was realised through the *strongest linkages* (linkages that were present in more than 90% of the days). Thus, in June 2005 *the topology seems fairly permanent in the sense that the majority of the payments are transferred through the strongest linkages*.

4.3. SIMILARITY OF THE STRONGEST LINKAGES

The invariability of the payment topology was examined from several dimensions. However, it is still an open question whether the linkages with the highest daily turnover from day to day the same are.

Table 4 includes some descriptive statistics of the strongest linkages, which are defined as the linkages with the highest daily turnover of sent or received payment orders. The first four columns of Table 4 show the *concentration ratio* of the linkages in the Hungarian large-value transfer system. The three strongest linkages covered 17.1% of the total payment orders on average, accounted for at least 13.63% of the total payment orders and never exceeded 23.35%.[19] The descriptive statistics of the 5, 10, 20 etc. strongest linkages are also demonstrated by Table 4. Interestingly, the linkages with the 50 highest daily turnover covered 74.76% of the total turnover on average, while the 100 strongest linkages accounted for nearly 90% of the transactions in the payment system. The last column of Table 4 shows the average share of the permanent linkages among the 3, 5, 10, 20, etc. strongest linkages. Not surprisingly, the majority of the strongest linkages are permanent linkages. A high proportion of the non-permanent linkages is related to transactions settled with the Hungarian State Treasury.

Table 4

Concentration ratio and permanency of linkages

	Minimum	Average	Maximum	Share of the stable links
Share of the 3 strongest links	13.63%	17.10%	23.35%	100.00%
Share of the 5 strongest links	19.86%	24.79%	31.14%	100.00%
Share of the 10 strongest links	32.03%	38.10%	44.57%	99.55%
Share of the 20 strongest links	48.95%	53.12%	58.45%	98.18%
Share of the 50 strongest links	71.51%	74.76%	77.79%	92.91%
Share of the 75 strongest links	80.61%	83.59%	86.95%	88.91%
Share of the 100 strongest links	86.88%	88.98%	92.25%	82.77%

Tables 5a-c refer to the *similarity of the strongest linkages*. Table 5a depicts how similar the strongest 5 linkages of one day are to the strongest 5 linkages of other days. According to Table 5a, the relation between, for example, Bank 1 (receiver of payment orders) and Bank 2 (sender of payment orders) existed in 81.82% of the days among the 5 strongest links.[20] As the table shows, there are altogether six banks that are responsible for the five strongest linkages across all days. One of the six banks can be seen as an "outlier", it was solely involved in a single transaction. Thus, there are five banks that are really active in the payment system. Again, these banks are not the largest Hungarian banks measured by asset size, but all of them play an active role in the FX swap market, either directly or as an intermediary.

Table 5a

Similarity of the 5 strongest linkages

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 6	Total
Bank 1		81.82%	59.09%	31.82%	18.18%	38.18%
Bank 2	77.27%		27.27%	9.09%		22.73%
Bank 3	72.73%	27.27%		4.55%		20.91%
Bank 4	36.36%	13.64%	9.09%			11.82%
Bank 5	4.55%					0.91%
Bank 6	18.18%	4.55%	4.55%			5.45%
Total	41.82%	25.45%	20.00%	9.09%	3.64%	

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[19] The concentration ratios in Table 2 were obtained by lining up in a decreasing order the sum of the bilateral payment orders for each couple of institutions for each day in June 2005. Afterwards, the percentage shares of the bilateral linkages were calculated and cumulated. The maximum, mean and minimum of these cumulative shares are presented in Table 2. Note that the most significant linkages are not necessarily the same; they can vary among different couples of institutions.

[20] The column and the row of *Total* should be understood on a bank level. For example, considering solely the 5 strongest linkages, in 38.18% of the cases Bank 1 was the one that received payment orders, and in 41.82% of cases Bank 1 was the one that sent payment orders.

Table 5b

Similarity of the 5 strongest linkages

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 9	Bank 11	Total
Bank 1		100%	95.45%	77.27%	18.18%	50.00%			4.55%	34.55%
Bank 2	90.91%		45.45%	18.18%	4.55%	13.64%				17.27%
Bank 3	95.45%	50.00%		22.73%	27.27%	4.55%	4.55%	9.09%		21.36%
Bank 4	72.73%	22.73%	18.18%			4.55%				11.82%
Bank 5	22.73%		22.73%							4.55%
Bank 6	50.00%	18.18%	9.09%	4.55%						8.18%
Bank 7	4.55%	4.55%								0.91%
Bank 9		9.09%							0.91%	
Part. 24	4.55%								0.45%	
Total	33.64%	20.00%	20.00%	12.27%	5.00%	7.27%	0.45%	0.91%	0.45%	

Tables 5b and 5c depict how similar are the strongest 10 and 20 linkages of one day to the strongest 10 and 20 linkages of other days, respectively. As Tables 5b and 5c show, there are only some relations which existed in more than 70% of the days among the 10 or 20 strongest relations. These relations, are exclusively among the five banks active in the payment system. There are a couple of relations which existed in 30-70% of the days. However, the majority of the relations among the strongest relations are ad hoc; they existed in less than 30% of the days.

Table 5c

Similarity of the 20 strongest linkages

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 11	Other	Total
Bank 1		100%	100%	86.36%	59.09%	63.64%	9.09%	4.55%	9.09%	22.73%	0.00%	22.95%
Bank 2	100%		86.36%	63.64%	22.73%	31.82%	31.82%	9.09%			0.00%	17.50%
Bank 3	100%	72.73%		54.55%	63.64%	31.82%	27.27%	4.55%	27.27%		0.00%	19.32%
Bank 4	86.36%	68.18%	40.91%		13.64%	4.55%	4.55%	9.09%				11.36%
Bank 5	63.64%	27.27%	54.55%	18.18%		9.09%						8.64%
Bank 6	72.73%	45.45%	31.82%	4.55%	4.55%			4.55%	4.55%			8.41%
Bank 7	4.55%	36.36%	27.27%	4.55%	4.55%				4.55%			4.09%
Bank 8	18.18%	4.55%		4.55%								1.36%
Bank 9	4.55%	4.55%	40.91%				4.55%				13.64%	3.18%
Bank 11	22.73%		4.55%									1.36%
Other	4.55%	9.09%	4.55%						4.55%		13.64%	1.82%
Total	23.86%	18.41%	19.55%	11.82%	8.41%	7.05%	3.86%	1.59%	2.50%	1.14%	1.82%	

It is worth mentioning that 190 relations out of the 220 relations[21], that is 86.36% of the relations of Table 5b were among the five active banks. Moreover, if we consider one further bank also as an active bank, 211 relations out of 220 relations (95.91%) are among the six active banks, which cover nearly 40% of all the transactions on average. (The six banks considered are the same as the banks with the highest valued in- and outdegree centrality.) According to Table 5c, 274 relations out of 440 (62.2%) belong to the five active banks, 348 relations to the six active banks, 381 to the seven most active banks and 403 relations to the eight most active banks. The payment orders realised among the eight most active banks cover more than 50% of all transactions on average.

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[21] The 10 strongest links on the examined 22 days.

In summary, the strongest relations only partly overlap, although the linkages among the five-six banks most active in the payment system are very strong. When the 5 strongest linkages were considered, more than 85% of the relations existed among the five banks most active in the payment system. When the 10 strongest linkages were taken into account, around two-thirds of the relations belonged to the five most active banks and 80% to the six most active banks. Thus, the strongest linkages are not the same each day, but they are dominated by a couple of the most active banks in the payment system. Based on this, the similarity of the strongest linkages is not a clear cut, but still the topology seems permanent.

5. Visualization

After examining the permanency of the payment topology, the underlying network structure is visualized. By visualizing the topology of the Hungarian payment system we can gain important insights into the network topology. In Figure 11 the graph of the Hungarian payment system was prepared in UCINET from Analytic Technologies, which is a software used in social network analysis. (Borgatti–Everett–Freeman [2002].)

The input data of Figure 11 produced a matrix showing bilateral payment orders based on the data of a randomly selected day, 8 June 2005. It was shown that the topology of the payment system is fairly permanent over time, thus we can assume that the topology on a randomly selected day is representative.[22]

Figure 11

The graph of the Hungarian payment system
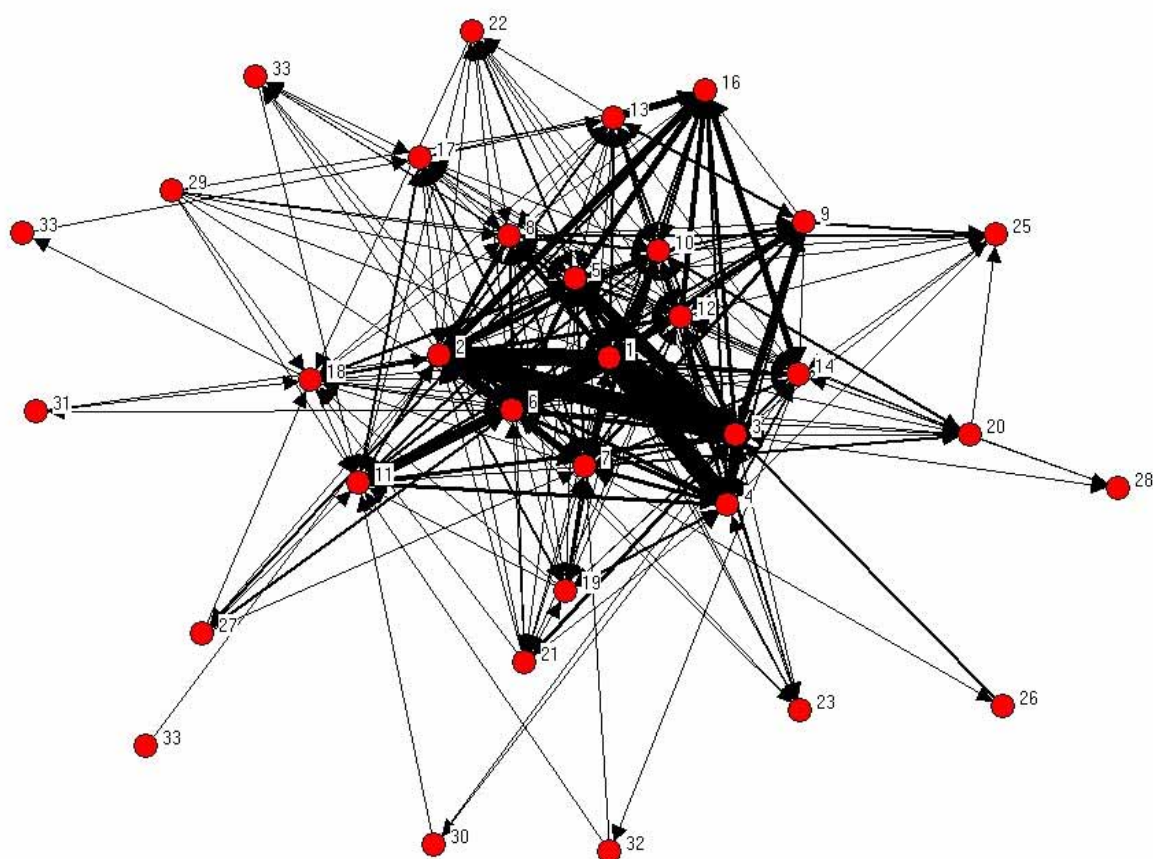
On 8 June 2005 the turnover of VIBER totalled 2,557 billion Hungarian forints and payment orders were settled through 295 linkages. According to Figure 11 half of the institutions have multiple connections with each other, while the other half have relationships with a few institutions in the centre. The *graph is directed*, the arrows showing the direction of the money flow. The graph is also *weighted*. The value of sent and received payments was scaled into 20 intervals and in this way the thickness of the lines reflects the tie strength. The payment topology of the Hungarian large-value transfer system could be best captured in a 34 dimensional frame of reference. This 34 dimensional frame of reference has many possible projections in two dimensions. Six of them are shown in Appendix 1. One commonly used illustration is the cir-

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[22] The transactions settled with the Hungarian Post and the items related to the manual account transfer of the central bank using the CAS workstation were not taken into account. One institution was neglected, as it did not settle any payment order on 8 June.

cle layout. The circle layout of the Hungarian payment system is shown in Figure A. Figure B is obtained by means of principal components. The principal components are the first two eigenvectors of the adjacency matrix of the payment system. In Figure B banks are close to each other if they have direct relationship to the same banks. Figure C of Appendix 1 is based on Gower scaling, which is a metric multidimensional scaling of geodesic distances. Institutions are close together if they have a short path distance to each other. Figure D is obtained by means of the Kruskal non-metric multidimensional scaling, which is the same as Gower scaling except that path distances are first converted to rank orders. As a result, the relationship between path distance and distance on the map is non-linear. Finally, in Figure E institutions are allocated on the basis of the principle of node repulsion, while Figure F applies the principle of node repulsion and equal edge length bias.

Figures A-H in Appendix 2 show the graphs of the payment and settlement system above certain thresholds. The graphs were prepared on the basis of node repulsion and equal edge length principle using the turnover data of June 2005. As Figure A of Appendix 2 depicts, the strongest relationships (sent or received payment orders above 2,000 billion Hungarian forints) existed among three banks in two reciprocated relations. According to Figure B of Appendix 2, payment orders above 1,000 billion Hungarian forints were realised among the five banks most active in the payment system in altogether 10 reciprocated relations.

According to the theoretical paper of Allen and Gale (2000), the structure of the interbank market can be *complete*, where banks are symmetrically linked to all other banks, or *incomplete*, where banks are only linked to neighbouring banks. Freixas, Parigi and Rochet (2000) distinguish another structure, named *money centre.* The money centre is symmetrically linked to other banks of the system, but those other banks are only linked together through the money centre. In banking systems *multiple money centres* could also exist, as in Belgium (Degryse and Nguyen [2004]). If there are multiple money centres, we can distinguish between two different theoretical market structures depending on the linkages of banks at the periphery. In both cases money centres transact with each other regularly. However, in the one case banks at the periphery are only linked to one money centre, while in the other case banks at the periphery are linked to most or all of the money centres. Of course, in reality market structures can be truly complex, reflecting a complicated combination of the above-mentioned market structures.

Based on the graphs of the Hungarian payment system, we can conclude that the system is fairly centralised, the *topology being dominated by a couple of institutions.* These dominant institutions have very strong relations among themselves and also have many linkages to other participants. Thus, the Hungarian payment system can be considered as a structure with *multiple liquidity centres.*[23]

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[23] In the theoretical literature the terminology of money centre was introduced by Freixas et al. (2000). According to the authors, the structure of the interbank market can be described as an interbank market with money centre, if there is one bank, named money centre, which is symmetrically linked to the banks of the system. At the same time, the banks at the periphery are only linked to the money centre. In the empirical literature Degryse and Nguyen (2004) describe the topology of the Belgian interbank market as a structure with multiple money centres.

6. Institutions generating contagion

Different measures of centrality focus on different aspects of the payment topology.[24] From the financial stability point of view the measures refer to whether the institution

1) is capable of generating a potential liquidity crisis,

2) can play an intermediary role in distressed situations, or

3) can be affected by a potential liquidity crisis.

A liquidity crisis could arise if funds are not transferred to institutions, although the institutions have expected it. *Institutions most capable of generating contagion* are determined on the basis of this argument. From the point of view of a central bank it could be an important question whether, in the case of a liquidity shock, it should provide an emergency loan to the institution generating contagion or to the institution suffering from the shock. As the objective function of a central bank depends not only on the costs involved, this kind of analysis is beyond the scope of this paper.

Obviously, an institution can be a dominant institution of the payment system if it has linkages to many other institutions, that is, it has many counterparties in the large-value transfer system. From a systemic point of view one could argue that banks with high indegree can be easily affected by a liquidity crisis and that banks with high outdegree can trigger the most severe contagious effects. However, *in- and outdegree centrality* are not meaningful measures of systemic importance. If an institution has many in- or outgoing relations it does not necessarily mean that the institution can have a high impact on the others. Let us consider the case of the Hungarian Post. The Post sends nearly all VIBER participants payments, although the amounts transferred are low. Thus, the illiquidity of the Post could not undermine the liquidity position of the others.

Systemically important banks should not only have many counterparties in the payment system, but they should be involved in transferring large amounts of payments. If an institution that has credit items (received payment orders) of high value becomes illiquid, it does not threaten the liquidity position of other VIBER participants. However, institutions having high *valued indegree centrality* could be the most seriously affected by a potential liquidity crisis and as a consequence could adversely affect the real side of the economy. By means of *valued outdegree centrality* institutions that are the most capable of generating contagion can be identified. This measure takes into account the fact that a liquidity crisis could emerge if an institution with a huge amount of debit items (sent payment orders) becomes illiquid.

Another feature of an institution playing an important role in the payment system is that liquidity problems arising at the institution could affect several other institutions directly or indirectly. In this case the importance of an institution depends on how close the institution is to all other institutions. *In-proximity centrality* is a measure of how resistant institutions are to shocks, as it shows how far institution *i* is from those participants which send payment orders to institution *i*. In contrast, *out-proximity centrality* takes into account how the illiquidity of institution *i* would affect the institutions that expect directly or indirectly funds from participant *i*. Thus, the index defined on the basis of the outgoing edges captures the ability of banks to trigger contagion.

According to the *betweenness centrality*, an institution could be systemically relevant if it lies on numerous potential contagion paths, that is, it connects many institutions with each other. Institutions with high betweenness centrality could transmit the initial shock. Betweenness centrality assumes that a participant is playing a crucial role in the network due to its intermediary role. The focus is not so much on the number of institutions a failed institution could affect, but rather on the probability that the institution is involved in a systemic event at all. Namely, the severity of the domino effect an

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[24] Thus the seven centrality measures (in- and outdegree centrality, valued in- and outdegree centrality, in- and out-proximity centrality and betweenness centrality) are not all highly correlated. Note that the rank centrality, defined either on the basis of the outgoing or the ingoing payments, is disregarded.

initial failure could generate not only depends on the failed institution *k* and the threatened institution *j*, but also on the shock absorbing capacity of all institutions *i* lying on the path between *j* and *k*.

Table 6 summarises whether the analysed centrality measures could be linked to the shock generating, shock transmitting or shock absorbing capacity of the institutions.

Table 6

Centrality measures and the role of the institution in distressed situations

	Shock generation	Shock transmission	Lower shock absorption
Indegree centrality			⊕
Outdegree centrality	⊕		
Valued indegree centrality			⊕⊕
Valued outdegree centrality	⊕⊕		
In-proximity centrality			⊕⊕
Out-proximity centrality	⊕⊕		
Betweenness		⊕	

According to the table *the institutions most capable of generating contagion* can be best captured by means of valued outdegree centrality and out-proximity centrality. It was shown earlier (Table 3) that the mean correlation coefficient between valued outdegree centrality and out-proximity centrality is moderate or even week. If the correlation was strong it would refer to the fact that, based on these two centrality measures, the group of institutions most capable of generating contagion is more or less the same. Although the correlation is week, it reflects the fact that the institutions most capable of generating contagion may differ. The daily averages of valued outdegree centrality and out-proximity centralities were multiplied on a bank level and the banks were ranked on the basis of this product. Figure 12 shows the relative value of the ranking, the product of valued outdegree centrality and out-proximity centrality of the bank with ranking 1

Figure 12

Institutions capable of generating contagion
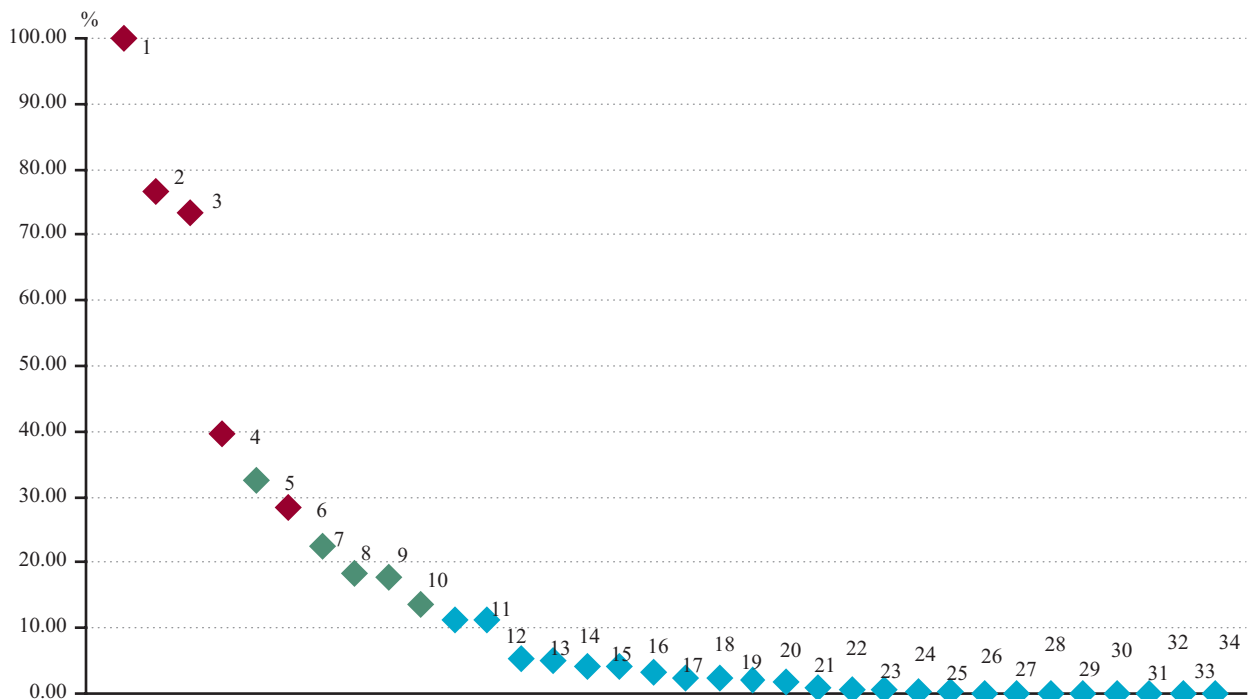
was considered as 100%. It can be seen from the figure that banks with ranking 2 and 3 are more or less equally central. The centrality of bank ranking 4 is far from banks with ranking 2 and 3, as is the centrality of banks with ranking 2 and 3 from the bank with ranking 1. Beyond this, the consecutive differences in the relative measures are small.

The systemically most important institutions can be classified into two major groups.[25] Banks with ranking 1, 2, 3, 4 and 6 are definitely not the largest banks by asset size, but they are the ones that play a very active role on the FX swap market. Banks with ranking 5, 7, 8, 9 and 10 are large Hungarian banks – in most cases foreign owned. It is important to note that in relation to Tables 5a, 5b and 5c and the graphs of the payment topology we could have arrived at a very similar ranking of the systemically most important institutions.

The central institutions of the Hungarian large-value transfer system are worth considering in all kinds of systemic risk analysis. However, it is still an open question how the centrality of the institutions and the related network topology influence the probability and the severity of a potential liquidity crisis. This is clearly an area for future research.

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[25] It is important to note that systemically important institutions – in addition to the position in the network of payments – have many other very important characteristics, such as the volume of deposits, the volume of interbank credits, potential impact on asset prices and level of liquidity, etc.

7. Conclusion

This paper has dealt with the *topology of the Hungarian large-value transfer system*, known as VIBER. A graph theoretical framework was applied, which allowed the system-wide assessment of high-value payments. Seven centrality indices were defined; the different measures of centrality focussing on different aspects of the payment topology. Degree centrality took the number of direct linkages into account and disregarded the line values and indirect relations. Valued degree centrality indices considered solely the aggregate payment orders (the sum of the line values) and disregarded the number of direct and indirect linkages. Proximity and betweenness centrality measures took both direct and indirect linkages into account, although they disregarded the line values. The aim of the application of graph theoretical methods was twofold.

Firstly, the paper aimed to analyse the *permanency of the network over time.* It was shown that the structure of the payments was stable over the one-month period. Those institutions that had high (low) centrality on one day tend to have high (low) centrality on the following days as well. The average of the correlations of certain centrality measures across days was in each case high. The mean correlation coefficients ranged from 0.7959 to 0.9611. By examining the permanency of relations over time the constancy of exact linkages were also taken into account. One interesting feature of the topology was that only 30% of the existing linkages were permanent linkages, although nearly 90% of the payment orders were sent or received through these linkages. It was also shown that the strongest linkages are not the same each day, but are dominated by a couple of banks most active in the payment system. The Hungarian payment system was characterised as a structure with multiple liquidity centres. In sum, the topology of the payment network seemed permanent; ad hoc relations did not dominate the topology of the payments. The most central institutions were the same; the key players did not vary across days.

Secondly, according to certain network criteria *systemically important institutions* were determined. The graph theoretical approach provided an ideal tool to determine the institutions most capable of generating contagion through the Hungarian large-value payment system. It was taken into account that a liquidity crisis could arise if funds are not transferred to counterparties, although the counterparties might have expected it. Based on the measures of valued outdegree and out-proximity centrality, a well-defined group of institutions was identified; the illiquidity of these institutions could cause the most serious contagion effects. Special attention should be devoted to these institutions when the payment system is monitored, and when the principles of the lender of last resort policy of the MNB is worked out. Surprisingly, the institutions most capable of generating contagion are not the largest Hungarian banks in terms of asset size. Instead, they are directly or indirectly active players of the USD/HUF FX swap market.

The present paper is generally descriptive in nature; the goal of the research was the assessment of the payment topology. The results could serve as a basis when the effects of Economic and Monetary Union accession on the Hungarian payment system are examined. Based on the applied analytical framework certain questions could be addressed, such as in which direction will the topology change when the euro is introduced.

Secondly, the paper could serve as an important input in assessing *FX settlement (or Herstatt)* risk. In VIBER a large proportion – at least one quarter – of transactions settled are related to the Hungarian forint (HUF) leg of FX swaps. Neither the spot nor the forward legs of the FX swaps are settled simultaneously. The HUF leg of the swap is executed in VIBER during VIBER operating hours (8 a.m.–4.30 p.m. Central European Time), while the USD leg of the swap is completed in the Fedwire during the Fedwire operating hours (8.30 a.m–5 p.m. Eastern Time).[26] (Federal Reserve Financial Services… [2005].) Accordingly, we can assume that the HUF leg of an FX swap is sent before the USD leg of an FX swap. It would be important to measure the significance of the settlement risk that the banks may face. Could it generate serious liquidity or solvency problems? Should VIBER operating hours be extended? Would such lengthened operating hours really mitigate the risks involved? What should the MNB do if the settlement risk is high, but the risk is not of an intraday nature?

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[26] 8.30 a.m.–5 p.m. Eastern Time corresponds to 1.30 p.m.–10 p.m. Central European time. Thus, during a normal working day there are three hours when both the VIBER and the Fedwire are open.

Thirdly, the results obtained highlight *various banking behaviour* in liquidity management. Do the behavioural differences stem from the distinct bank profiles? Do some banks manage their liquidity more efficiently? Is the efficient liquidity management conscious or enforced by the course of business? What are the most important factors influencing the timing of outgoing transactions? Do the banks time their outgoing payments at all? Do the banks cooperate and finance their transactions from the incoming payments? Are there some banks that delay their payments intentionally and free ride on the liquidity of others? Could the MNB promote cooperation among banks if it introduced a throughput rule, similar to that of the Bank of England? Is the functioning of the system optimal or could it be more efficient, for example by altering the timing of payments? It is obvious that more research is needed to answer such questions.

Finally, even after the topological analysis it remained an open question how the centrality of the institutions and the related network topology influence the severity of a *potential liquidity crisis*. As for future research, the effects of a potential liquidity crisis should be modelled and the importance of the lender of last resort function of the MNB should be investigated. In relation to this, there are at least three distinct areas needing elaboration. Firstly, a liquidity crisis could evolve as a consequence of an operational failure of one of the VIBER participants. By means of simulations the ability of the banks to withstand certain types of operational disruptions of other banks could be assessed quantitatively. Do the banks have sufficient liquidity buffer to allow them to absorb the shocks? If not, to what extent are payments between unaffected settlement banks either delayed or prevented from being settled? Secondly, by means of simulations abnormal market conditions could be also captured. Namely, how significantly would the payment system be distorted if the liquidity markets dried up? Thirdly, the impact of bank runs based on non-fundamental signals could also be modelled. In the literature the sunspot phenomenon is widely discussed; the occurrence of a signal which co-ordinates the expectations of the public without being actually related to the health of financial institutions. It is shown that sunspots can lead to self-fulfilling bank runs. However, the quantitative assessment of a potential bank run on the liquidity of other banks is not handled.

Appendix

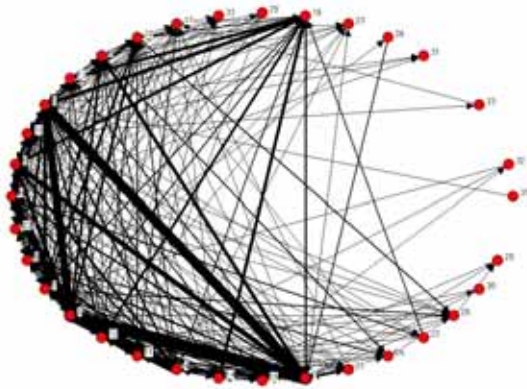## APPENDIX 1: ADDITIONAL GRAPHS OF THE HUNGARIAN PAYMENT SYSTEM

Figure A

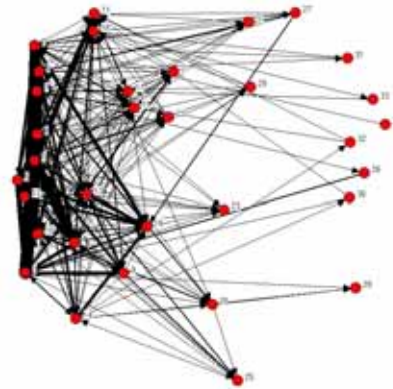Circle layout

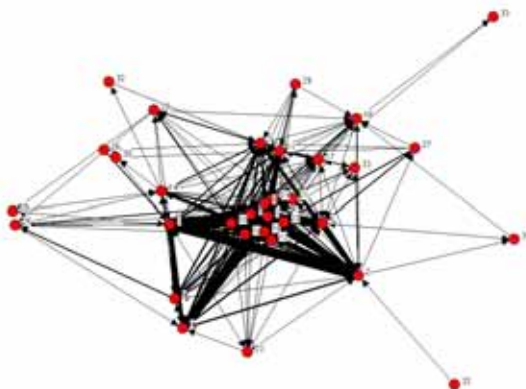### Figure B

Principal components

Figure C

Gower-metric

Figure D
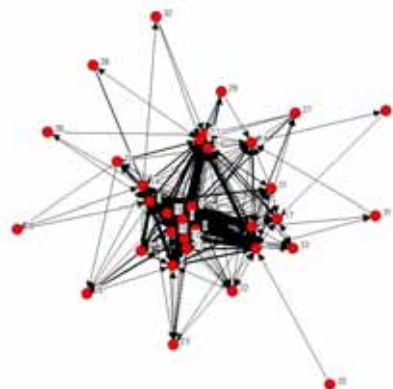
Kruskal-distance

Figure E
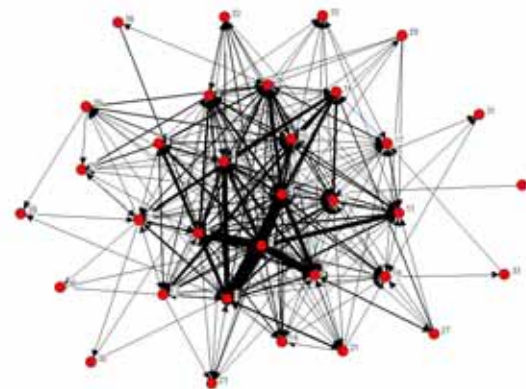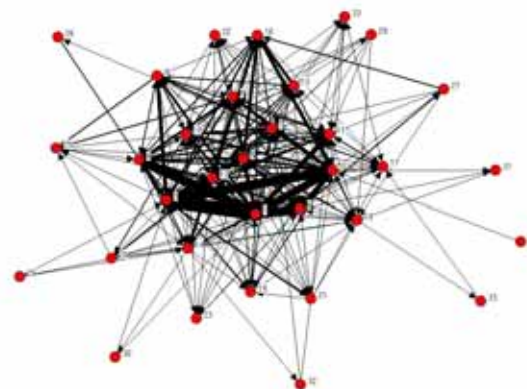
Node repulsion

Figure F

Node repulsion and equal edge length

APPENDIX 2: TOPOLOGY OF THE HUNGARIAN PAYMENT SYSTEM ABOVE CERTAIN THRESHOLDS

Figure A

Threshold of 2000 billion HUF

Figure B

Threshold of 1000 billion HUF

Figure C

Threshold of 500 billion HUF

Figure D

Threshold of 250 billion HUF

Figure E

Threshold of 100 billion HUF

Figure F

Threshold of 50 billion HUF

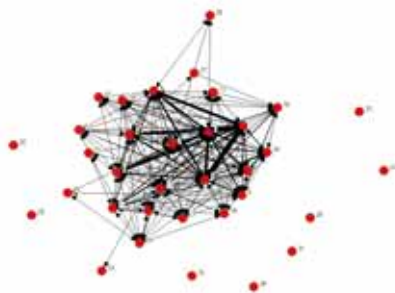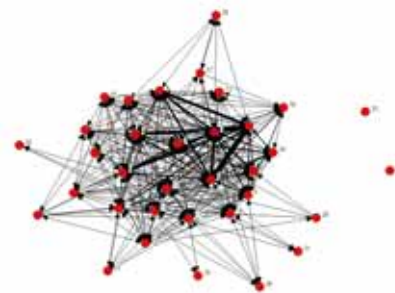

Figure G

Threshold of 10 billion HUF

Figure H

Threshold of 1 billion HUF

Bibliography

Act LVIII of 2001... [2001]: Act LVIII of 2001 on the Magyar Nemzeti Bank. CompLex CD Archive. http://www.complex.hu/. Accessed on 8 December 2003. (In English can be downloaded from http://english.mnb.hu/Engine.aspx, link: For Students/Central Bank Act).

ALLEN, F.–GALE, D. [2000]: Financial Contagion. Journal of Political Economy, Vol. 108. No. 1. p. 1-33.

BARABÁSI, A.-L.–ALBERT, R.–JEONG, H. [1999]: Mean-field Theory of Scale-free Random Networks, Physica A, Vol. 272. p. 173-187.

BARABÁSI, A.-L.–ALBERT, R.–JEONG, H. [2000]: Attack and Error Tolerance of Complex Networks. Nature, Vol. 406. p. 378-382.

BARABÁSI, A.-L. [2002]: Linked. Perseus Publishing. Cambridge.

BECH, M.–MADSEN, B.–NATORP L. [2002]: Systemic Risk in the Danish Interbank Netting System. *Working Paper* No. 8. Danmarks Nationalbank.

BLÅVARG, M.–NIMANDER, P. [2002]: Interbank Exposures and Systemic Risk. *Sveriges Riksbank Economic Review*, No. 2.

BORGATTI, S. P.–EVERETT, M. G.–FREEMAN, L. C. [2002]: Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies.

BOSS, M.–ELSINGER, H.–SUMMER, M.–THURNER, S. [2004]: The Network Topology of the Interbank Market. *Quantitative Finance* 4 (6), p. 677-684.

DEGRYSE, H.–NGUYEN, G. [2004]: Interbank Exposures: An Empirical Examination of Systemic Risk in the Belgian Banking System. *National Bank of Belgium Working Paper*, No. 43.

FAUST, K.–WASSERMAN, S. [1994]: Social Network Analysis: Methods and Applications. Cambridge University Press.

Federal Reserve Financial Services... [2005]: Federal Reserve Financial Services National Settlement Service, Information for Settlement Agents. Accessed on 5 January 2006 from http://frbservices.org/Wholesale/InfoSettleAgent.html.

FREIXAS, X.–PARIGI, B. M.–ROCHET, J.-C. [2000]: Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank. *Journal of Money, Credit and Banking*, Vol. 32. No. 3. p. 611-638.

HANNEMAN, R. A.–RIDDLE, M. [2005]: Introduction to Social Network Methods. Riverside, CA: University of California, Riverside (published in digital form at http://faculty.ucr.edu/~hanneman/).

INAOKA, H.–NINOMIYA, T.–TANIGUCHI, K.–S., TOKIKO–TAKAYASU, H. [2004]: Fractal network derived from banking transaction – An analysis of network structures formed by financial institutions. *Bank of Japan Working Papers* No. 04-E-04. April 2004.

KOPONEN, R.–SORAMÄKI, K. [2005]: Intraday Liquidity Needs in a Modern Interbank Payment System – A Simulation Approach. In: LEINONEN, HARRY (ED.) [2005]: Liquidity, Risks and Speed in Payment and Settlement Systems – A Simulation Approach. Bank of Finland Studies. E:31. Helsinki, Edita Prima Oy. p. 73-116.

KUUSSAARI H. [1996]: Systemic Risk in the Finnish Payment System: An Empirical Investigation. *Discussion Paper* No. 3. Bank of Finland.

LEINONEN, H. (ED.) [2005]: Liquidity, Risks and Speed in Payment and Settlement Systems – A Simulation Approach. *Bank of Finland Studies* E:31. Helsinki, Edita Prima Oy.

LEINONEN, H.–SORAMÄKI, K. [2005a]: Simulating Interbank Payment and Securities Settlement Mechanisms with BoF-PSS2 Simulator. In: LEINONEN, H. (ED.) [2005]: Liquidity, Risks and Speed in Payment and Settlement Systems – A Simulation Approach. Bank of Finland Studies. E:31. Helsinki, Edita Prima Oy. p. 17-71.

LEINONEN, H.–SORAMÄKI, K. [2005b]: Optimising Liquidity Usage and Settlement Speed in Payment Systems. In: LEINONEN, H. (ED.) [2005]: Liquidity, Risks and Speed in Payment and Settlement Systems – A Simulation Approach. Bank of Finland Studies. E:31. Helsinki, Edita Prima Oy. p. 117-150.

MÜLLER, J. [2006]: Interbank Credit Lines as a Channel of Contagion. *Journal of Financial Services Research*, Vol. 29. No. 1. p. 37-60.

Developments in the structure of … [2005]: Developments in the structure of financial markets. In: *MNB Report on Financial Stability*, Special Topics. October. p. 75-84.

NORTHCOTT C. A. [2002]: Systemic Risk, Designation and the ACSS. Financial System Review. December 2002. Bank of Canada.

Report on Financial Stability… [2005]: Report on Financial Stability. Magyar Nemzeti Bank. April 2005. Downloadable from http://english.mnb.hu/engine.aspx?page=mnben_stabil.

SORAMÄKI, K.–BECH, MORTEN L.–ARNOLD, J.–GLASS, R. J.–BEYELER, W. E. [2006]: The Topology of Interbank Payment Flows. Federal Reserve Bank of New York, Staff Report No. 243. March 2006.

VIBER System… [2005]: VIBER System Description. Version 3.3 Annex No. 1 of Business Terms and Conditions of Bank Accounts Managed by the Magyar Nemzeti Bank and settlements in forint and foreign exchange. 30 June 2005. Accessed on 2 January 2006 from http://english.mnb.hu/engine.aspx?page=mnben_penzelszforg.

WATKINS, J. J.–WILSON, R. J. [1990]: Graphs – An Introductory Approach. John Wiley & Sons.