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# LIQUIDITY MANAGEMENT AND INTERMEDIATION IN UNSECURED CREDIT MARKETS

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***Ph.D. dissertation***

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# 1. Introduction

The bankruptcy of Lehman Brothers in 2008 and the ensuing lightning-fast knock-on effects leading to a global financial crisis highlighted the importance of understanding interbank networks and, through them, the importance of systemic risk management. Central banks, which had used micro-prudential instruments until then almost exclusively, recognised the importance of macro-prudential regulation, and it became a key factor to identify the so-called Systemically Important Financial Institutions (SIFIs) and to rethink regulations governing them.

The Basel Committee on Banking Supervision (BCBS), the body shaping the regulatory framework for the banking sector on a global level, published its methodology for the assessment of systemically important banks in 2011 *(BCBS [2011])*, by updating it in 2013 *(BCBS [2013b])*. In its recommendation, the Committee included five characteristics to be used for the identification of systemically important banks, namely the size of an institution, its substitutability, its complexity, the global scope of its activities, and its interconnection with other market participants within the financial system.

Owing to that latter interconnection, network science was officially included in regulatory processes, a fact creating regulatory support for its application, in addition to a demand arisen for it before. As academic literature suggests, this gradually growing demand has led to an extremely rapid advancement of network science in the field of finance over the past decade.

The birth of graph theory, which had laid the foundations for network science, is connected to Leonhard Euler, who solved the famous Königsberg bridge problem in 1735. The former capital of East Prussia, Königsberg, was divided into several parts by the river Pregel, and seven bridges provided the interconnection between these parts of the city at that time. And one of the most famous puzzles of the age was whether one could go through all seven bridges in a single walk by going through each bridge exactly once. To solve the problem, Euler drew a graph whose vertices corresponded to the parts of the city separated by the river, and the edges connecting them symbolised the individual bridges. The proof was based on purely mathematical arguments, and the degrees helped accept that there was no such way *(Alexanderson [2006])*.

In the following centuries, graph theory (and then network science that emerged from it) began to develop and took its place among the disciplines of mathematics owing to Hungarians mainly, a fact representing a special motivation for me. The first complete book on graph theory was published two centuries after Euler's epoch-making study by a Hungarian mathematician, Dénes Kőnig, (in German), under the title "Theorie der endlichen und unendlichen Graphen" in 1936 *(Biggs–Lloyd–Wilson [1976])*.

In the middle of the 20th century, network science, building on the basics of graph theory, soon appeared and evolved owing to the undying merits of Hungarian mathematicians Pál Erdős and Alfréd Rényi. Between 1959 and 1968, they published eight studies to establish the relationship between probability theory and graph theory, thus laying the foundations for a new field of science, the theory of random graphs.

The next significant milestone in network science was also laid by two Hungarians, Albert-László Barabási and his student Réka Albert, in their article on the discovery of scale-free networks published in the journal Science in 1999 *(Barabási–Albert [1999])*. Since its publication, the article has counted more references than classic articles on complex systems, such as Edward Lorenz's theory of chaos *(Lorenz [1963])*, Benoit Mandelbrot's book on fractals *(Mandelbrot [1982])*, John Hopfield's articles on neural networks *(Hopfield [1982])*, or the publication of Watts and Strogatz on small-world networks *(Watts–Strogatz, [1998]; Barabási et al. [2016])*.

Network science, in general, is made particularly attractive to me by its relevance to Hungarians, as presented above. Network science tools have now been widely used, starting from brain research through curbing a worldwide spread of viruses to detecting terrorist networks (to name just the most extreme examples).

Viewing my research from an intellectual perspective, I consider network science an exciting challenge, which is constantly evolving while combining the results of several disciplines and has an extremely deep, complex mathematical background beyond its aspects of economics. I want to conclude the presentation of my motivations with the words of the recently deceased British theoretical physicist Stephen Hawking: *"I think the next [21st] century will be a century of complexity."*[1]. And network research is nothing else but the science of understanding complex systems, so if Stephen Hawking's statement

[1] The quote comes from a "turn of the millennium" interview of 23 January 2000 (San Jose Mercury News).

turns out to be right, then I can’t imagine any greater motivation than to unravel the driving forces of the complex world around us in the “century of complexity”.

My research on the Hungarian unsecured interbank deposit market and intermediation activities therein is carried out at three levels that are built on each other.

At the first level, a descriptive research is conducted to examine, from several angles, a significant segment of the interbank market: the unsecured interbank deposit market. In the spirit of this, Chapter 2 of my thesis provides a general academic literature review. In addition to describing the domestic interbank market, I also cover similarities and differences observed between interbank markets of some countries in the CEE region. As the main motivation for participants in the interbank market is liquidity management, the various levels at which liquidity management activities are carried out in a general economy – together with the different concepts of liquidity related to these levels – are presented.

This presentation is followed by a detailed discussion of the main features of loan transactions made in the unsecured interbank deposit market; limits affecting the market as a whole; typical interbank interest rates; and the central bank's toolbox used for influencing these interest rates. Events of the period ending 31 March 2021 are analysed, and any developments thereafter are beyond the scope of my thesis.

Based on academic literature, three recent shocks are presented (the 2008 global financial crisis, the shocks generated by the Treasury Single Account, and the deterioration of the sovereign debt rating of the Hungarian state), which significantly affected the interbank market in Hungary. Then, some impacts exercised by these events on participants and the market as a whole are identified to shed light on some new aspects, additional to existing ones, of the operation of the interbank market. This chapter is closed by an analysis of interbank loans and deposits (carried out by using publicly available MNB data on credit institutions), covering past changes in their portfolios, foreign exchange structures, maturities and delinquencies.

In Chapter 3, a detailed database of transactions (received for research purposes) is used to examine certain dimensions characterising the network of the unsecured interbank deposit market in the period of 2012-2015 and to analyse how stable the examined parameters were over time. This examination aims (1) to provide a general picture of the market, presenting magnitudes of volumes and typical maturities of transactions; (2) to compare my results with previous studies found in academic literature so as to draw interesting conclusions about processes observed in the period analysed; and (3) to examine the stability of the network over time, subject to different dimensions, an effort definitely worthwhile to make, as a sufficiently stable network structure is essential for drawing robust conclusions and exploring causal relationships.

In Chapter 3, the following research hypotheses are examined:[2]

*H1:* *The distribution of overnight and longer-term unsecured interbank transactions significantly differ.*

*H2:* *The concentration of borrowing is significantly higher than the concentration of lending, both in terms of volume and the number of transactions.*

Several methods are used to examine differences in the distribution of overnight and longer-term transactions, and the stability of such differences over time is also examined. After that, an insight is provided into the evolution of interest rates and monthly aggregated transaction amounts, focusing on overnight transactions used exclusively for liquidity management purposes.

Then the Gini index, the Herfindahl-Hirschman index and the so-called effective number are used to illustrate the dynamics of the concentration of O/N unsecured interbank transactions on the borrowing and lending side. The chapter ends with a description of the basic indicators of network science.

Differences in indicators characterising the different types of connectivity clearly show that there is a high level of interconnection in the interbank market, despite the relatively few connections, which indicates a kind of modular structure (hierarchy) in the network. As presented in my thesis, network indicators found (mainly related to the Czech and Austrian interbank markets) in regional academic literature almost perfectly coincide with indicators describing the Hungarian market. This suggests that the set of features characterising unsecured interbank deposit markets (lack of physical collateral, the purpose is liquidity management) and the underlying factors associated with market failures (information asymmetry, transaction costs, provision of liquidity, economies of

[2] Reasons for my choice of research questions and my hypotheses, as well as their in-depth explanations, are provided in each individual chapter; this introductory section lists them only for the sake of transparency.

scale and scope, and risk sharing) provide a special structure; therefore, the network structure of interbank markets is worth examining more closely.

Chapter 4 presents three essential network models: random, scale-free, and hierarchical. A special type of this latter, hierarchical network model is discussed in detail: the core-periphery structure, which is typical of interbank networks. The discrete and continuous versions of the core-periphery model found in the academic literature are described, together with the coreness measure that can be calculated in connection with the continuous version. One of the main scientific results of my thesis is a methodological innovation (a modified alternative to the coreness measure published in the literature), enabling a more accurate classification of core and periphery participants.

Accordingly, the hypothesis examined in Chapter 4 is as follows:

*H3:* *A coreness measure adjusted by a concave weight function allows for a better and more robust classification than before.*

At this point, building on the descriptive part, I move on to the next level of research, where deeper connections and causal relationships are examined. The key to the above-mentioned core-periphery network structure is intermediation. Core participants act as intermediaries between peripheral banks, in addition to managing their own liquidity.

It is important to emphasise that the term "intermediary" will be used in the sense of *dealer* and not *broker*. So by the term intermediary, I mean a player who not only connects parties (such as a real estate agent) but whose transactions are recognised in its own balance sheet (by taking a position, it takes a risk and performs a transformation).

Chapter 5 starts with an examination of the role played in the economy by the broader financial intermediation system, related to which banks have faced a number of challenges in recent decades. The examination seeks an answer to the question of whether traditional financial intermediaries are still needed in the 21st century.

Then, focusing on interbank markets, an examination is carried out to explain why even financial intermediaries need intermediaries in such markets. As the academic literature processed suggests, intermediaries perform five main functions: they (1) provide liquidity and facilitate a more efficient allocation of funds; (2) alleviate information asymmetry; (3) reduce transaction costs in the market; (4) take advantage of economies of scale and scope; and (5) allow for a higher degree of risk sharing. Intermediaries perform beneficial activities that tend to increase the efficiency of operations in interbank deposit markets and to reduce market failure attributable to the factors listed above.

Therefore, simple economic arguments are sufficient to present why markets need intermediaries. But, from the other side, what motivates intermediaries when stepping in between two periphery participants? Based on business logic and academic literature, an assumption is used, namely, that such intermediation services are provided by core banks for making profits. According to most of the relevant studies, intermediaries make substantial profits, and it significantly increases the size of core (intermediary) banks, which further enhances the differences in size between core and peripheral players in interbank markets.

Using the detailed transaction database described above, an estimate is provided of the volume of intermediation activities in the Hungarian interbank market, and their significance is examined. Then a weighted average estimate and an upper estimate is provided of the annual profits made by intermediation activities. To the best of my knowledge, no other authors have attempted to quantify the amount of profits made by intermediaries in the interbank market; so this part is the next major research result of my dissertation.

In Chapter 5, the following research hypotheses are examined:

*H4: Intermediation activities in the Hungarian unsecured interbank deposit market are of significant volume.*

*H5: In the Hungarian unsecured interbank deposit market, the main motivation of intermediation activity is to make profits.*

My results allow for the conclusion that – although intermediation is significant in the unsecured interbank deposit market – this activity is performed by participants for something other than profits. I assume that the main motivation for intermediaries is risk sharing. Credit institutions in the interbank market operate an insurance scheme based on reciprocity, under which intermediaries are willing to lend more funds to others than what is needed for their own liquidity management purposes, so that they can get funds from their counterparties at a later stage, in the event of a liquidity shortage. Thus, all participants in the network are interested in the smooth operation of the interbank deposit market.

In Chapter 6, building on the results of a joint research with my co-authors, I present the network of informal interpersonal loans made by the Roma majority population of an underdeveloped small Hungarian village; and compare that network with the interbank deposit market. These two – seemingly distant – markets have not been compared before by any other authors, so the results achieved here can be considered as a novelty that expands our current knowledge.

As shown by a comparison between them in terms of their structural characteristics, basic network indicators, degree distributions, and clustering coefficients, the two credit markets are similar in many respects. This allows us to conclude that similar processes work in the background, and essentially the same problems have to be solved by players in both markets, which creates similar patterns.

After that, the chapter seeks answers to the questions of whether intermediation activities are present in interpersonal lending markets and what is the main motivation for granting loans. The network of informal loans of households is examined, broken down by both income situation and ethnicity.

In Chapter 6, the following research hypotheses are examined:

*H6:* *The network of the examined interpersonal loan market differs significantly from the Hungarian unsecured interbank deposit market network.*

*H7:* *The main motivation for transactions in the interpersonal loan market is selfless, philanthropic assistance provided by the rich to the poor.*

Finally, after exploring causal relationships, I move to the third, normative level of my research in Chapter 7, formulating proposals and policy recommendations and summarising possibilities for utilising my research results in relation to interpersonal loans and the interbank deposit market.

# 2. The Hungarian unsecured interbank deposit market

The inherent feature of banks' activities is that their liquidity position is constantly changing. The primary platform for eliminating their possible liquidity shortage and disbursing their temporary excess liquidity is the unsecured interbank deposit market.

At what levels is liquidity management implemented in an economy? And what exactly does “liquidity” mean in the interbank market? The latter question is relevant because there are several interpretations and aspects of liquidity, even within the financial literature.

After clarifying the conceptual framework, I describe the general characteristics and stylised facts of the interbank market described in the literature. Then I present in detail the Hungarian monetary policy framework that significantly influences the forint liquidity of the banking system, as well as the recent transformation of the central bank's toolset.

In the next subsection – focusing on the Hungarian unsecured interbank deposit market – I present primarily how the participants and the market as a whole reacted to various events that negatively affected the interbank market, relying primarily on Hungarian and regional academic literature.

To conclude the chapter and build on the previous sections, I will summarise the dynamics of the foreign currency composition, maturity and arrears of interbank loans and deposits based on publicly available MNB data on the credit institution sector.

The purpose of this chapter is to provide a comprehensive picture of unsecured interbank deposit markets, in which I primarily rely on the academic literature of Hungarian and regional interbank markets, highlighting regional specifics. I will summarise the primarily foreign literature on more specific topics (such as network models, intermediary profit in the interbank market, and interpersonal networks) at the beginning of the related chapters as an integral and inseparable part of the subsequent analyses.

Table 1 summarises the main features and the most important results of the Hungarian and regional unsecured deposit market studies from various aspects, which are important for my dissertation.

*Table 1:*

Empirical studies on the Hungarian and regional interbank deposit markets, significant for my dissertation in a chronological order

| | Molnár [2010] | Berlinger–Michaletzky–Szenes [2011] | Homolya et al. [2013] | Hausenblas–Kubicová–Lešanovská [2015] | Berlinger et al. [2017] | Kolozsi–Horváth [2020] |
|---|---|---|---|---|---|---|
| **Subject of the analysis** | Hungarian interbank forint liquidity | examination of the unsecured interbank forint deposit market dynamics | limit setting practice of Hungarian banks | potential contagion channels in the Czech banking system | core-periphery structure in the Hungarian interbank deposit market | liquidity demand of Hungarian banks |
| **Key concepts** | interbank forint liquidity, liquidity forecast | interbank transaction volumes, concentration | limits (partner limits) | systemic risk, contagion | core-periphery model, coreness measures, partner limits | central bank liquidity, Hungarian interbank liquidity market |
| **Qualitative / quantitative** | qualitative | quantitative | qualitative | quantitative | quantitative | quantitative |
| **Applied methodology** | descriptive | network indicators, concentration measures | questionnaire and interview | network indicators and simulation | continuous asymmetric core-periphery model | segmented OLS regression estimation of cross-sectional data |
| **The investigated period** | 2008 - 2010 | December 2002 - March 2009 | August 2012 - September 2012 | March 2007 - June 2012 | 2003 - 2012 | 15 November 2016 - 15 September 2019 |
| **Sample size** | - | 51 banks (71,836 transactions) | 12 banks | 31-40 banks | 46 banks (92,619 transactions) | 37 banks (706 daily observations) |
| **The main contribution, conclusion for the dissertation** | presents the factors affecting interbank structural liquidity | the characteristics of changes in interbank transaction volumes and concentration in a crisis situation | partner limits strongly drive the Hungarian deposit market; the impact of interbank market disruptions on partner limits | it allows a regional comparison of network metrics characterising the Hungarian interbank market | the Hungarian interbank deposit market has a core-periphery structure, and partner limits play a key role | present the role of liquidity; the presence of short squeezing was empirically confirmed |

*Source: own edition.*

## 2.1. The driving force of the interbank market: liquidity

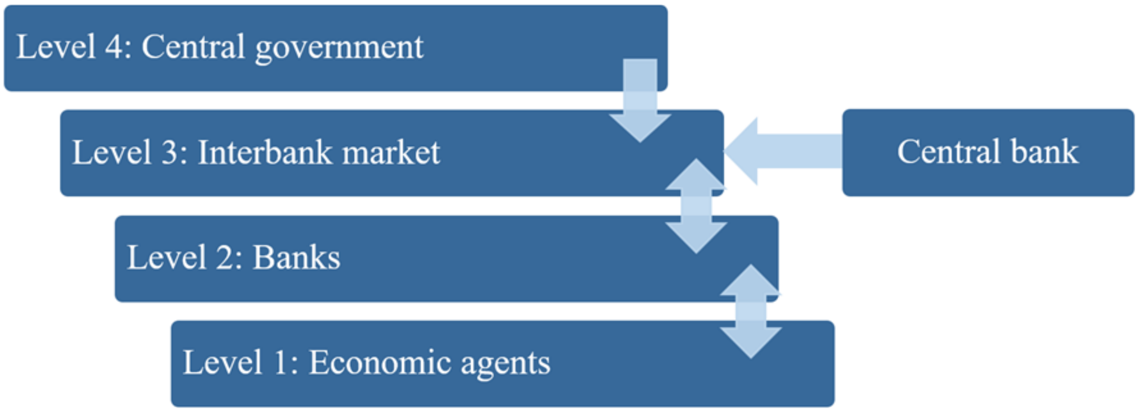
In this part of the chapter, I first present the levels of liquidity management in an economy and how these levels interact. I then clarify the dimensions of the concept of liquidity, gradually focusing on liquidity management in banks and the interbank market.

### 2.1.1. Levels of liquidity management

In an economy, forint liquidity management is implemented on several levels. And these levels are in constant interaction with each other.

*Figure 1:*

Levels of forint liquidity management in an economy




*Source: own edition.*

At the most elementary level (Figure 1.), economic agents (such as companies, municipalities, or households) seek to maintain their solvency and manage their liquidity position. Most of these economic actors actively use the services of the banking sector: they have a bank account, a significant part of their transactions are processed by electronic payment, and they often invest their savings through their bank.

At the second level, the liquidity positions of their customers are aggregated at each bank. The bank reallocates its customers' money with excess liquidity (savings) to participants short of liquidity in the form of loans. And banks affect the liquidity situation of their customers, e.g., by pricing their loans and placing them according to their risk appetite so we can talk about an actual interaction between the two levels.

The platform of the third level of liquidity management is the interbank market, where the more important goal of the participants is usually to smooth out the imbalances in their net liquidity position with short-term borrowings and deposits. Excess liquidity reduces the profitability of a credit institution, and, on the other hand, a lack of liquidity can jeopardise solvency. At the same time, liquidity risk is an asymmetric risk for banks. Not investing excess liquidity – especially in the current low-yield environment – is nowhere near as much of a problem as failing to obtain extra funds (or only very expensive). Regarding the internal structure of banks, the task of the Assets and Liabilities Committee (ALCO) is mainly to develop a liquidity strategy, and at the operational level, the treasury concludes the transactions necessary for it in the interbank market *(Kovács–Marsi (ed.) [2018])*.

An important player in the interbank market is the Magyar Nemzeti Bank (Central Bank of Hungary) (MNB), which can influence interbank forint liquidity and the interest rate on interbank unsecured forint loans with various tools. "The primary objective of the MNB is to achieve and maintain price stability." *(Act CXXXIX of 2013, Section 3. § (1))* Without jeopardising its primary purpose, its other tasks include, for example, maintaining the stability of the financial intermediation system.

The ultimate goal of the Hungarian central bank is therefore to influence the price level. The MNB is unable to directly influence the price level (the pricing of economic agents); therefore, it sets intermediate goals, which it can already influence with the available tools. And changing intermediate targets has an impact on the behaviour of economic actors and, through them, on price levels. The designation of an intermediate target is a strategic issue for which the central bank must develop and maintain a monetary policy toolset at operational level as well as operational objectives that have a direct impact on the intermediate target and, indirectly, on the final target. Such an operational target could be, for example, the interest rate prevailing in the interbank market. The whole process in which the pursuit of the operational goal helps to achieve the intermediate goal, then spreading through the whole economy, is known as the transmission mechanism *(Antal et al. [2001])*.

At this point, through the system of objectives and instruments of monetary policy, it can be genuinely understood that influencing the interbank market and interbank forint liquidity is indeed a key issue for the MNB to achieve its ultimate goal. The impact of monetary policy instruments on the interbank market will be discussed in more detail in Section 2.2.4.

There is also a fourth level (Figure 1) of liquidity management in an economy, and this is related to central government payments. The Hungarian government's HUF current account is the Treasury Single Account, which is maintained by the central bank (this is a significant item on the MNB's liability side). When economic agents meet their VAT obligations or pay various contributions, the balance of banks' current accounts with the central bank (also the MNB's liability side) decreases, while the balance of the Treasury Single Account increases. As economic actors fulfil the payment mentioned above at the same time, the forint liquidity of the entire banking system decreases suddenly and to a large extent as a result. The opposite is true (structural liquidity of the banking system increases) when payments (such as pensions) are made from the Treasury Single Account.

The government always tries to keep the balance of the Treasury Single Account in a certain band to "smooth out" its fluctuations. The Government Debt Management Agency (ÁKK) assists in this, using repo[3] transactions with banks as a tool. Consequently, central government expenditures and revenues continuously affect the liquidity of the interbank market as a whole as an exogenous factor. Neither the central bank nor the banks have a significant[4] influence on the changes of the balance of the Treasury Single Account *(Molnár [2010])*.

### 2.1.2. Dimensions of liquidity

The concept of liquidity[5] is used in the literature in several senses, so at this point, it needs to be clarified what I mean by it later.

First, let us narrow the concept to financial liquidity, i.e., basically, we will discuss the liquidity of financial markets, actors and assets. The literature also distinguishes four dimensions of financial liquidity: market-, funding-, bank-, and central bank liquidity. As

[3] A repo (also known as a repurchase agreement) is essentially a borrowing against collateral. In case of an active repo, the borrower sells a security (usually a government bond) on the spot market while simultaneously committing to repurchase it at a pre-determined price in the future *(Ács [2011])*. The reverse of this (buying securities on the spot market and selling futures) is the passive (or reverse) repo *(Ligeti–Sulyok-Pap (ed.) [2006])*.

[4] Banks have so much influence over this that they may not accept repo offers from the Government Debt Management Agency.

[5] Liquidity originally comes from the Latin word *liquidus*, which means: dilute, flowing, clear, transparent, light, calm, quiet, undisturbed, understandable, certain *(Finály [1884])*.

we will see, these concepts are mostly consistent with the levels of liquidity management presented in the previous subsection.

In defining the concepts, I rely primarily on the definitions of *Király [2008]*, but I also present alternative interpretations from the academic literature.

#### *2.1.2.1. Market liquidity*

Market liquidity is linked to the third level of liquidity management. By definition, it examines whether large volumes of transactions may be executed in a given market in a short period of time without significantly shifting the market price *(Páles–Varga [2008])*.

Interpreting the term for the unsecured interbank deposit market, market liquidity – as we shall see in Section 2.2.2. – is determined mainly by interbank limits. Under ordinary market conditions, these limits provide market participants with the ability to manage their own bank liquidity position “easily and cheaply”.

A shock to the interbank market (or even just some of its actors) could disrupt the liquid market. In the absence of financial collateral, the interbank deposit market is held together by trust. If this confidence is shaken, banks will drastically reduce their limits against each other, participants with surplus funds (who would play a major role in eliminating the shock to the market as a whole in such a situation) will “close up” and start favouring central bank assets to place excess liquidity, instead of dealing with partners. In this case, banks simply hold their excess liquidity or roll it in the overnight central bank deposit and view it as a kind of buffer in the event of a subsequent systemic liquidity shock *(Molnár [2010])*.

In this way, a kind of paradoxical situation arises in the interbank market: no player dares to lend because they are afraid of their own (and the market's) illiquidity; and the market is illiquid precisely because no one dares to lend. This phenomenon is the complete or partial cessation of market liquidity, i.e., the drying up of the interbank market.

#### *2.1.2.2. Funding liquidity*

The next type of liquidity to be examined is funding liquidity, which does not refer to the market but to its specific actor or an asset.

The concept of funding liquidity is interpreted in several ways in the literature. According to one interpretation, an actor is considered liquid if it is able to create and maintain a securities position in a given market *(Király [2008])*. Funding liquidity can be provided from own or external sources. As the loans present in the interbank unsecured deposit market are not securities, the funding liquidity dimension of liquidity is not relevant to my dissertation in this sense.

According to *Borio [2000],* funding liquidity is the ability of an asset to realise its value in money (either by selling the asset or by obtaining external financing to involve it as collateral). Among other things, this aspect of liquidity determines the extent to which a bank will be able to meet its obligations in a stress situation.[6]

#### *2.1.2.3. Bank liquidity*

Bank liquidity is linked to the second level of liquidity management and examines the credit institution's ability to meet its obligations at all times: to meet the claims against it and to meet regulatory requirements *(Király [2008])*. The literature is not uniform in this sense either; the Basel Committee on Banking Supervision *(BCBS [2008])*, *Nikolaou [2009]* and *Kolozsi–Horváth [2020]* use funding liquidity in this sense. In my dissertation, I use the concept according to the terminology of *Király [2008]* because, in my opinion, it better expresses that it is about the ability to pay (liquidity) of a given bank, and thus it is more separate from the last, central bank liquidity concept.

Before moving on to central bank liquidity, it is worth separating bank liquidity from solvency at this point. This is what Act CCXXXVII of 2013 on Credit Institutions and Financial Enterprises (generally known by the Hungarian abbreviation as Hpt.) makes an attempt to do: "Credit institutions, in compliance with the provisions on prudent operation, shall manage the funds placed in their custody as well as its own resources so as to maintain immediate solvency (liquidity) and solvency at all times." *(Hpt. [2013], Section 79. § (1))*

The previously presented bank liquidity (here immediate solvency) expresses whether the bank has sufficient funds at its disposal to meet its current payment obligations. On the contrary, a credit institution is solvent (according to the Hpt., solvent at all times) if the market value of its assets exceeds the value of its liabilities, i.e., the market value of its capital in the broadest sense is positive *(Berendi [2016])*.

[6] This funding liquidity is the focus of the LCR *(Liquidity Coverage Ratio*) indicator introduced in the Basel III banking regulations. The LCR indicator sets out a short-term liquidity requirement: that the institution has sufficiently high-quality, liquid assets in the event of a 30-day severe stress situation. The range of high-quality, liquid assets is defined in detail in the regulations *(Somogyi–Trinh [2010])*.

So basically, we can understand the difference between liquidity and solvency in that the former is mainly an asset-side problem and the latter is rather a liability-side problem. In this respect, I would like to draw attention to the fact that the expressions used in the Hpt. “immediate” and “at all times” solvency are misleading because the main difference between the two concepts is not in the time dimension.

*Table 2:*

Different states in terms of liquidity and solvency

| | **Solvent** | **Insolvent** |
|---|---|---|
| **Liquid** | **1. Healthy bank** | **3. It operates seemingly smoothly, but is in trouble** |
| **Illiquid** | **2. Temporary disruption (mismanaged assets and liabilities)** | **4. It is heading for bankruptcy** |

*Source: Based on Berendi [2016] own editing.*

Table 2 illustrates the four possible states of a bank by liquidity (rows) and solvency (columns). Of course, the ideal credit institution is both liquid and solvent (1st upper left position) with sufficient liquid assets and adequate capital at the same time.

The capital position of a solvent and illiquid bank (lower left state 2) is adequate, but it mismatched the maturity structure of its assets and liabilities. It can restore its liquidity position primarily on the interbank market (or turn to the central bank).

In a liquid and insolvent (3rd upper right) state, the credit institution has sufficient liquid assets, but its realised and latent losses have already consumed its equity. In Table 2, the arrows indicate that this is an unstable state. In the better case, a bank consolidation process can help restore the capital position, and the credit institution can return to state 1 (turquoise arrow) or, in a worse case, after a while, the disruption affects its liquidity position (for example, it does not access funds on the interbank market) from where the road leads directly to bankruptcy (4th lower right, with a red arrow pointing towards it).

#### *2.1.2.4. Central bank liquidity*

Of course, the bank liquidity presented above is strongly influenced by the market liquidity of the financial markets surrounding the institution (mainly the interbank market), as it is usually the easiest and cheapest way to obtain funds here.

This brings us to the fourth concept of liquidity. Central bank liquidity means the ability of a central bank to meet the financial intermediation system's demand for funding at any time *(Nikolaou [2009])*. In this way, I will later call the aggregate funding available to the banking system structural or systemic liquidity.

As the previously presented market liquidity wears out (the market dries up), the refinancing loans provided by the central bank come to the fore, and the central bank, as a "lender of last resort", tries to help otherwise solvent but currently illiquid banks. In the absence of such a refinancing loan for banks, the illiquid institution would be forced to sell its other liquid assets immediately and in large quantities.[7] Its massive appearance, due to a sudden increase in their supply, would lead to a drastic fall in the price of some financial instruments, and this loss could make the previously solvent credit institution (or, in extreme cases, the entire banking system) insolvent *(Kovács – Marsi (ed.) [2018])*.

## 2.2. General characteristics of the interbank market

After presenting the different levels of liquidity management in the previous chapter, clarifying the different aspects of liquidity, as well as separating them from solvency, I will now turn to the general characteristics and stylised facts of the interbank market. I will build on the characteristics described here by including them in several steps in Chapters 5 and 6 of my thesis.

First, I review the main features of interbank loans, then I focus on the limits that determine the market as a whole (including partner limits) and the interest rate developed in the interbank market. At the end of the chapter, I present in detail the MNB's monetary policy framework and its recent transformation, which interacts continuously and strongly with the interbank unsecured HUF deposit market.

[7] This is also called a fire sale.

### 2.2.1. Characteristics of the interbank loans

As a result of their activities, banks may generate excess liquidity or a lack of liquidity on a daily basis (or even more frequently). Excess liquidity is disbursed and liquidity is mainly obtained on the unsecured interbank HUF deposit market or the forint repo market. The main difference between the two markets lies in counterparty risk.

Repos are backed by securities as collateral, which almost completely eliminates counterparty risk. In some countries (such as Turkey or Australia), the interbank market typically suffers from a structural lack of liquidity, so local banks continue to lend in some form (usually through repos) to their central bank. In these countries, repo transactions can be considered the main monetary policy instrument in most cases *(Kollarik–Lénárt-Odorán [2017])*.

In contrast, the typical excess liquidity banking systems, such as the Hungarian one, encounter much larger loan volumes in the interbank deposit market than in the repo market *(Berlinger–Michaletzky–Szenes [2011])*. The average daily turnover of the latter unsecured HUF deposit market amounts to seven times the turnover of the repo market *(Erhart–Mátrai [2015])*.

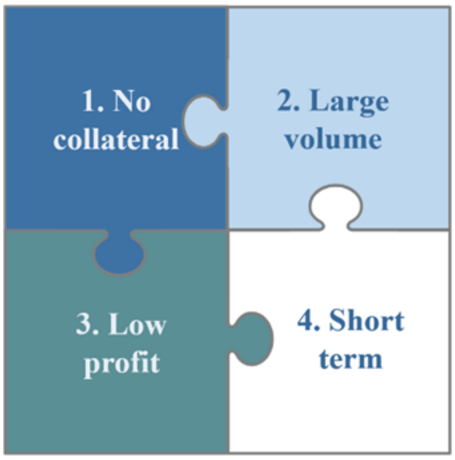
Besides interbank markets in the region, not only the Hungarian one but also the Polish *(Smaga et al. [2018])*, the Czech, the Lithuanian and the Estonian banking sectors typically have structural liquidity surplus *(Hryckiewicz [2021])*.

The low weight of the repo market in bank liquidity management can be explained mainly by legal obstacles and the low limits between the participants. The MNB's survey of banks highlighted this, and a repo working group was also set up with market participants to solve the problems. The most important obstacles hindering market participants were the lack of a standard repo framework contract and the shortcomings of the settlement system of KELER Central Depository and ÁKK (Government Debt Management Agency) *(Kolozsi–Horváth [2020])*.

Thus, the most important platform for banks' liquidity management is clearly the unsecured interbank HUF deposit market, which is similar in many respects to other financial markets, but has some special features (or rather a combination of these special features) that create different patterns than any other market.

*Figure 2:*

General characteristics of interbank lending transactions




*Source: own edition.*

Figure 2 shows the main features of interbank lending transactions, which fundamentally affect the network of interbank loans. In the figure, the interlocking puzzle pieces symbolise that these features appear in other markets separately, while their co-occurrence forms a unique image to the interbank deposit market.

One of the most important features of the interbank deposit market is that the transactions (1) are unsecured, i.e. in the event of the counterparty's default, there is no credit collateral behind them from which even partial satisfaction could be obtained. In addition, this lack of collateral is often coupled with tens of billions of (2) large loan volumes[8], which induces significant risk *(Veres–Gulyás [2008])*. With such a high risk, (3) the profit margin for a provider of funds in the interbank market is very low, but access to funding from the other side is usually the cheapest here. I will write in more detail about low intermediation profit later in Chapter 5 of my dissertation, and I will give two estimates of its extent for the Hungarian unsecured interbank deposit market.

In addition to the above characteristics, it is worth noting that (4) the maturity of interbank loans is typically short[9] compared to other markets. As the primary function of the market is liquidity management, one-day transactions are concluded in the vast majority of cases. A typical example – and I will analyse these transactions later in my dissertation – is the

[8] I examine the size of the transactions and the loan volumes in more detail in Section 3.1.

[9] This will be presented on the basis of real transactions and with the help of the literature in Section 3.1.1. in detail.

overnight (O/N) loan, where the starting date of the transaction is the same as the date of concluding the contract, and the transaction closes on the next trading day.

In addition to spot transactions, a less common transaction in the overnight deposit market is the tomnext (T/N) loan, which runs from the business day following the day of the contract to the next business day, and the spot-next (S/N) transaction, which lasts from the second working day after the contract to the following working day *(Berendi [2016])*.

### 2.2.2. The market as a whole is driven by limits – partner limits in the foreground

Moving from the characteristics of interbank loans to the characteristics of the market as a whole, an unsecured and significant exposure brings to the fore counterparty risk in the interbank market. The actors constantly monitor and rate each other. If a bank perceives that a counterparty has an increased default risk, it can respond by raising the interest rate (price adjustment) and reducing the amount of loan available (quantity adjustment) *(Berlinger [2017])*.

It can be seen from the above that the presence of information asymmetry is very significant in this market (it is difficult to get real-time, reliable information about the current asset quality, profitability, capital adequacy and liquidity position of the partner), and the stake is high due to significant credit volumes and lack of collateral. This information asymmetry raises the possibility of adverse selection and moral hazard, so lenders then respond to the perceived increase in counterparty risk less by raising interest rates than by reducing the amount of loan provided. The literature calls this phenomenon credit rationing *(Tirole [2006])*. This phenomenon is a problem especially in the case of high concentration on the lending side of the interbank market, where banks with a lack of liquidity are more likely to be exposed to a liquidity supply concentrated at a small number of participants *(Nyborg–Strebulaev [2004])*.

The phenomenon referred to in the literature as short squeezing has a similar effect on the interbank market as credit rationing. The information asymmetry mentioned above exists not only between banks, but also between banks and the duo of the central bank and the state. On the one hand, I have previously shown that the central government generates shocks in the liquidity of the interbank market through the Treasury Single Account, and the central bank is also an actor capable of influencing the behaviour of banks with its toolset. If, as a result, market participants feel that the liquidity available on the interbank market is uncertain in the short term, the banks with excess liquidity may adopt a reasonable decision to retain (leave it on the balance sheet as a kind of buffer) excess liquidity[10] *(Kolozsi–Horváth [2020])*.

Due to these phenomena, the most important tool for managing counterparty risk in the interbank deposit market is not price adjustment (as in many other markets) but the containment of the amount lent. The participants set a partner limit against each other, which means the amount of maximum exposure they wish to hold against a given bank.

The work of *Homolya et al. [2013]*, who examined the limit setting practices of Hungarian banks with the help of questionnaires and interviews, is particularly interesting and relevant in relation to partner limits. This is highly sensitive information for a bank, which is why this article is so valuable; the interviews revealed information that greatly helps to understand the mechanisms of influence of the interbank market.

According to their study, the practice of setting limits largely depends on the role of a given credit institution within their banking group. Some of the banking groups operating in Hungary perform global risk management. The domestic subsidiaries and branches of these banking groups receive the limits "from above" from their parent bank; they usually have no say in the specific limit levels or the methodology of their determination, as this is done centrally in all cases. For the other credit institutions, the parent bank only sets the guidelines and methodological frameworks, so the limit is set in a multi-level decision, giving space to the local subsidiary in smaller decisions with a local impact.

In the interbank market, lending transactions usually take place in established relationships, as unused limits are cut back over time, which can prevent the re-establishment of the relationship and close a previously live lending relationship between two participants.

There are 5 types of generally used limits. In addition to the (1) partner limits, credit institutions also set (2) country risk limits to limit the size of their joint position towards the banks in a given country. There are also the following limit types: (3) transaction type limit, (4) maturity limit, and (5) settlement limit.

The transaction type limit indicates the maximum amount that can be held for a transaction type, and banks use the maturity limit to limit the risk along a certain

[10] It is especially true in a low-yield environment, where they do not lose significant interest income.

maximum maturity, which upper limit typically depends on the type of transaction and the counterparty's credit risk rating *(Kovács–Marsi (ed.) [2018])*.

So the names are very eloquent and express well what the particular type of limit applies to. Perhaps the settlement limit needs a little more extensive explanation. Settlement risk arises from the fact that two opposite legs of a transaction (usually denominated in different currencies) are settled independently of each other, and often at significantly different times *(Galati [2002])*.

As has been observed for decades, changes in bank regulation and the development of risk management are driven by crises. Settlement risk, for example, first came to the attention of the risk management in 1974, when the German authorities closed a medium-sized German bank, Bankhaus Herstatt, while it was receiving huge payments in German marks from its partners, but the associated dollar consideration had not been settled with its New York partner yet. As a result of the bankruptcy of Herstatt, transfers were stopped in the market to other partners until banks were sure that the consideration had arrived. Of course, this mechanism froze international payment systems, confidence has only slowly recovered *(Bech–Holden [2019])*.

Therefore, the settlement risk is a really serious threat that can jeopardise a bank's liquidity, so the banks try to protect against this with, among other things, settlement limits.[11] The topic is still actual; the agenda of the meeting of the Basel Committee on Banking Supervision (BCBS) in Madrid on 30-31 October 2019, included the issue of settlement risk management, i.e., it is an issue whose regulation is expected to change in the near future *(BCBS [2019])*.

From the perspective of interbank lending, the partner limit is clearly a bottleneck and is also the most commonly used type of limit. *Berlinger [2017]* examined the relevance of partner limits (more precisely, the implicit partner limits estimated by her in the absence of their knowledge) and the interest rate (as a financing cost) of interbank unsecured forint transactions on transaction data between 2003 and 2012. The findings are in line with the results of the research mentioned earlier. The interbank market is more driven by quantity factors (partner limits), while price components – in this case, the interest rate on transactions – are less important in this market.

[11] Risk-mitigating clearing techniques such as Delivery versus Payment (DvP) for financial instruments is also on the horizon.

A similar result has been obtained by the authors *Geršl–Lešanovská [2014]* when examining the Czech interbank market during the crisis of 2008. They established that, in reaction to an increase in counterparty risk during the crisis, banks decided not to change interest rates but rather to reduce counterparty limits and introduce maturity limits. According to their analysis, interbank interest rates were affected almost exclusively by the spillover effect coming from parent banks from abroad rather than by credit relationships in the interbank market.

Thus, in light of the literature, the interbank deposit market seems to be driven mainly by partner limits. However, the setting of partner limits is also the result of a multivariable (and, as I presented earlier, multi-level) decision-making process for some banks. From the perspective of understanding the market, it is worth looking behind the limits on the surface and going a level deeper by exploring the elementary factors that shape it.

As a result of their qualitative research, *Homolya et al. [2013]* found that limits are fundamentally shaped by three factors, (1) the counterparty's (or country's sovereign) credit rating, (2) its CDS spread, and (3) certain financial ratios. In general, financial ratios are intended to numerically involve the profitability, asset quality, capital adequacy and liquidity of the partner credit institution in the limit setting process.

Relying on the implicit rating indicator used by her, *Berlinger [2017]* found that after the 2008 crisis, the most active banks became the most creditworthy players in the market, and therefore they were able to access funds under the best conditions.

### 2.2.3. Interest rates in the unsecured interbank deposit market

Although price adjustment (interest rate changes) is less significant in the interbank market, its extent reveals much about the state of the market as a whole.

In addition to examining interbank interest rates, there is also a compelling argument. Namely, banks keep partner limits the highest secret, and even with the most detailed transaction data, only a generous estimate can be given for them (see, for example, the implicit partner limits calculated in the previously described *Berlinger [2017]* article). In contrast, the average overnight interbank interest rates (BUBOR and HUFONIA) are published daily by the Central Bank of Hungary *(MNB [2021])*.

The HUFONIA (Hungarian Forint Overnight Index Average) is the weighted average interest rate on overnight interbank unsecured transactions, which is calculated by the MNB on a daily basis from the regular data reporting of credit institutions *(MFT [2020])*.

HUFONIA has been quoted by the MNB since 1 September 2010, and was introduced with the aim of supporting the mass emergence of OIS (Overnight Indexed Swap) interest rate swaps, enabling participants to manage their interest rate risk more effectively.

BUBOR is a much more accepted and widely used interbank interest rate indicator than HUFONIA. BUBOR (Budapest Interbank Offered Rate) means the (trimmed) average interest rate at which the interest quoting banks present on the interbank market on a given banking day are willing to provide unsecured loans denominated in HUF to each other for different maturities *(MNB [2019c])*.

At the initiative of the Hungarian Forex Association, the quoting of BUBOR fixings started on 1 August 1996, with the participation of 8 active interest rate quoting banks. At the start, only for two terms (1 and 3 months) and calculated for the term, most important for my dissertation, i.e., the 1-day (O/N) maturity since 1 June 1999. Since then, the number of maturities has initially been increased. As a result of the 2008 crisis and the LIBOR manipulation scandal that erupted in 2012, the Hungarian Forex Association issued new regulations in 2013, in which the former listed but still active maturities were reduced to nine[12] *(Fliszár [2015])*.

*Erhart–Mátrai [2015]* detail the BUBOR reform, which was led by the Central Bank of Hungary in the wake of the international manipulation scandal. Under the reform, one of the essential institutional steps was the establishment, within the Hungarian Forex Association, of a Quotation Committee having greater independence than before, where members to represent the Hungarian Banking Association and the MNB were present. Regarding the BUBOR calculation method, the trimming methodology for average calculation was adjusted to the number of market makers, and the selection process of BUBOR rate quoting banks was changed and, as I mentioned, the number of listed maturities was reduced. In order to increase transparency, individual bank quotations are now also public, and Quotation Committee meeting minutes have been public since July 2014.

[12] 1 day, 1 week, 2 weeks, 1 month, 2 months, 3 months, 6 months, 9 months and 12 months

As of 1 November 2016, the MNB took over the calculation and management of BUBOR from the Hungarian Forex Association and published its current values at 11 am every Hungarian banking day *(MNB [2019c])*.

The role of interest rates in the interbank market is far from being limited to the market itself. They appear as reference interest rates for thousands of HUF billion in retail and corporate loans and deposits, and directly affect the most diverse markets for derivatives. The most significant derivative products tied to BUBOR are forward rate agreements (FRAs) and interest rate swaps (IRSs) with tens of thousands of billion HUF portfolios *(Erhart–Mátrai [2015])*.

In addition to the above, BUBOR has a critical role in the efficient operation of monetary policy, as it is a key variable in one of the most important channels of monetary transmission, the interest rate channel *(Horváth–Krekó–Naszódi [2005])*.

### 2.2.4. Central bank instruments affecting the interbank market

The period following the fall of Lehman Brothers on 15 September 2008 has shown that a market that is "floating" in abundance of liquidity can dry up from one moment to the next. And the unfolding crisis has highlighted the serious consequences of the volatility of liquidity, not only for the interbank market but also for the real economy. Therefore, the amount of liquidity has come to the forefront of the world's central banks as a monetary policy variable in the last decade.

After the crisis erupted, most central banks cut base rates to boost the economy. When it was already approaching the 0% effective lower limit (zero lower bound) and no further reduction was possible, the large central banks resorted to a tool that had not been used before, known as quantitative easing. Central banks began to use their balance sheet total as a monetary policy instrument from then on, which proved to be effective *(Blanchard et al. [2012])*. As a result of quantitative easing, the long end of the yield curve was also reduced, a move through which central banks intended to stimulate investments.

Below, I shall review the Hungarian monetary policy framework and its recent transformation in the light of the MNB's Self Financing Program and the system of quantitative restrictions. Relying primarily on the studies of *Csávás–Kollarik [2016], Kollarik–Lénárt-Odorán [2017]* and *Kolozsi–Horváth [2020],* I present how the change in the monetary policy toolset affected the behaviour of banks in the interbank market, and how it affected the structure of the market as a whole. These changes will explain a number of phenomena in Chapter 3 of my dissertation, examining the dynamics of the interbank network.

#### *2.2.4.1. Main monetary policy instrument*

In countries where the banking system typically has a structural excess of liquidity, the central bank often issues securities in an attempt to withdraw (sterilise) the excess liquidity. The interest rate on the main monetary policy instrument issued by a central bank is generally the base rate (e.g. in Hungary) and has a short maturity.

The short maturity of the main monetary policy instrument usually means at least 1 day but not more than 1 month. Of course, there are both pros and cons in favour of using shorter and longer maturities in this interval. In the case of short maturities (in extreme cases 1 day), banks are able to respond to liquidity shocks to the market at any time using the main monetary policy instrument, so the central bank facilitates liquidity management for participants.

However, this is also the main disadvantage of using short-term maturity, as banks are not interested in accurately forecasting their liquidity position. Central bank assistance is constantly available, and in a well-functioning market, funds can also be accessed through this channel close to the interbank interest rate. With its too short maturity, the main monetary policy instrument does not encourage the development of an efficient interbank market and activity there. In this case, the central bank essentially assumes the role of liquidity redistribution in the interbank market.

On the one hand, it is costly for the central bank to fix excess liquidity with the main monetary policy instrument (since it pays interest to banks on the securities issued), yet it can significantly increase the efficiency of the base rate, keeping interbank interest rates close to the interest rate of the main monetary policy instrument *(Molnár [2010])*. Without it, an oversupply of liquidity could lower interbank forint interest rates to the bottom (or below) of the interest rate corridor.

The main monetary policy instrument is thus able to simultaneously manage excess interbank liquidity and help the efficiency of monetary transmission. By issuing such an instrument, the central bank can play a price-determining role in the interbank market.

Self-issued sterilization instruments are typically used by central banks in emerging markets. We have seen this in the cases of Israel, Chile, China, Indonesia, Malaysia, Thailand or India, for example. The world's major central banks (Fed, ECB, Bank of England, Swiss National Bank) did not introduce such instruments, so excess liquidity in these countries was deposited in the banks' reserve accounts *(Kollarik–Lénárt-Odorán [2017])*.

In Hungary, the main monetary policy instrument – joining the above-mentioned group of emerging countries – from 10 January 2007 to 31 July 2014 was the two-week central bank bond; before 10 January 2007 and from 1 August 2014 to 22 September 2015, the two-week central bank deposit, and from 23 September 2015 to 18 December 2018, the three-month central bank deposit. From 19 December 2018, the role of the governing instrument was taken over by the required reserves *(MNB [2021])*.

The changes in the main monetary policy instrument are mainly explained by the MNB's Self-financing Programme announced on 24 April 2014, which primarily aimed at reducing Hungary's external vulnerability, but also reduced the central bank's balance sheet total.

The central bank planned to reduce external vulnerabilities primarily through financing government debt mainly from internal sources, the key element of which was to stimulate demand for forint-denominated government securities. This growing demand, in turn, had an additional monetary easing effect through cuts in government bond yields, which supported the central bank's policy of cutting interest rates *(Csávás–Kollarik [2016])*.

The programme was primarily aimed at stimulating demand for government securities, to the detriment of the use of the main monetary policy instrument. This required a transformation of the central bank's entire monetary policy toolset, which took place in three stages. As I mentioned, until the summer of 2014, the central bank's governing instrument was the two-week bond, which became a two-week time deposit under the first phase of the programme. In addition, the MNB introduced a new interest rate swap (IRS), with which banks could receive floating interest rates for a fixed interest rate.

The second phase of the Self-financing Programme was announced by the central bank on 2 June 2015. A new 3-month central bank deposit became the governing instrument instead of the 2-week central bank deposit, and the MNB limited the use of the remaining two-week deposit.

The conversion of the main monetary policy instrument into a deposit and its subsequent maturity reduced its liquidity, making it less and less attractive to banks, diverting banks' funding to other markets and indirectly increasing banks' demand for eligible collateral (primarily government securities) *(Hoffmann–Kolozsi [2017])*.

The third phase of the programme was announced on 12 January 2016, in which the MNB projected to phase out the two-week deposit and interest rate swaps.

In support of the Self-financing Programme, the MNB presented a framework for quantitative restrictions in autumn 2016, aiming to exclude interbank liquidity from the main monetary policy instrument by restricting access to three-month deposits. The essence of the effect mechanism is that the liquidity displaced from the main monetary policy instrument appears primarily in the unsecured interbank deposit market and the government securities market, and to a lesser extent, in overnight central bank deposits. The Monetary Council of the MNB decides on the amount of liquidity to be displaced on a quarterly basis, adjusting to the liquidity situation of the interbank market and the monetary policy orientation *(Kolozsi [2017])*.

There are two main differences between the system of quantitative restrictions and the quantitative easing applied by the world's major central banks after the crisis. The first is that quantitative restriction, like quantitative easing, increases the free liquidity of banks but does not change the balance sheet total of the central bank (only the liability side is rearranged). In contrast, in the case of quantitative easing, the central bank buys (primarily) long-term securities, and it swells its balance sheet. Another important difference is that quantitative easing directly affects long-term yields by purchasing long-term instruments by the central bank, whereas quantitative restrictions can only indirectly affect long-term yields by changing short-term yields.

In addition to the system of quantitative restrictions affecting the supply of liquidity, it is worth examining the other side, namely the demand for liquidity from the banking system. *Kolozsi–Horváth [2020]* estimated the unsecured liquidity demand function of Hungarian banks at overnight maturity using segmented OLS regressions based on cross-sectional data between 2016 and 2019.

According to their results, in the case of narrow excess liquidity of less than HUF 130 billion displaced from the base interest rate instrument, the relative price[13] of central bank liquidity was between 10 and 60 basis points with significant volatility over the given

[13] On average, how much more does a bank receive for its excess liquidity in the interbank market than in the case of using a one-day central bank deposit (HUFONIA, minus O/N deposit interest rate).

period. With a stable crowding-out (between HUF 130 billion and HUF 410 billion), the price-depressing effect on the interbank market is still significant; in the case of excess liquidity of HUF 100 billion, the relative price of liquidity decreases by 2 basis points according to the demand function. The saturation point of the Hungarian banking system was at HUF 410 billion excess liquidity. Above this value, the overnight liquidity demand function became practically horizontal.

Another interesting observation is that some banks did not place excess liquidity on the interbank market but showed complete passivity. It was shown that the previously presented short squeezing phenomenon might have been present in the Hungarian interbank market; in the case of low (or perceived low) liquidity, banks tended not to lend to each other, which increased the interbank interest rate.

#### *2.2.4.2. Interest rate corridor*

The Central Bank of Hungary seeks to prevent the extreme volatility of interest rates on transactions on the interbank market and is currently maintaining an asymmetric interest rate corridor in order to achieve this goal *(MNB [2021])*.

At the top of the interest rate corridor, it is willing to provide unlimited amounts of overnight loans to banks with temporary liquidity shortages, with collateral. In theory, this prevents the interest rate on interbank transactions from rising above the top of the interest rate corridor. “In theory” because some banks may not be willing (or unable) to offer adequate collateral to the central bank and are therefore willing to pay a higher interest rate to a partner bank than in case of an O/N central bank secured loan.

The bottom of the interest rate corridor is the interest rate on overnight central bank deposits, in addition to which the MNB accepts an unlimited amount of excess liquidity generated by market participants. This instrument is designed to prevent interest rates on interbank transactions from leaving the interest rate corridor downwards.

If the interest rate corridor narrows, it will encourage players to engage in passive liquidity management and lower activity in the interbank market. This is because the central bank's overnight secured loan and overnight deposit are available at a rate, which is relatively close to the prevailing interest rate, making the use of central bank assets less expensive compared to interbank transactions. With a broader interest rate corridor, the use of a central bank overnight deposit is less worthwhile, and central bank borrowing is also relatively more expensive, resulting in a more active interbank market, while on a broader interest rate corridor, interbank interest rate volatility may be higher, which is undesirable for monetary transmission efficiency *(Kollarik–Lénárt-Odorán [2017])*.

*Table 3:*

Changes in the Hungarian interest rate corridor

| Date of change | O/N central bank deposit interest rate | O/N central bank loan interest rate | Central bank base rate | Interest rate corridor width |
|---|---|---|---|---|
| 01.01.2002 | 8.25% | 11.25% | 9.75% | **3%** |
| 01.09.2002 | 8.5% | 10.5% | 9.5% | **2%** |
| 17.01.2003 | 3.5% | 9.5% | 6.5% | **6%** |
| 25.02.2003 | 5.5% | 7.5% | 6.5% | **2%** |
| 22.10.2008 | 11% | 12% | 11.5% | **1%** |
| 24.11.2009 | 5.5% | 7.5% | 6.5% | **2%** |
| 25.09.2015 | 0.1% | 2.1% | 1.35% | **2%** |
| 23.03.2016 | -0.05% | 1.45% | 1.2% | **1.5%** |
| 27.04.2016 | -0.05% | 1.3% | 1.05% | **1.35%** |
| 25.05.2016 | -0.05% | 1.15% | 0.9% | **1.2%** |
| 26.10.2016 | -0.05% | 1.05% | 0.9% | **1.1%** |
| 23.11.2016 | -0.05% | 0.9% | 0.9% | **0.95%** |
| 20.09.2017 | -0.15% | 0.9% | 0.9% | **1.05%** |
| 19.12.2018 | -0.15% | 0.9% | 0.9% | **1.05%** |
| 27.03.2019 | -0.05% | 0.9% | 0.9% | **0.95%** |
| 08.04.2020 | -0.05% | 1.85% | 0.9% | **1.9%** |
| 24.06.2020 | -0.05% | 1.85% | 0.75% | **1.9%** |
| 22.07.2020 | -0.05% | 1.85% | 0.6% | **1.9%** |

*Source: MNB [2021]*

Table 3 shows the changes in the width of the interest rate corridor and the position of the central bank base rate within the interest rate corridor since 2002.[14] It can be observed that most of the changes in the width of the interest rate corridor were made in the year and a half after the start, and in the next 12 years, despite the crisis in 2008, the central bank changed it only twice.

Between August 2012 and May 2016, the MNB implemented a gradual interest rate cut, within which the base rate decreased from 7% to 0.9%, which became possible and justified because of the low inflation environment, the unused capacities of the Hungarian economy and the improved assessment of risks *(Csávás–Kollarik [2016])*.

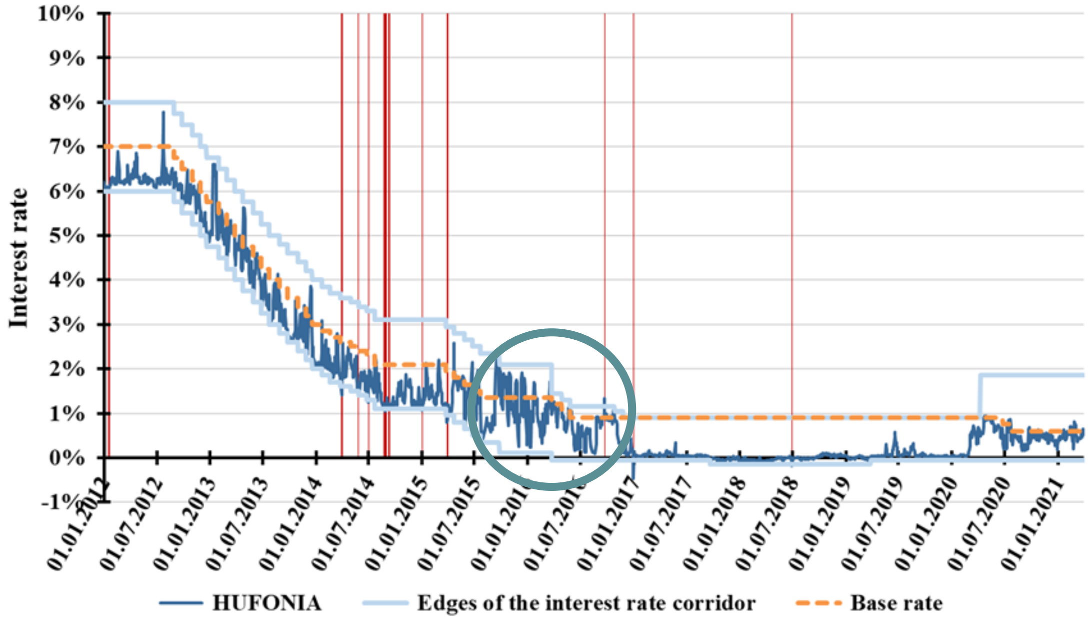
[14] As indicated in the introduction, ending 31 March 2021.

In terms of the interest rate corridor, the most significant turnaround occurred in the second phase of the Self-financing Programme (September 2015), when the previously symmetric interest rate corridor became asymmetric; on the one hand, the MNB began to narrow the interest rate corridor gradually, and on the other hand, it pushed the two edges of the interest rate corridor down beyond the reduction of the base rate. This led to a negative interest rate on the O/N central bank deposits in March 2016, and from 23 November 2016 to 8 April 2020, the interest rate on the overnight secured MNB loans (top of the interest rate corridor) has been the same as the base rate.

The average interest rate on overnight unsecured interbank transactions (HUFONIA) was also most significantly affected by the second phase of the Self-financing Programme.

*Figure 3:*

HUFONIA and the interest rate corridor (2012-2021)




*Source: Own editing based on MNB data (MNB [2021]).*

*Csávás–Kollarik [2016]* showed that while after the crisis, the overnight unsecured interbank interest rate fluctuated in the lower half of the interest rate corridor due to the accumulation of overnight central bank deposits until September 2015. After that, it rose and became close to the base rate in the upper part of the asymmetric interest rate corridor (turquoise ellipse in Figure 3), which had a beneficial effect on the efficiency of monetary transmission.

This was precisely the aim of making the interest rate corridor asymmetric: making overnight central bank deposits less and less attractive to banks, and enabling the interbank liquidity to look for other channels.

As a side effect of the September 2015 restructuring of the central bank's toolset, the overnight unsecured interbank interest rate volatility increased within the interest rate corridor.[15] To address this, the central bank gradually reduced the width of the interest rate corridor, which brought the intraday spread of interbank interest rates back to close to the previous 10-20 basis points.

As a result of the Self-financing Programme, the structural liquidity of the banking system narrowed significantly[16], which increased the banks' limits on the MNB. Due to tighter systemic liquidity, the occurrence of interbank transaction rates under the previously relatively common overnight central bank deposit rate (bottom of the interest rate corridor) (Figure 3, red vertical lines) declined,[17] which also had a supportive effect on the efficiency of monetary transmission.

The next major turn in monetary policy took place in the wake of the outbreak of the coronavirus crisis in the spring of 2020. On 1 April 2020, the MNB decided to announce one-week deposit tenders on a weekly basis.[18] The purpose of this tool was to achieve that the banking system's liquidity is placed into deposits at the base rate *(MNB [2020b])*. As a result, interbank interest rates rose significantly and began to fluctuate around the base rate. The 0.9% interest rate on the one-week deposit instrument was much higher than the -0.05% interest rate on the O/N deposit instrument, which was the bottom of the interest rate corridor, so the effectiveness of the bottom of the interest rate corridor decreased significantly.

[15] There were two reasons for this: on the one hand, overnight interbank interest rates moved away from the edge of the interest rate corridor, and on the other hand, the two-week central bank deposit limit increased the volatility of two-week interest rates, which also affected the one-day horizon.

[16] The total central bank liquidity of the banking system decreased from the previous HUF 4,500-6,500 billion to HUF 2,200 billion by June 2016 *(Csávás–Kollarik [2016])*.

[17] The fact that the interest rate on the central bank deposit has been negative since 23 March 2016 also contributed to this.

[18] The one-week deposit instrument had already been part of MNB's potential toolkit since autumn 2016.

#### *2.2.4.3. Required reserves*

The required reserves system of banks, when it was established, still had a primarily prudential function. This function has been slowly filled by other instruments (such as deposit insurance, see *Diamond – Dybvig [1983]*), which in some countries (e.g., Sweden, Denmark, Canada, Australia, Hong Kong) has led to the disappearance of this central bank instrument and elsewhere began to serve liquidity management purposes *(Hoffmann–Kolozsi [2017])*.

The operation of the required reserves system is similar to changing the width of the interest rate corridor in that the looser the minimum reserve rules (the longer the time window banks have to meet their average reserve requirements), the lower the interbank activity yet interbank rates are, but more stable than in the case of strict reserve rules *(Kollarik–Lénárt-Odorán [2017])*.

In Hungary, the interest rate paid on the required reserves has been the same as the interest rate on the main monetary policy instrument[19] since 1 May 2004 (accession to the European Union). As mentioned earlier, the required reserve has been the main monetary policy instrument of the MNB since 19 December 2018 *(MNB [2021])*.

As the interest rate corridor became asymmetric, the previously optional reserve ratio (2%, 3%, 4% or 5%) was uniformly changed to 2% on 1 December 2015 and then was dropped to the current level of 1% on 1 December 2016, which steps were aimed at further crowding out liquidity from central bank instruments *(MNB [2020e])*.

As an important element of the Central Bank's response to the coronavirus crisis, banks were temporarily exempted from the required reserves, starting from the spring of 2020, which freed up about HUF 250 billion in extra liquidity *(MNB [2020g])*.

## 2.3. Effects of past shocks on the Hungarian interbank deposit market

In order to understand the impact mechanisms and structure of the Hungarian interbank market, it is important to be aware of the recent events that had a significant impact on it. It is worth noting how the participants reacted to smaller and greater market shocks,

[19] With this change, the covert taxation function of the mandatory reserve system has been abolished *(MNB [2020e])*.

central bank actions, and how the structure of the interbank market changed from one moment to the next.

The regulators recognised the importance of systemic risk after the Lehman bankruptcy in 2008, after which special attention was paid to the interbank markets and the shocks affecting them. It is interesting, however, that the Hungarian literature began to deal with the topic very early – already in the late 1990s – first, in connection with the repo market *(Szakály–Tóth [1999])*, and then in *Gereben [1999]* examined the Russian crisis. It took place in the unsecured interbank credit market between September 1998 and March 1999 and identified the underlying causes of the imbalances. The study of *Lublóy [2004] and [2005]*, who first examined the systemic risk aspects of the Hungarian market, can also be included among the pioneering works.

In this section, I list three important events of the last decade and a half, documented in the academic literature, in the Hungarian interbank market. I will focus on different types of events that have influenced the behaviour of market participants and changed the structure of the market as a whole (even only temporarily). Following the reaction to the shocks and the changes in the market structure, I would like to shed new light on the operation of the Hungarian interbank forint market.

### 2.3.1. The 2008 global financial crisis

The bankruptcy of Lehman Brothers in mid-September 2008 was felt in Hungary at the end of the month. Market liquidity began to leak out, with disturbances in the government securities market as well as the swap market. On October 9, 2008, the government securities market froze almost completely, the leading stock market shares and the forint began to fall, and the interbank market came to a halt *(Király [2008])*.

Based on the responses of the surveyed Hungarian banks, *Homolya et al. [2013]* concluded that the spread of the crisis in October 2008 clearly had the greatest impact on partner limits – and thus directly on the interbank market – when almost immediately market participants began to cut partner limits significantly.

Confidence in the interbank market recovered slowly; the average daily transaction amounts of the interbank forint deposit market reached the level before Lehman Brothers' fall only in 2012. This event also left its mark on the practice of setting limits in the interbank market: financial institutions introduced early warning systems, and the reaction time of banks was significantly shortened compared to the past.

In the unsecured interbank forint deposit market, which is the focus of my dissertation, the volume of transactions and the average monthly number of counterparties fell by half, and the number of active banks fell by one third in a short time, while the central bank overnight deposit portfolio grew in the banking sector.

*Berlinger–Michaletzky–Szenes [2011]* examined changes in the unsecured interbank deposit market network based on detailed transaction data between December 2002 and March 2009. Their findings are consistent with those described previously in terms of the volume of transactions. The weekly sum of transaction amounts halved from the pre-crisis level of HUF 600 billion, fell to HUF 300 billion, and then stuck around this level for a longer time.

Regarding the change in the number of active banks, the lending and borrowing sides were examined separately. Concerning the latter, they measured an even greater fall than the (general) one-third decline described by *Homolya et al. [2013]*: until mid-2007, there were approx. 12 active borrowing banks in the market, which number fell to 10 by the end of 2007 and then, after the Lehman bankruptcy, to 4, a figure never seen before.

Examining the structure of quantity adjustment in detail, it was found that there was no significant change in the concentration of loans as a result of the crisis, as it fluctuated in the same band throughout their analysed time horizon. On the borrowing side, however, a significant increase started already at the end of 2007, which jumped significantly due to the crisis. Based on the concentration measures, it appeared that banks with an essentially unchanged amount of surplus funds lent to fewer and fewer partners.

In addition to transaction amount and concentration, we can also read exciting findings in their article about changes in interbank interest rates. On 15 September 2008, following the bankruptcy of Lehman Brothers, the daily weighted average unsecured HUF money market interest rate jumped by 3.5%, interest rate volatility increased, and was further boosted by the 300 basis point base rate increase announced on 22 October. Subsequently, in 2009, interest rates fluctuated in the lower half of the interest rate corridor, with surprisingly low fluctuations.

That is, significant interest rate hikes and counterparty risk increased in the context of the crisis had a smaller impact on interest rates than expected by the authors. If price adjustment had been dominant in the market, interbank interest rates would have had to stick to the top of the interest rate corridor. The fact that this did not happen in the end was explained by the authors as follows: they stated that a clear and lasting quantity adjustment dominated the interbank market, and the participants responded to the increased uncertainty by cutting back on lending.

Analysing the behaviour of individual players, it was found that after the crisis, role changes were frequent in the market: liquidity sinks (basically liquidity buyers) became sources (typically financing the activities of partners by committing their excess liquidity), and former sources became sinks.

Looking at foreign (and primarily regional) interbank markets, *Allen et al. [2014]* studied the spread of liquidity shocks within large international groups of banks during the crisis in 2008. The study was based on a relatively large sample of 51 international parent banks together with their 269 foreign subsidiaries in total (from a total of 63 countries, including the Visegrad countries). They found that, upon the outbreak of the crisis, some subsidiary banks in individual countries were faced with a decline in funds available from their parent banks and that, in most developing regions, primarily banks with a foreign parent bank decided to slow down their lending activities in the interbank market, a move leading to a decline in credit supply.

Based on the study of *Allen et al. [2014]*, we can conclude that the fact that a significant number of large banks in Hungary were foreign-owned and thus they could expect less parent bank help at the end of 2008 than before significantly contributed to the freezing of the Hungarian interbank market and the decline in activities on it.

### 2.3.2. Liquidity shocks generated by the Treasury Single Account

Earlier, I briefly presented the Hungarian government's current account kept in the MNB, the Treasury Single Account. Economic actors face various tax obligations at the same time, which, when settled through their account-holding bank, lead to a sudden and large reduction in the overall systemic liquidity of the interbank market. The Treasury Single Account is referred to in the academic literature as an autonomous factor, which means that it is an exogenous variable that cannot be directly influenced by central bank instruments *(Antal et al. [2001])*.

Individual actors can only predict the resulting shocks to interbank forint liquidity only with a significant error. The uncertainty in the forecast is compounded by the fact that, in addition to VAT and other tax payments, the central government may have a number of other ad hoc expenditures and the repo transactions executed by the Government Debt

Management Agency to smoothen the balance are occasionally obstructed by the banks' limits and cannot be executed in the projected volume.

*Molnár [2010]* dealt with this problem in more detail and highlighted two events in this regard. The first took place on 15 December 2009, when, as a result of the monthly tax payments due, the liquidity of the interbank market as a whole decreased to such an extent that the participants were forced to borrow more than HUF 100 billion in central bank O/N loans. On the next business day, banks were able to terminate their central bank borrowing by reducing their two-week MNB bond portfolios.

A series of events very similar to the events at the end of 2009 took place on 21 April 2010, when banks underestimated the volume of monthly VAT payments at the system level and, unfortunately, significantly increased their two-week bond holdings on the same day. This market shock had a longer-lasting effect than before, with central bank overnight borrowing being extensive for an entire week[20] until market participants were able to write off their two-week MNB bond holdings.

From the events of December 2009 and April 2010, it appears that the shocks to the interbank market following the tightening of liquidity tend to be reflected in a sharp increase in central bank overnight lending (and the interbank interest rates sticking to the top of the interest rate corridor).

Figure 4 shows the difference between the total overnight deposits placed by banks and total overnight central bank loans, using the MNB's regularly published data series entitled "Volume of overnight assets in use" *(MNB [2021])*. A positive amount means a net deposit; a negative amount means a net central bank loan. The daily net deposit placement (dark blue line) is extremely volatile, so I also displayed its 30-day[21] moving average (light blue line) to make it easier to observe the longer-lasting trends. I also highlighted the days when the entire banking system was a net central bank borrower with red vertical lines. The intensification of these days indicates liquidity disturbances in the market. I highlighted the one-day interbank liquidity disturbance of 15 December 2009

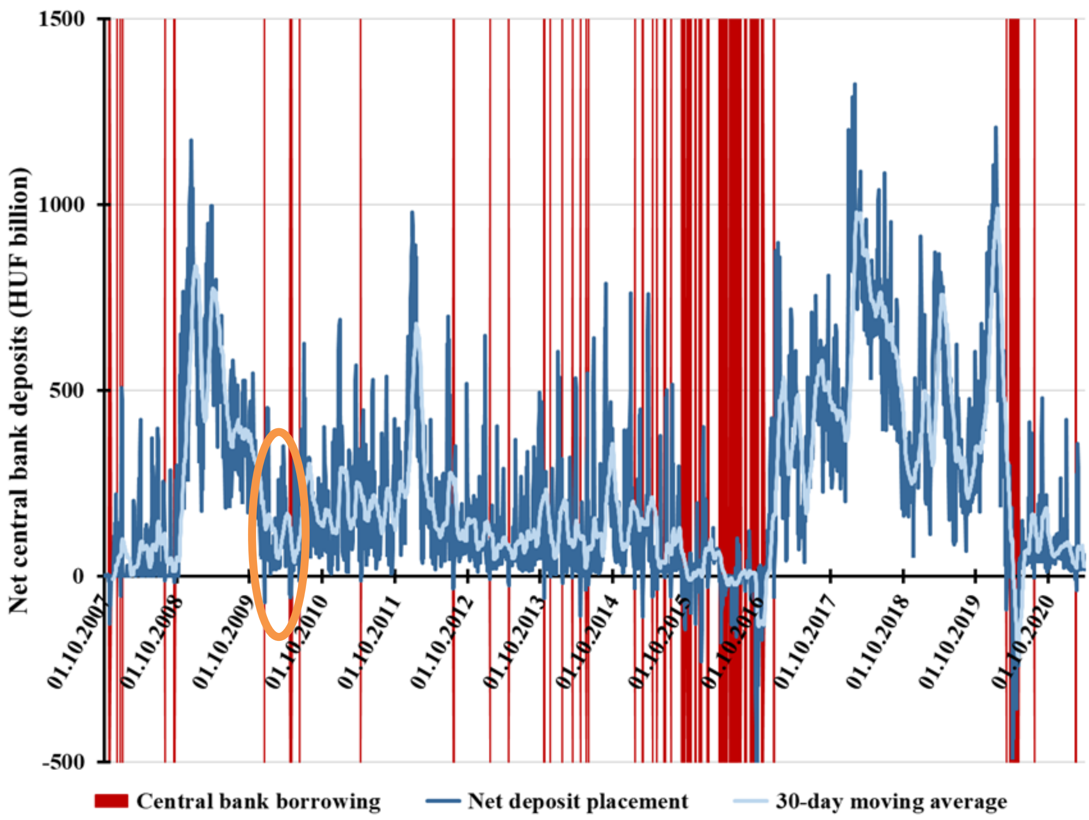
[20] The fact that Greece requested a bailout on 23 April 2010 from its creditors probably also contributed to the banks' one-week continuous central bank O/N borrowing.

[21] Earlier I showed that due to the movements of the Treasury Single Account, a strong monthly periodicity (seasonality) appears in the liquidity shocks, that is why I chose the 30-day time window for the moving average.

and a longer (one week) of 21 April 2010 described in detail earlier with an orange ellipse in Figure 4.

*Figure 4:*

Aggregate, netted amount of overnight central bank assets




*Source: Own editing based on MNB data.*

Among other things, in response to these types of events, on 6 September 2010, the Monetary Council of the MNB decided to publish a weekly forint liquidity forecast, helping participants prepare for possible market shocks ever since *(MNB [2020c])*. The aim of the introduction was for participants to rely less on central bank assets forming the two ends of the interest rate corridor (overnight secured central bank loans and overnight central bank deposits) in the event of market shocks, and for participants to enter into the necessary liquidity transactions in the interbank market *(Molnár [2010])*.

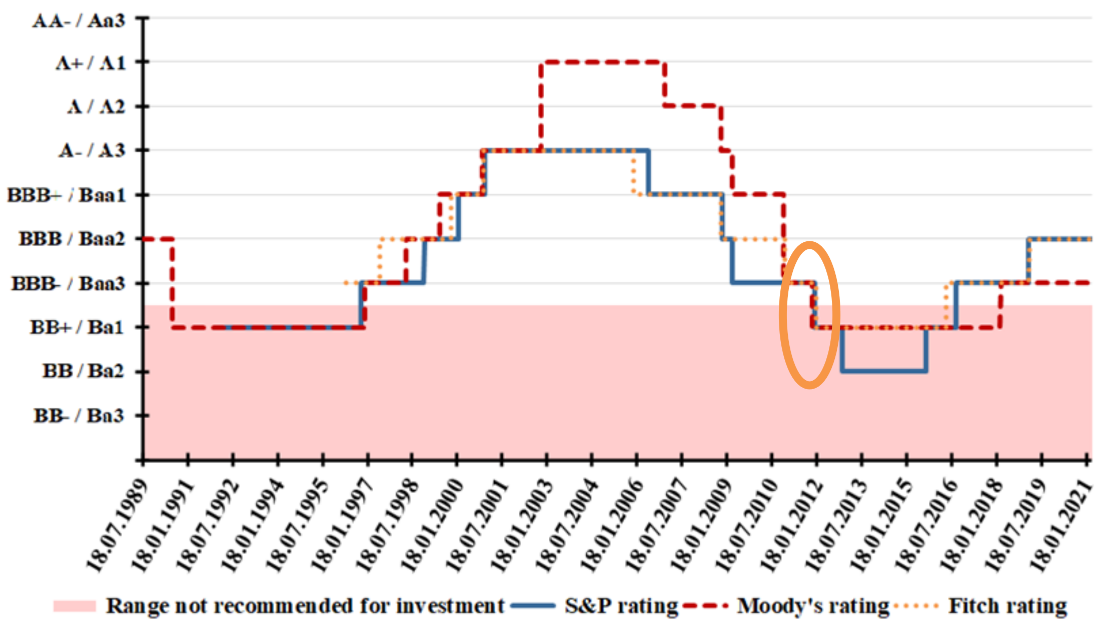
As can be seen in Figure 4, partly due to the MNB's regular liquidity forecast, the frequency of central bank overnight borrowing decreased somewhat in the 2-3 years following the events mentioned above in 2009-2010, but did not completely solve the problem.

### 2.3.3. Changes following the deterioration of the Hungarian state's sovereign credit ratings

The next significant event – also mentioned in the academic literature – is the events of the end of 2011 and the beginning of 2012, when Hungary's long-term credit ratings fell at the three major credit rating agencies (S&P, Moody's and Fitch) in the junk, speculative category within a short time (Figure 5, orange ellipse).

*Figure 5:*

Changes in Hungary's long-term sovereign credit ratings (1989-2021)




*Source: Own editing based on MNB data.*

Figure 5 shows the change in Hungary's long-term sovereign credit ratings. On 24 November 2011, Moody's (dashed red line) downgraded Hungary's long-term sovereign rating from Baa3 to Ba1 (not recommended for investment, speculative).[22] Subsequently, on 21 December 2011, Standard & Poor's (continuous blue line) similarly downgraded Hungary's rating (from BBB- to BB+), and then on 6 January 2012 Fitch also followed the other two credit rating agencies (dotted orange line) *(MNB [2020a])*.

In their study, *Homolya et al. [2013]* dealt with the events in detail, and based on the responses of the interviewed Hungarian banks, they concluded that in the period before

[22] Being downgraded into a non-investment grade (speculative) category happened only once, on 13 July 1990 in Hungarian history.

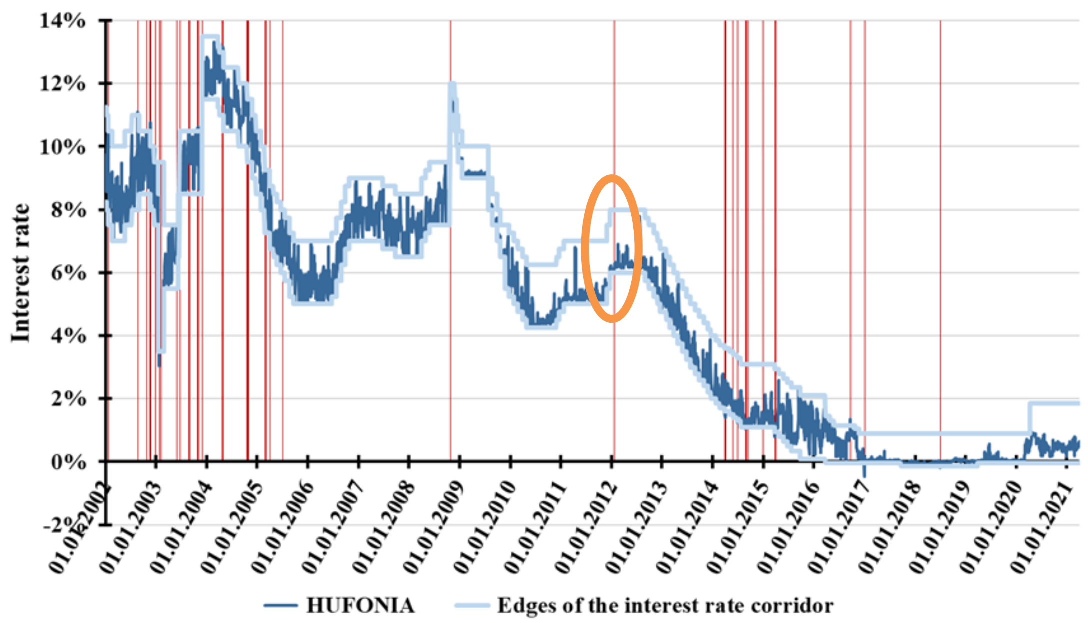
2013, the most significant impact on counterparty limits – in addition to the Lehman bankruptcy – was the deterioration of the credit ratings of the Hungarian state at the end of 2011.

As a result of the deterioration of the credit ratings, on the one hand, the daily transaction amounts increased significantly and, on the other hand, the original maturity of the interbank forint loan portfolio fell drastically by 80%. Most credit institutions introduced a one-week maturity limit in the interbank market, hence the shortening of maturities.[23]

Another interesting consequence of the sovereign downgrade of the Hungarian state is that the parent banks of the Hungarian subsidiaries significantly reduced their limits for the MNB, so they could not place their excess forint liquidity in overnight deposits with the central bank and were able to place a considerable portion of it only a rate lower than the bottom of the interest rate corridor. As a result of this turning into a mass phenomenon, the HUFONIA (average overnight interbank forint interest rate) exited the interest rate corridor on 17 and 18 January 2012.

*Figure 6:*

HUFONIA's exit from the interest rate corridor (2002-2021)




*Source: Own editing based on MNB data (MNB [2021]).*

[23] Within the interbank forint unsecured loan portfolio, the share of transactions with a maturity of one week or less rose above 90% from the previous 70% *(Homolya et al. [2013])*.

Figure 6 shows the development of HUFONIA since the beginning of 2002 (dark blue line), the two edges of the current interest rate corridor (light blue lines), and the red vertical bars indicate the days on which HUFONIA stepped out of the effective interest rate corridor. This was last seen more than 3 years before the mentioned events of January 2012, on 22 October 2008, and even then it only happened for one day. In addition, on the same day in autumn 2008, the Monetary Council decided on a drastic 300 basis point rate hike (from 8.5% to 11.5%), which explains the imbalances in the interbank market at that time *(MNB [2020d])*.

## 2.4. Development of interbank loans of credit institutions

In this section, I review the MNB's regularly published time series on interbank deposits and loans. For this purpose, I will primarily use the tables of the database entitled “Time series of the data of the sectors supervised by the MNB - Credit Institutions”, published regularly from the end of 2005 to 31 December 2018 *(MNB [2019d])*. The examined time series covers 13 years, while methodological changes have taken place several times, to which – and their effects – I will always draw attention and assess the possible distortions arising from it.

### 2.4.1. The place of interbank loans in the balance sheets of credit institutions

Before analysing the statistics of credit institutions, I will briefly review exactly where and how these interbank loans appear on a bank balance sheet's asset and liability side.

As the balance sheets of companies, the balance sheets of banks are also a snapshot, i.e., the available assets of a credit institution are shown in aggregate on the asset side by their role in banking and by their source on the liability side for a given date *(Baricz [2009])*. The differences from a traditional corporate balance sheet are almost without exception due to the specifics of banking. Table 4 shows a typical layout of a bank balance sheet.

*Table 4:*

Scheme of the bank balance sheet

| Assets | Liabilities |
|---|---|
| - Cash and cash equivalents<br>- Securities<br>- **Interbank loans**<br>- Loans (granted)<br>- Long-term investments<br>- Tangible assets<br>- Other assets | - **Interbank borrowings**<br>- Deposits<br>- Liabilities due to securities issued<br>- Other liabilities<br>- Provisions<br>- Equity |

*Source: Radnai – Vonnák [2010] p. 13.*

In the bank balance sheet, the order of assets is determined by their liquidity and risk, while in the order of liabilities, their maturity is the dominant aspect. The bank's liquid assets (including interbank loans), are included in the first three asset groups. They can be liquidated, accessed almost immediately, but have no return (cash) or minimal return *(Ligeti–Sulyok-Pap (ed.) [2006])*.

Due to their activities, banks may occasionally generate excess liquidity or lack of liquidity. In the former case, the excess funds are mostly placed on the interbank market, which appears on the asset side of the balance sheet under Interbank loans (left side of Table 4, highlighted in blue) and embodies the bank's receivables from other financial institutions.

In the latter (lack of liquidity) case, they can satisfy their liquidity "hunger" the fastest and with the lowest transaction costs on the interbank money market. The loans taken out in this way are shown at the top of the liabilities side of the balance sheet, under Interbank borrowings (right side of Table 4, highlighted in blue) and show the bank's liabilities to other credit institutions.

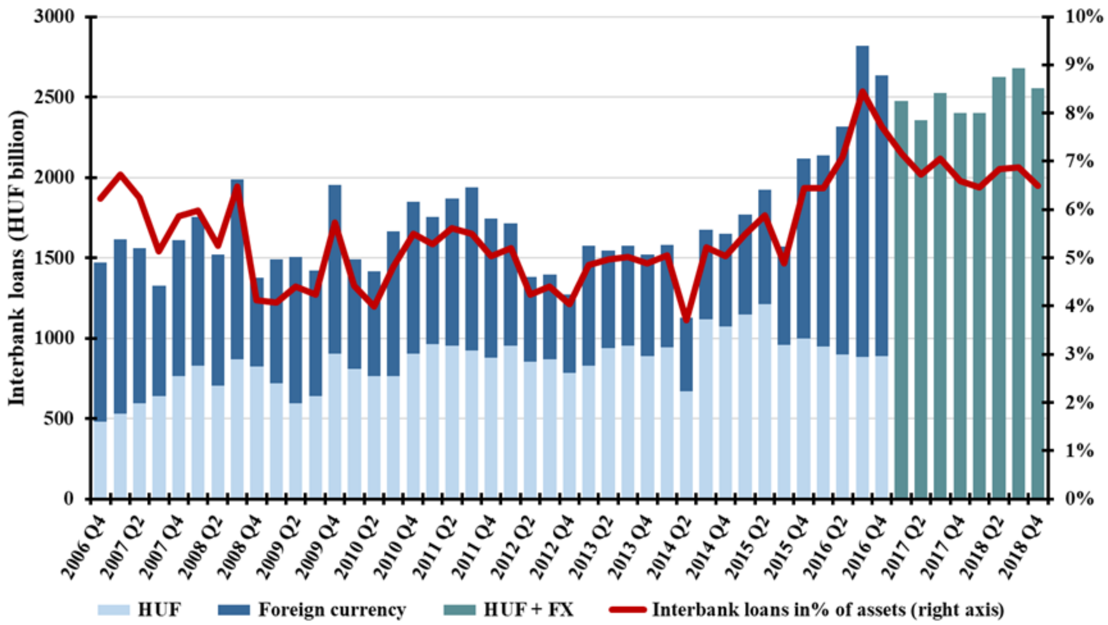
### 2.4.2. Development of interbank loans and deposits in the credit institution sector

Below, I will present the development of the interbank loans and borrowings, using, among other things, the publicly available data tables entitled "Time series of the data on the sectors supervised by the MNB - Credit Institutions". The time series referred to above are compiled by aggregating the non-consolidated data provided by banks to the MNB for supervisory purposes. The MNB published its first such statistics for 31 December 2005, and thereafter at the end of 2006. From then until the end of 2018, the data were published on a quarterly basis. Since there is a 1-year difference between the first two data points in the time series thus obtained, and a quarter difference thereafter, I omitted the first (2005) observation and examined the period 2006-2018.

Over the past decade and a half, there have been several methodological changes in the way data are provided, and in the way they are summarised. In the future, I will pay special attention to these changes to ensure the consistency and comparability of the examined data sets.

*Figure 7:*

Changes in the aggregated amount of interbank loans, broken down into forint-foreign currency, and their share within assets (right axis)




*Source: Own editing based on MNB data (MNB [2019d]).*

Examining the asset side of the aggregated balance sheet of a credit institution, Figure 7 shows the end-of-quarter aggregated amount of interbank loans (loans granted) broken down by forint (light blue, bottom bar) and foreign currency (dark blue, top bar). In ten years, the forint interbank loans almost doubled from HUF 483 billion at the end of 2006 to HUF 889 billion. Meanwhile, after a low of HUF 500-600 billion between 2012 and 2015, the portfolio of interbank loans denominated in foreign currency tripled by the end of 2016, in a single year (to HUF 1,747 billion).

The Self-financing Programme presented earlier also played a significant role in the changes seen in 2015-2016, the MNB's foreign exchange tenders related to the settlement and forint conversion of retail foreign currency loans, and some of the liquidity displaced from the central bank's governing instrument all landed in this market *(Csávás–Kollarik [2016])*.

In the MNB's time series, the forint-currency breakdown of balance sheet items is not available for banks using IFRS[24]; since the first quarter of 2017, this breakdown was not available. In Figure 7, in the last two years, in the columns distinguished by turquoise, I showed the total amount of interbank loans (forint and foreign currency on a consolidated basis), reflecting a stagnant interbank loan portfolio of around HUF 2,500 billion.

In the figure, the red line indicates (with the corresponding right-hand secondary axis) the aggregated amount of interbank loans in proportion to the credit institution's balance sheet total. With the help of this, it can be examined whether the increase in interbank lending is due to the general expansion of the sector (increased balance sheet total) or whether there has been a kind of reorganisation in the structure of the asset side.

Figure 7 shows that the granted loans (bars) moved more or less together with the ratio within the balance sheet total (red line). An exception to this is the period after the third quarter of 2016, where the previously described stagnation in lending was accompanied by a clear declining ratio to the balance sheet total (from a share above 8% to 6.5%). It therefore seems that it has somewhat lost its importance in the recent period on the asset side of the interbank market, but even based on this 6.5% ratio, it can be said that interbank lending can be considered a significant activity of banks.

The question may arise as to why I am looking at the time series only until the end of 2018. The explanation for this is basically to be found in the change in accounting reporting standards. I have already pointed out that from the beginning of 2017, e.g., there will be no forint-currency breakdown for banks applying international reporting standards (and thus for the entire sector).

On 1 January 2017, 14 credit institutions switched to IFRS from Hungarian accounting standards. In addition, these credit institutions had significant market weight (their balance sheet total accounted for 56.5% of the total balance sheet of the credit institution sector). This process did not significantly affect the time series, only audited IFRS data appeared as “additional data”.

[24] International Financial Reporting Standards

In early 2018, this trend continued, and an additional 25 institutions switched to international accounting standards. With this, banks using IFRS now accounted for 86% of the balance sheet total of the entire credit institution sector. This was also a significant turning point because, as of 1 January 2018, the previous IAS 39, which regulates financial instruments, has since been replaced by IFRS 9 *(MNB [2018])*.

As of the end of the IFRS accession process, from 1 January 2019, all credit institutions operating in Hungary will have uniformly prepared their reports based on international accounting principles. Another development is that at the beginning of 2019, the range of data providers changed: the Agri-Business Credit Guarantee Foundation and Garantiqa Hitelgarancia PLC, two financial companies qualifying as credit institutions from a prudential point of view, were added to the statistics *(MNB [2019a])*.

Regarding the consistency of the time series, a bigger problem than described so far is that by the end of 2018, the data set was compiled from individual-level supervisory data, but from the beginning of 2019, it was compiled from data consolidated at the highest level in Hungary. This means that e.g. the data of cross-border subsidiaries of OTP were also included which, in my opinion, results in a level of distortion that renders data after 2019 not directly comparable to those of quarters before 2019 *(MNB [2019b])*.[25]

It should be noted that the MNB still publishes 4 tables of the time series for the new credit institution sector according to the old methodology, at a non-consolidated level; however, their information content on interbank loans and deposits is low.

In the light of these facts, I have come to the conclusion that I would use a mostly consistent time series between 2006 and the end of 2018 for my analysis.

The MNB also regularly published data on the arrears of interbank loans between 2015 and the end of 2018.

Table 5 shows that, although counterparty risk in the interbank lending market is very high, the proportion of overdue loans is negligible. At the end of 2018 alone, there are

[25] With the new consolidated summary, the MNB calculated the data retrospectively to 31 December 2015. Examining them, the time series would have been too short (from which trends can thus be observed only to a limited extent), and, on the other hand, the detailed interbank transaction database examined later is available for the period 2012 and 2015, for which I would not have any portfolio data if I used the consolidated figures.

approx. HUF 21 billion gross overdue amount in the statistics,[26] which is only 0.8% of the total loans (HUF 2,558 billion). Moreover, we can only see loans with overdue within 90 days, interbank loans overdue for more than 90 days did not appear in the market at all between 2015 and 2018.

*Table 5:*

Arrears of interbank loans of credit institutions at the end of each year, in HUF billion

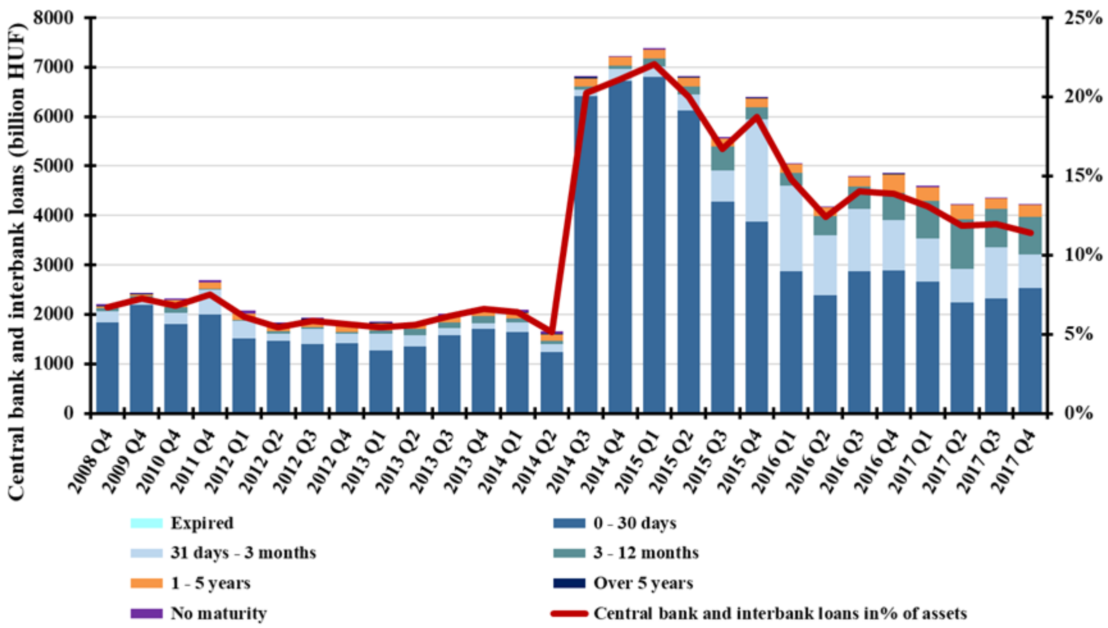
| Item | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|
| **Interbank loans** | **2,116.632** | **2,538.647** | **2,398.860** | **2,557.923** |
| *of which not overdue* | *2,116.632* | *2,538.589* | *2,398.859* | *2,537.053* |
| *of which overdue within 90 days* | *0.000* | *0.000* | *0.000* | *20.869* |
| *of which overdue for more than 90 days* | *0.000* | *0.057* | *0.001* | *0.001* |

*Source: Own editing based on MNB data (MNB [2019d]).*

Remaining on the asset side, among the data published by the MNB, we can also find statistics on the maturity of interbank loans.

*Figure 8:*

Maturity of the central bank and interbank loans, and its share within assets (right axis)




*Source: Own editing based on MNB data (MNB [2019d]).*

[26] I do not know the exact reason for the arrears due to the lack of public data, but it may have been related to the fines imposed on NHB Növekedési Hitel Bank in 2018 and the liquidity problems that developed at the end of the year. (On 14 March 2019, the MNB ordered the liquidation of the bank) *(MNB [2019e])*

As shown in Figure 8, in the MNB's statistics on the analysis of maturity matching, the interbank loans are unfortunately available only in combination with central bank deposits, so only limited conclusions should be drawn from that.

From the second to the third quarter of 2014, there was a significant jump in the aggregated amount, which was not due to interbank loans but clearly to the central bank deposits. The drastic change in the portfolio is explained by the MNB's Self-financing Programme announced on 24 April 2014. As part of this, in the summer of 2014, the central bank's two-week bond was replaced by a two-week deposit, the volume of which will now appear in the consolidated statistics on interbank loans and central bank deposits.

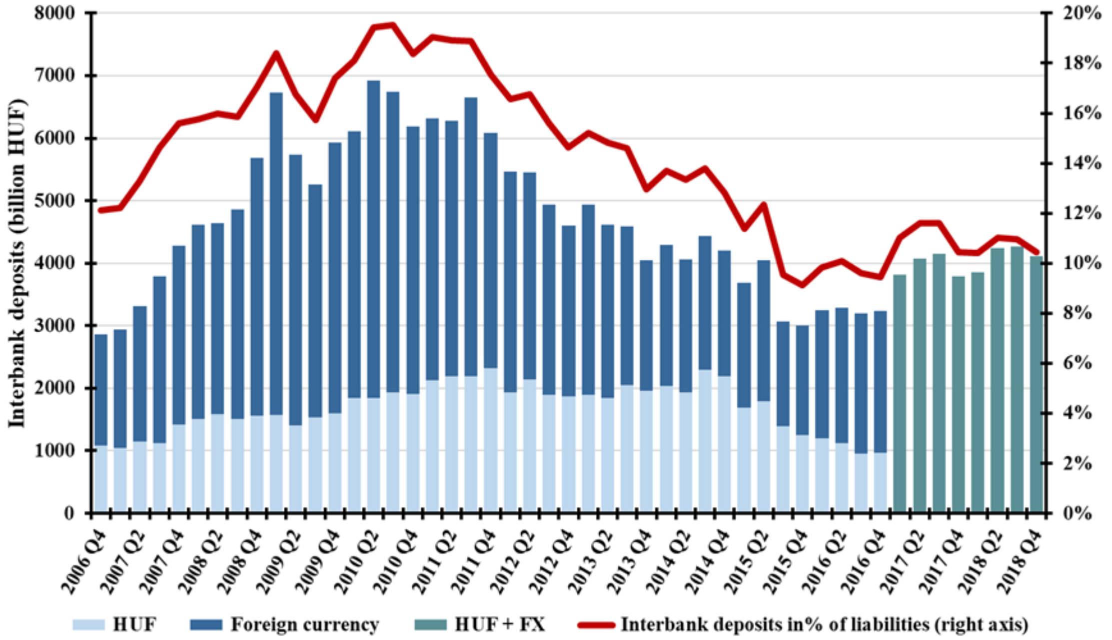
Thus, from the third quarter of 2014, the aggregated data are dominated by the central bank deposits, so no meaningful conclusions may be drawn regarding interbank loans. The increase in maturity observed from the third quarter of 2015 is also due to the fact that on 2 June 2015, the three-month central bank deposit became the main monetary policy instrument instead of the two-week central bank deposit, and the subsequent decline was the result of central bank action to phase it out.

Along with the above, something is still clearly shown in Figure 8: namely, that the typical maturity is significantly within 30 days, with short-term lending clearly dominating the interbank market. I will examine the maturity of the transactions in subsection 3.1.1. of my dissertation in more detail based on transaction data.

Turning to the liability side of the credit institution's aggregated balance sheet, I also showed the development of interbank deposits.

*Figure 9:*

Evolution of interbank deposits, in a breakdown by HUF and foreign currency



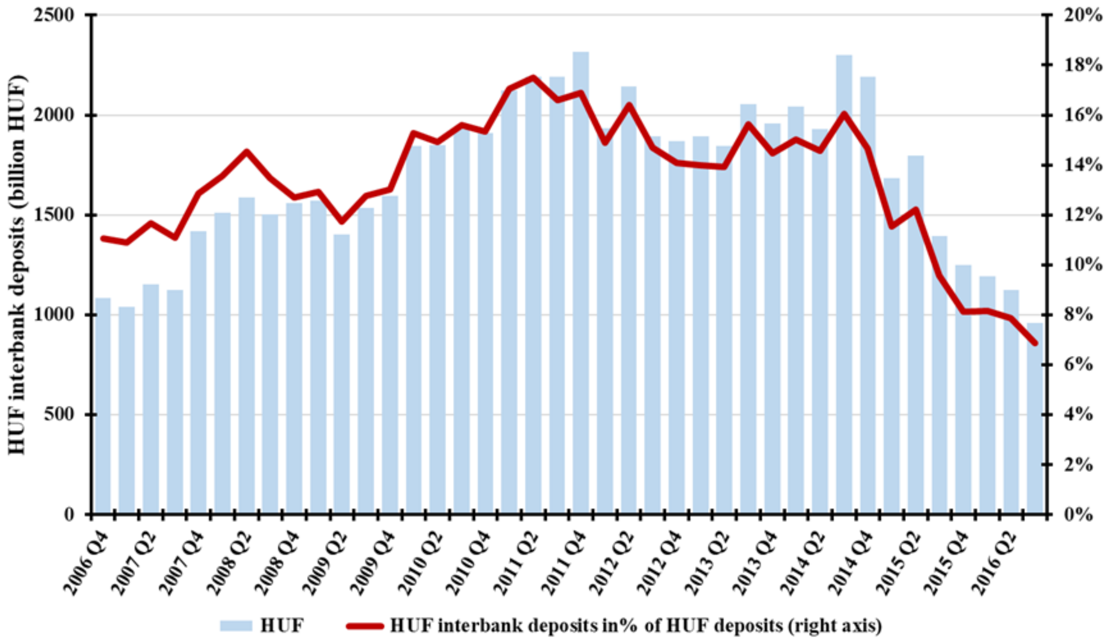

*Source: Own editing based on MNB data (MNB [2019d]).*

As Figure 7, Figure 9 also shows only consolidated (HUF + foreign currency) data starting from 2017, as only such data was available to me. Trends in interbank deposits show that, in the period between 2008 and 2011, foreign currency items (upper column section in dark blue) dominated the market, and their proportion, as compared to HUF deposits, was especially high.

For reasons described earlier, I was only able to work with aggregate (HUF + foreign currency) data for years starting from 2017, a fact indicated by turquoise columns at the end of the time series. Analysing the total interbank deposit portfolio, one can establish that, after an outstanding period of 2008-2011, a clear decline is observed both in nominal terms and relative to total assets (red line and the right-hand secondary axis belonging to it) until the end of 2016, with the portfolio stabilising at around HUF 4,000 billion in the last two years examined. This value of around HUF 4,000 billion is more than 10% of the total assets of the entire credit institutions sector, i.e. the importance of the interbank market is even more significant on the liabilities side than among assets.

*Figure 10:*

Evolution of the portfolio of HUF interbank deposits and their proportion within HUF deposits (right axis)




*Source: Own editing based on MNB data (MNB [2019d]).*

In Figure 10, I "zoomed in" on HUF deposits, which are truly important for my dissertation. In this way, on the one hand, a more pronounced view is provided on a clear and very significant decline in the proportion of HUF interbank deposits (from HUF 2,300 billion to HUF 960 billion) within all interbank deposits after the third quarter of 2014 and, on the other hand, the red line shows an equally dramatic decrease in the proportion of HUF interbank deposits (right-hand-side secondary axis) within all HUF deposits during this period. Between the third quarter of 2014 and the fourth quarter of 2016, the proportion of HUF deposits placed on the interbank market, as compared to all HUF deposits, decreased by 9.7 percentage points, representing a very significant decline.

# 3. Analysis of the unsecured interbank deposit market's network dynamics

In the previous chapter, I reviewed the changes in interbank loans and deposits over time, based on the credit institution data regularly published by the Central Bank of Hungary (MNB), and I identified the fundamental tendencies. Now, based on a detailed transaction database also received from MNB for research purposes, I will particularly examine the period between 2012 and 2015.

My research question examined in the chapter is the following:

> *What characterises the interbank unsecured credit market network subject to different dimensions, and how volatile were the examined parameters over time?*

The purpose of the examination, on the one hand, is to see, via different parameters, how stable the structure of the network along the different dimensions was over time. A stable network structure is essential for drawing robust conclusions. The second purpose of the analysis is to get an overview of the orders of magnitude, typical maturities regarding the market. Thirdly, there can be, for example, incorrectly recorded transactions or outlier values in the database, which may distort the obtained results. I also deemed the filtering of these necessary.

As it will be shown, the dynamics of maturities, interest rates, aggregated transaction amounts and concentration on the interbank market were influenced by the transformation of the central bank toolbox performed within the framework of the Self-financing Programme presented in Section 2.2.4, as well as by the changes of the sovereign credit rating of the Hungarian State. However, the fundamental structure of the network remained stable throughout, which facilitated the performance of deeper analyses in the coming parts of my dissertation.

I will give special attention to the distribution of overnight and longer-term loans and to the analysis of the concentration of the borrowing and lending sides. My hypotheses examined in the chapter are:

*H1: The distribution of overnight and longer-term unsecured interbank transactions significantly differ.*

*H2: The concentration of borrowing is significantly higher than the concentration of lending, both in terms of volume and the number of transactions.*

The relevance of my first hypothesis lies in the fact that if the overnight and longer-term transactions of the unsecured interbank deposit market significantly differ, their joint analysis would lead to distortions. The appropriate selection of the circle of transactions to be analysed is a cardinal question concerning what follows.

The relevance of my second hypothesis lies in the concentration-related connections published in the academic literature. I compared the obtained results with the *Berlinger–Michaletzky–Szenes [2011]* study. The authors studied the network dynamics of the Hungarian unsecured interbank HUF deposit market for the period between December 2002 and March 2009. Their study found that the different network metrics and the general features of the market were stable until 2006-2007, after which – as if forecasting the crisis –, part of the indicators began to change. I partly considered this study the preamble of the present chapter when I examined the data series of the same market between 2012 and 2015.

In the closure of the chapter, I will examine the network of overnight unsecured HUF loans in preparation for the network models presented in the next chapter.

Phenomena observed on and network metrics calculated for the Hungarian market will be compared with the academic literature on the Central and Eastern European Region's interbank markets. There is a striking similarity in most cases, suggesting that a special network structure is created by the unique set of features of unsecured interbank deposit markets (lack of physical collateral and liquidity management as the primary goal), and some underlying factors associated with market failures (transaction costs, asymmetric information, provision of liquidity, economies of scale and scope, and risk sharing). The latter factors are covered in detail in Sub-chapter 5.2 of my thesis.

## 3.1. General characteristics of the examined database

I performed the analysis on the highly detailed database compiled from the regular reports of the Hungarian banks provided by MNB for research purposes, which contained every unsecured interbank lending transaction performed between 2 January 2012 and 31 December 2015. As these pieces of information are deemed strictly confidential, the different banks are included anonymously with random sequence numbers in a directly unidentifiable manner. The purpose of my dissertation is not the linking of the results to a given credit institution. The goal is clearly the examination of the whole market, the exploration of the structure of connections.

The transactions of the database (records) contain the following information: fictitious code of borrowing (data supplying) bank, identifier of the lender partner, contract amount of the credit, (annualised) interest rate paid for the transaction, date of contracts, the start and end date of the transaction and the direction of the transaction (which, in every case, is borrowing to avoid duplication in the data table[27]).

I will examine the key parameters and changes of the database (maturity, individual transactions, interest rate, aggregated transaction amount) over time before performing deeper analyses. The purpose of the examination is twofold: on the one hand, it is worth examining the potential changes in the key parameters of the Hungarian interbank market compared to the studies of the previous period; on the other hand, I would like to give a general overview of the market showing the orders of magnitude in the volume and the typical maturities. The stability of the examined variables over time can provide an appropriate base for later analyses – for a comparison with an interpersonal loan market, for example.

### 3.1.1. Examination of the maturity

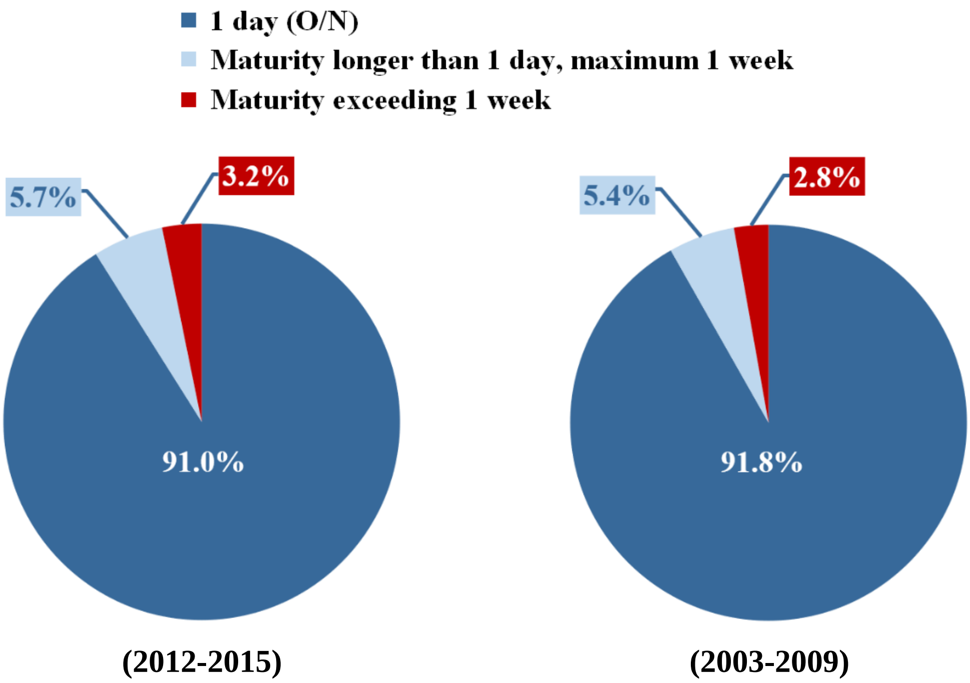
I calculated the maturities based on the start and end dates of the transactions, taking into account the days on which there was no trading on the interbank market (due to weekends or state holidays, for example).

I downloaded the quotation dates of official BUBOR fixings from 2 January 2012 until the end of 2019 from the website of MNB *(MNB [2021])*. Longer data series was necessary because although I had interbank data at my disposal only until the end of 2015, there was a transaction concluded on 23 December 2014, the maturity date of which was 20 December 2019. I took the BUBOR quotation days as trading days on the interbank market, and I calculated the maturity of the deals on their basis.

[27] Both the lender and the borrower must report every transaction to MNB but duplication resulting from this has previously been filtered from the data table.

*Figure 11:*

The distribution of the maturities of unsecured interbank HUF loans 2012-2015 (pie chart on the left) and 2003-2009 (pie chart on the right)




*Source: MNB data and own editing based on Berlinger–Michaletzky–Szenes [2011].*

Between the beginning of 2012 and the end of 2015, a total of 40,565 unsecured HUF deals were concluded by the market participants in the examined database. The vast majority of them, 91%, were overnight transactions (dark blue slice in the pie chart on the left in Figure 11).

According to *Homolya et al. [2013]*, maturity limits were pushed to the foreground on the interbank deposit market due to the significant deterioration of the sovereign rating of the Hungarian State at the end of 2011. Many banks maximised the maturity of unsecured transactions to be concluded with the partners in one week. Consequently, the market structure changed significantly considering the duration of the transactions, the percentage of transactions with the maturity of one week or shorter increased to over 90%. The examined database perfectly confirms this percentage exceeding 90%; in other words, it seems that the events at the end of 2011 did not only leave a temporary but a long-term mark on the unsecured interbank HUF deposit market, and the pre-crisis proportions in terms of maturities were more or less restored.

The aforementioned maturity limits also show that the one-week dividing line plays an outstanding role on the market; the banks deem transactions shorter than one week deals of lower risk. 2,332 credit transactions with a maturity exceeding one day but of maximum one week (5 trading days) were concluded in the examined period, constituting 5.7% of the total transaction number (light blue slice in the pie chart on the left in Figure 11). The percentage of more risky transactions with a duration exceeding one week was extremely low, a mere 3.2% (red slice in the pie chart on the left in Figure 11).

The percentages mentioned above are also worth comparing with the results of *Berlinger–Michaletzky–Szenes [2011]* (pie chart on the right in Figure 11). From the period between 2003 and the first quarter of 2009 examined by them, only a few months followed the Lehman bankruptcy (when the number of transactions dropped drastically). Therefore the proportions presented by them mostly feature the pre-crisis period deemed dormancy period.

The pie charts for the periods of 2012-2015 and 2003-2009 in Figure 11 are surprisingly similar. It seems that this O/N proportion slightly exceeding 90% can be considered as a certain “balance” value; overnight loans used for liquidity purposes clearly dominate and appropriately represent the Hungarian interbank market.

Information on the distribution of maturities of transactions can also be found in the academic literature on regional interbank markets. For example, a study by *Geršl–Lešanovská [2014]* shows that unsecured credit transactions represented the majority of transactions made in the Czech interbank market and that O/N transactions represented about 80% of the daily trading volume, which shows, in the dominance of overnight transactions in this market, a similar data for Hungary also show. Although *Šiaudinis [2010]* did not treat overnight transactions as a separate category when examining the Lithuanian interbank market, his analysis clearly shows that transactions with a (short) maturity of within 1 month represented 84-94% of unsecured interbank loans between 2005 and 2010.

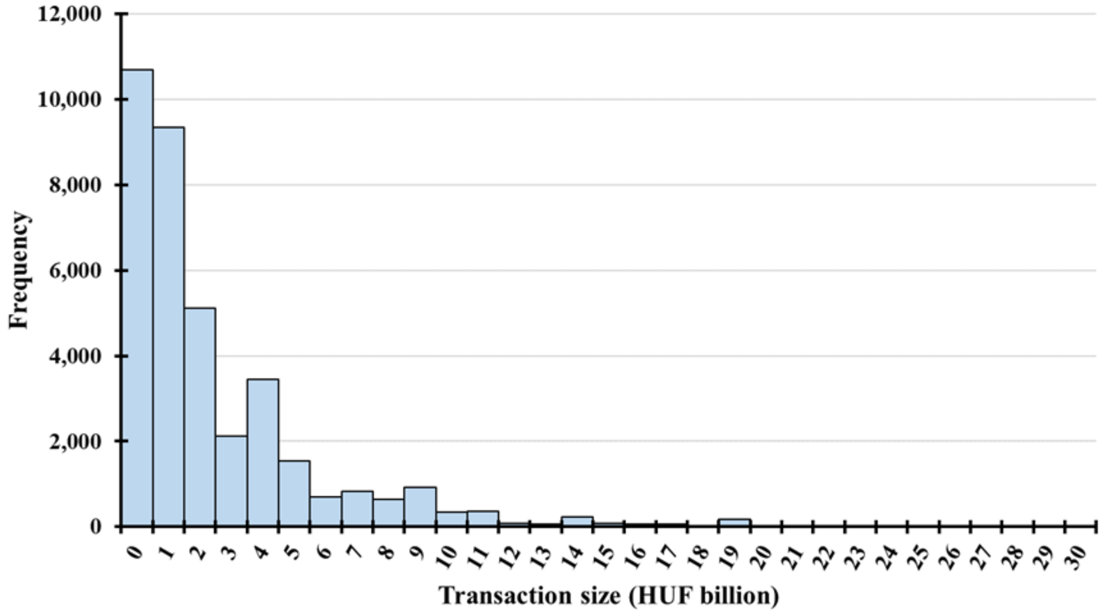
In the Polish interbank market, O/N transactions represented 93% of all transactions in 2013, and the proportion of overnight interbank loans was above 90% also on interbank markets in the broader region, in Russia and Belarus as well *(Smaga et al. [2018])*.

### 3.1.2. Examination of the distribution of individual transactions

Let us now divide the database into two parts based on the results of the previous section, and let us examine the transactions of the market of overnight loans (purely serving the purpose of bank liquidity management) and loans longer than one day.

*Figure 12:*

Histogram of O/N unsecured interbank HUF transactions between 2012 and 2015

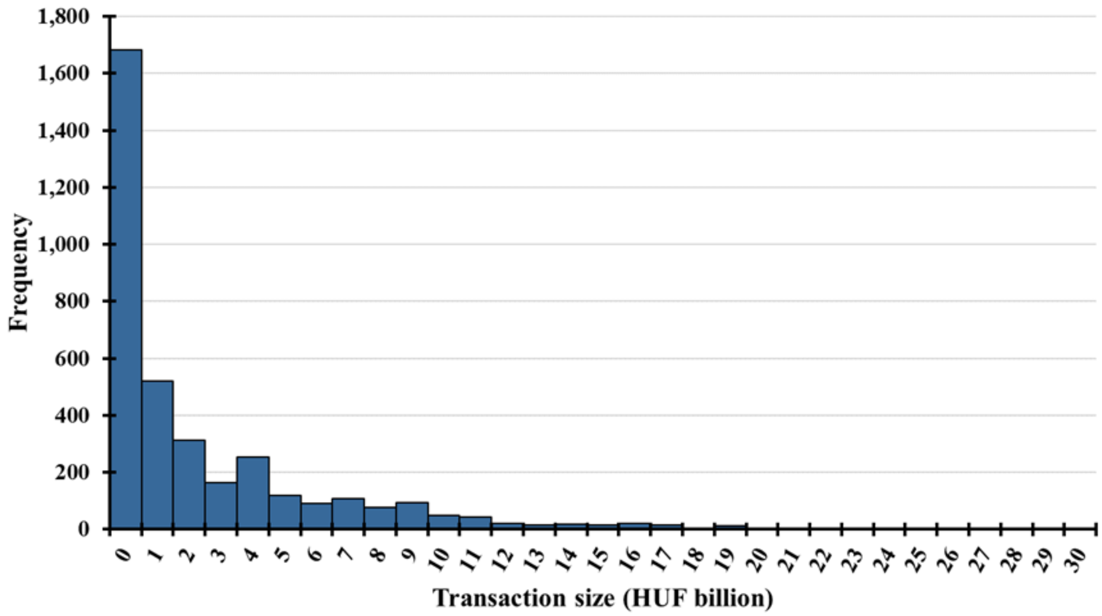



*Source: Own editing based on MNB data.*

It can be seen from the histogram of O/N transactions (Figure 12) that the distribution of the transactions stretches out long to the right; the majority (68.1%) of the transactions are in the first three bins; in other words, their amount is under HUF 3 billion. Regarding the distribution stretching out long to the right, it is a telltale figure that 98.7% of the transactions (36,444 transactions) are under HUF 15 billion, although there were three credits of HUF 28 billion and one credit of HUF 30 billion on the market in the examined period.

*Figure 13:*

Histogram of unsecured interbank HUF transactions with maturity exceeding 1 day between 2012 and 2015




*Source: Own editing based on MNB data.*

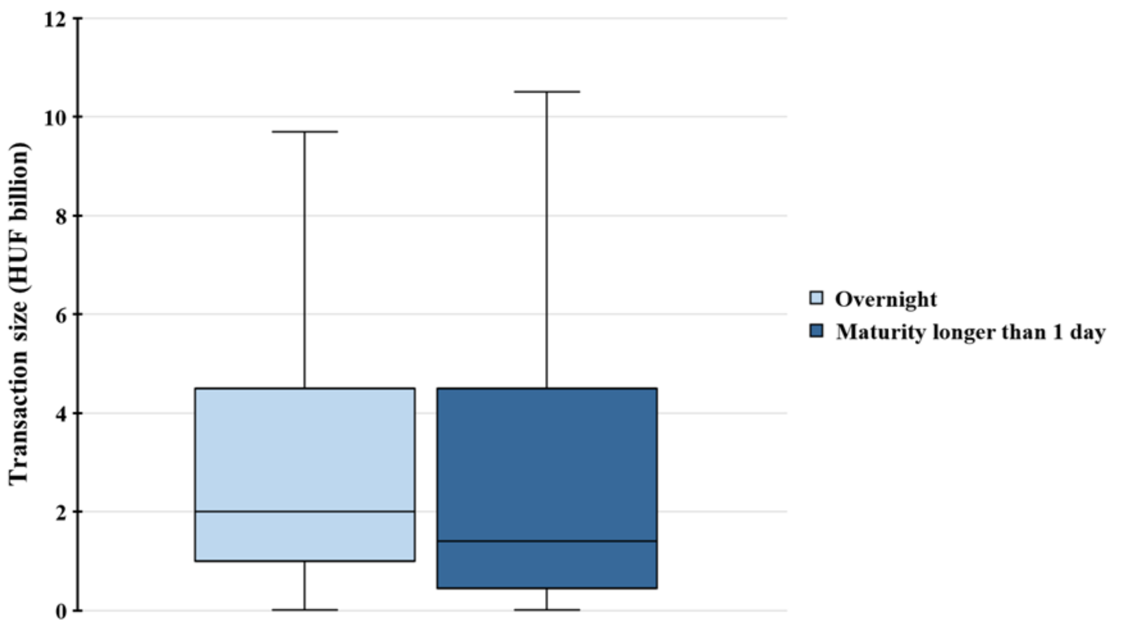
The histogram of transactions with maturity exceeding one day is presented in Figure 13. The bins of the horizontal axis are set up the same way as in Figure 12, so the two distributions can be compared directly. It is obvious that the distribution of the longer-term interbank loans (Figure 13) stretches out to the right even longer; nearly half of the transactions (46.2%) are under HUF 1 billion, while the same proportion was only 29% in the case of overnight loans. Concerning longer-term loans, the outlier values are also more extreme than in the previous example, as credit transactions of HUF 50 billion and HUF 67 billion in May 2012 were found.

The difference between the two distributions is worth examining further as if the two segments differ significantly, the overnight and longer-term loans are worth separating because their joint analysis may lead to serious distortions.

We can see a so-called box and whiskers in Figure 14 separately for the overnight transactions (light blue on the left) and transactions with tenor longer than 1 day (dark blue on the right).

*Figure 14:*

Box and whiskers of overnight and longer-term unsecured interbank HUF transactions between 2012 and 2015 (without the outlier values)




*Source: Own editing based on MNB data.*

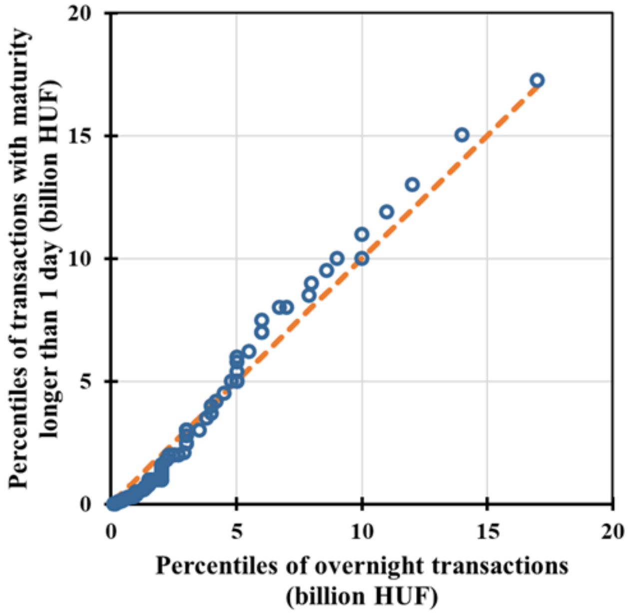
This type of chart offers a generous and clearly visible picture of the type of distribution *(Hunyadi–Vita [2008a])*. The bottom of the boxes (coloured rectangles) indicates the lower quartile of the transactions ($Q_1$), the top of the boxes indicates the upper quartile ($Q_3$), the dividing line within the box is the median. The endpoint of the tongue under the box (so-called whiskers) indicates the amount of the smallest transaction, and the endpoint of the tongue above the box is the top of the box, it indicates the height of the box one and a half times. I deem transactions with amounts higher than this latter point transaction of outliers, extreme values. I deliberately did not show these outliers in the chart, as they would have drawn our attention away from the essence, which is now the examination of the difference between the two distributions.

The entire box shows the "medium" half of all examined criteria values, and its position shows that a significant portion of the transactions was in the relatively small tier of HUF 1-5 billion. The height of the box, in other words, the interquartile range ($Q_3$ – $Q_1$) is bigger in the case of transactions with longer maturity, which means that the variance is smaller in O/N transactions. The median is very close to the bottom (lower quartile) of the box in both cases, which points to the – previously established – significant obliquity of the distribution.

The so-called Q-Q (or quantile-quantile) chart facilitates the comparison of the two distributions in a different type single graph, which shows the same quartiles of two arbitrarily selected distributions on one point diagram. If the depicted points are situated along the diagonal line of 45-degree (broken orange line in Figure 15) or are situated randomly around this line in a narrow band, the two distributions can be considered identical *(Kovács [2011])*.

*Figure 15:*

Q-Q chart of overnight and longer-term unsecured interbank HUF transactions between 2012 and 2015 (without the outlier values)




*Source: Own editing based on MNB data.*

It is evident from Figure 15[28] that the percentiles (dark blue rings) of the overnight and longer-term interbank transactions are not on the diagonal dashed line or deviated randomly around it; however, concerning lending transactions under HUF 5 billion transaction size, the data points are situated under the 45-degree straight line, and regarding transactions larger than HUF 5 billion, over the line. Meaning that transactions under the amount of HUF 5 billion are more typical of the O/N transactions (horizontal axis), while concerning the percentage of larger volume deals, transactions with a

[28] For the easier interpretation of the results I did not show percentile 99 with extreme (outlier) value, which amounted to HUF 30 billion in overnight transactions and to HUF 67 billion in transactions with maturity longer than one day.

maturity longer than 1 day (vertical axis) are more frequent. It can also be deducted from the Q-Q graph that the rings are more frequent in transaction size under HUF 5 billion, which points to the two compared distributions being oblique on the left and stretching out to the right.

Based on the presented histograms, the box and whiskers and the Q-Q graph, it seems that the distribution of overnight and longer-term unsecured interbank HUF loans differs. This assumption is worth confirming (or rejecting) with a hypothesis test based on the available sample.

We wish to examine whether the two populations (O/N and longer-term transactions) have the same distribution, which can be tested with a test for homogeneity *(Hunyadi–Vita [2008b])*. According to the null hypothesis of the test for homogeneity, the distribution of one variable (size of transaction in this case) in two populations (overnight and longer-term transactions) is identical. In contrast, the alternative hypothesis states that the two examined distributions are not identical. Let us test the homogeneity of the distributions at 1% significance level (at 99% confidence level).

The acceptability of the null hypothesis in large samples[29] can be tested with the following $\chi^2$ test:

$$\chi^2 = n_{ON}\, n_{LT} \sum_{i=1}^{k} \frac{1}{n_{ON_i} + n_{LT_i}} \left(\frac{n_{ON_i}}{n_{ON}} - \frac{n_{LT_i}}{n_{LT}}\right)^2 \qquad (1)$$

where $n_{ON}$ means all overnight transactions, $n_{LT_i}$ is the number of loans with maturity over one day (*longer-term* loans); $i$ lower index indicates the value of both variables in the given $i$ bin everywhere; and $k$ is the number of bins. I selected the bins of equal size for the examination in a manner to allow for the largest possible granularity with minimum one observation in every bin in the process[30].

[29] A sample including more than 30 elements is usually deemed large sample according to the thumb rule. In the present case the two samples contain 36,928 and 3,637 elements respectively, so we can use the large sample assumption in any case.

[30] If this were not fulfilled, the problem of division by zero would rise in the test statistic.

*Table 6:*

Test for homogeneity of O/N and longer-term transactions

| Classes | O/N transactions ($n_{ON_i}$) | Longer-term transactions ($n_{LT_i}$) | $\frac{1}{n_{ON_i}+n_{LT_i}}\left(\frac{n_{ON_i}}{n_{ON}}-\frac{n_{LT_i}}{n_{LT}}\right)^2$ |
|---|---|---|---|
| **0-2** | 20,043 | 2,202 | 0.00000018 |
| **2-4** | 7,237 | 475 | 0.00000055 |
| **4-6** | 4,990 | 373 | 0.00000020 |
| **6-8** | 1,520 | 198 | 0.00000010 |
| **8-10** | 1,562 | 171 | 0.00000001 |
| **10-12** | 696 | 92 | 0.00000005 |
| **12-14** | 158 | 34 | 0.00000013 |
| **14-16** | 325 | 33 | 0.00000000 |
| **16-18** | 122 | 36 | 0.00000028 |
| **18-20** | 193 | 16 | 0.00000000 |
| **20-22** | 34 | 3 | 0.00000000 |
| **22-24** | 26 | 0 | 0.00000002 |
| **24-26** | 17 | 1 | 0.00000000 |
| **26-28** | 4 | 0 | 0.00000000 |
| **Over 28** | 1 | 3 | 0.00000016 |
| **Total** | $n_{ON}$ **= 36,928** | $n_{LT}$ **= 3,637** | **0.00000169** |

*Source: Own calculation based on MNB data.*

Substituting it in formula 1, the value of $\chi^2$ test statistic is:

$$\chi^2 = 36{,}928 \times 3{,}637 \times 0.00000169 = \mathbf{227.35}$$

In the case of the fulfilment of the null hypothesis (the distribution of the two variables are identical), the test statistic follows $\chi^2$ distribution[31] with $v = k - 1$ degree of freedom. In the present case $v = 15 - 1 = 14$. The more significant the difference between the two distributions is, the larger the value of the $\chi^2$ test statistic is, for which reason test for homogeneity can be performed with a right-tailed test.

The upper critical value is the inverse of the distribution function of $\chi^2$ distribution of degree of freedom 14 by 1%[32], which is 29.14. The 227.35 test statistic value is much higher than this upper critical value; it is in the right-hand side critical (rejection) range;

[31] The distribution of the sum of squares of $n$ independent variables with standard normal distribution is called chi-squared ($\chi^2$) distribution of $n$ degree of freedom *(Ramanathan [2003])*.

[32] As we wish to perform the test at 1% significance level (or at 99% confidence level).

in other words, the homogeneity of distributions (null hypothesis) can be rejected at the 99% confidence level.

After the calculation of the p-value[33], the result is $1.36\times10^{-40}$, which means that the homogeneity of the distribution of O/N credit amounts with the distribution of longer-term loans can be rejected not only at the 1% level, but at any generally used significance level. In addition to the histograms and box and whiskers, we also established with a formal test that the distributions of the amount of O/N and longer-term transactions differ.

In addition to the final conclusion drawn based on the result of the test for homogeneity, we can see interesting results if we analyse the details. The test statistic of the presented hypothesis test is a certain weighted sum of the square difference of the relative frequency of the different bins (last column of Table 6 and formula 1). A conclusive percentage of the test statistic's value comes from the difference in the relative frequency of the first three bins. While in these categories 87.39% of all transactions are of smaller amount (under HUF 6 billion), in the case of the overnight transactions, the same proportion is only 83.86% in the longer-term transactions.

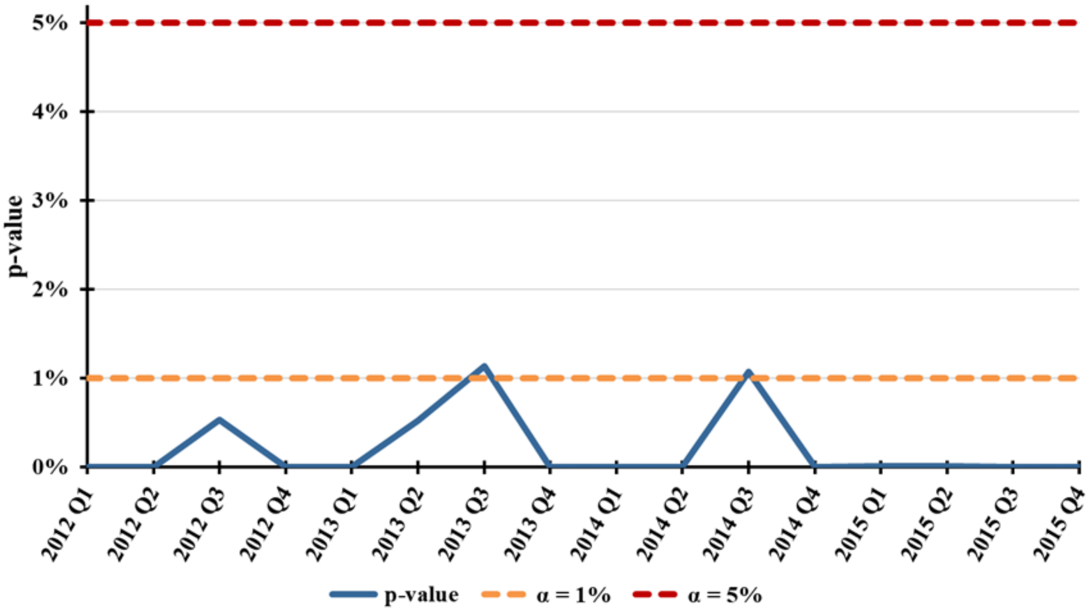
This observation contradicts the intuition, according to which the transaction sizes of longer-term unsecured transactions are typically smaller due to more significant risk and dominant quantity adjustment on the interbank market. Moreover, every extreme, outlier transaction (credit transactions of HUF 50 and 67 billion) had longer maturity in the examined period. From this result, the conclusion can be drawn that in unsecured interbank loans, the markets of overnight and longer-term loans are partial markets largely segmented from each other with different risks and functions.

In addition to the static test, I also examined the difference of the overnight and longer-term transactions dynamically over time. I chose quarterly division for the analysis, as in the case of monthly division, only a sample with very few elements – typically under 100 – would have been at my disposal from the longer-term transactions for one month. If I had examined a time window longer than this (1 year, for example), it would have been challenging to draw the tendencies over time due to the small number of periods.

[33] p-value covers the smallest significance level at which the null hypothesis can just be rejected as opposed to the alternative hypothesis *(Hunyadi–Vita [2008b])*.

Figure *16:*

Stability of the heterogeneity between the O/N and longer-term transactions over time




*Source: Own editing based on MNB data.*

I tested the homogeneity of the distribution of O/N and longer-term transactions with the earlier presented $\chi^2$ test separately for each quarter at 1% and 5% significance levels generally used for hypothesis tests. It can be established at 95% confidence level (broken red line in Figure 16) in every quarter that the distribution of the overnight and longer-term unsecured interbank transactions differed from each other significantly. The two distributions can be deemed homogeneous at a higher, 99% reliability level only in two quarters, in the third quarters of 2013 and 2014, but even in these quarters, the p-value of the test for homogeneity (continuous blue line) exceeded the 1% threshold (straight broken orange line) only in minimum extent.[34]

Overall, it can be established that the distributions of the overnight transactions and transactions with maturity longer than one day differed from each other significantly, and this difference was stable over time in the period between 2012 and 2015, by which I confirmed my *H1* hypothesis specified in the introduction.

The interbank liquidity market is best represented by the unsecured deposit market because, on the one hand, the participants of other markets also perform trading for purposes other than liquidity management (they hedge their foreign exchange risk on the

[34] The p-value was 0.0113 in 2013 Q3 and 0.0108 in 2014 Q4.

FX swap market, for example), and, on the other hand, other markets are influenced not only by the Hungarian liquidity environment but also by other factors (international processes on the mentioned FX swap market) *(Kolozsi–Horváth [2020])*.

I presented above that the interbank deposit market is not uniform in this respect either; the function of interbank loans with maturity longer than one day is not always the placement of temporary liquidity surplus or the balancing of the liquidity position but often the establishment of the maturity match of the asset and liability sides of the balance sheet.

My dissertation focuses on interbank transactions concluded for liquidity management purposes, which criterion is only met by O/N deals. The inclusion of transactions with longer-term would distort my results; therefore, in the remaining part of the study, I will only examine overnight transactions representing the vast majority of the market from the database.[35]

### 3.1.3. Interest rate and price adjustment on the interbank market

This time I examine the interest rates of individual transactions for the unsecured overnight HUF loans only. My primary goal here is to filter extreme values, to clean the database from data, the correctness of which (due to a recording error, for example) is in question, and the presence of which in the database could distort the results of the analysis. As we saw it in the last part, the size of the transactions is rather wide-ranging; therefore, there is no rational reason to question the correctness of extreme values there. Regarding the interest rates, the situation is completely different.

I also presented the operation of the asymmetric interest rate corridor in Section 2.2.4. At the top of the interest rate corridor, the central bank is willing to extend overnight loans to the banks against collateral without limitation, preventing the establishment of deal interest rates (significantly) higher than this on the interbank market.

Considering the period between 2012 and 2015, the top of the interest rate corridor was fairly effective; out of 36,928 O/N transactions the interest rates exceeded the ceiling of the interest rate corridor in only 79 cases (0.2%), and only in minimum extent in the case of excess.

[35] There were a total of 36,928 overnight transactions between 2012 and 2015.

At the bottom of the interest rate corridor the banks can place their liquidity surplus in overnight central bank deposit at MNB without limitation, which is destined to prevent deal interest rates lower than this. 898 transactions (2.4%) exceeded the threshold of the interest rate corridor in the examined period. This is a significant number already, which is worth having a look at in more detail.

On an efficiently operating interbank market, the interest rate corridor effectively restricts the volatility of the interest rates, but it may happen that the parent bank of certain domestic market participants cuts limit against MNB, and the subsidiary bank is forced to place its liquidity surplus at an interest rate lower than the bottom of the interest rate corridor. After the 2008 crisis, the average overnight interbank HUF interest rate (HUFONIA) left the interest rate corridor in January 2012 for the first time due to the deterioration of the sovereign rating of the Hungarian State[36] *(Homolya et al. [2013])*.

In the first round, I will consider extreme deal interest rate every value, which differs from any end of the interest rate corridor with more than half of the width of the effective interest rate corridor.[37] These outlier values are worth examining individually, and their potential exclusion from the analysis is worth considering.

There was no transaction between 2012 and 2015, which would have had an interest rate higher by half the width of the interest rate corridor than the interest rate of the O/N secured central bank credit (ceiling of the interest rate corridor). There were outlier interest rates significantly lower than the overnight central bank deposit interest rate (bottom of the interest rate corridor) on three occasions.

The first was a transaction on 19 November 2012, the size of which was a mere HUF 156 million, which is considered insignificant on the interbank market. The interest rate of the transaction was 3.8%, the bottom of the interest rate corridor was at 5% at this time, and the average deal interest rate weighted with the daily volumes was 5.66% on the interbank market, so it did not seem an incorrectly recorded transaction. Interestingly, based on the volume of its summary transactions, the lender was presumably a smaller bank, and the

[36] I described the phenomenon and its impacts on the interbank market in more detail in Section 2.3.3.

[37] Several statistical programme packages contain half of the +/- value of a range as dividing line in default to detect outlier values.

borrower was the third-largest borrower of the period (presumably a core market participant).

The second outlier transaction on 28 March 2014 with HUF 1 billion value was a smaller loan in the first quartile based on Figure 14 with 0.5% interest rate. The average daily interest rate at this time was 1.71% on the market, and the bottom of the interest rate corridor was 2%. In other words, the entire market stepped out of the interest rate corridor on that day. Based on their credit volumes, both the lender and borrower are significant central market participants on the interbank market, which means that this low interest rate of 0.5% does not seem to be unreal between two market participants with frequent transactions between them.

The third outlier transaction was a significant loan on 31 March 2014, in the volume of HUF 21.5 billion. Similarly to the previous transaction, it was also contracted between two influential market participants (which could probably be deemed reliable) at an interest rate of 0.5%, identical to the previous one. On this day, compared to the 2% central bank O/N deposit interest rate, the average interbank interest rate dropped to 1.4%, even lower than on the previous day.

Regarding data cleaning, we can draw the conclusion that none of the examined three extreme transactions seemed to be incorrect data inputs. There is a logical explanation as to which the deal interest rate could be this size. In other words, it is not necessary to discard any record from the data table, in my opinion. I will continue working with the previous 36,928 overnight transactions.

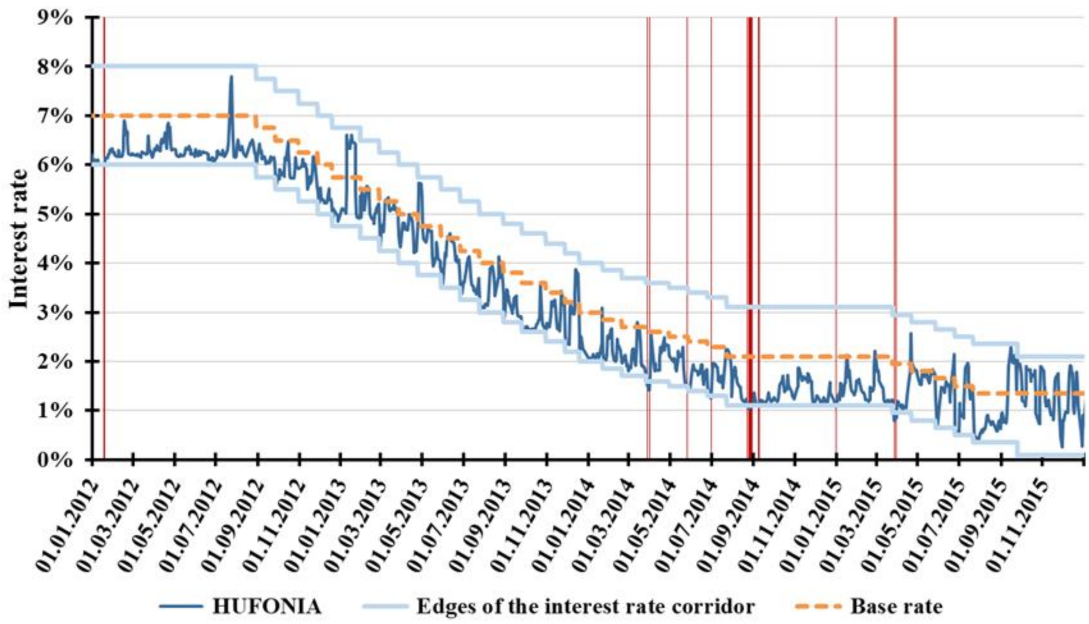
Examining the transactions, it is difficult to recognise the tendencies due to the high volatility; therefore, I will examine daily average interest rates weighted by the transaction amounts (HUFONIA).

The light blue line indicates the two edges of the effective interest rate corridor in Figure 17; the dark blue line shows the changes in HUFONIA. The red vertical lines indicate the days when the average interest rate left the interest rate corridor (there were 17 such days in total). In every case, step-outs of the interest rate corridor happened downward. It can be stated in general that except the third quarter of 2015, the average interest rate was around the interest rate of overnight central bank deposits (bottom of the interest rate corridor) crossing it occasionally, from which we can conclude that the period between 2012 and 2015 was fundamentally characterised by liquidity surplus.

The reason for the anomalies at the beginning of 2012 was clearly the deterioration of the sovereign debtor rating of the Hungarian State to the speculative category (see Section 2.3.3 and *Homolya et al. [2013] for more details*).

*Figure 17:*

The daily weighted average interest rates of the overnight unsecured interbank HUF deposit market and the interest rate corridor between 2012 and 2015




*Source: Own editing based on MNB data.*

Afterwards, via the continuous central bank base rate reductions (broken orange line) and informing the public opinion, the successful anchoring of the expectations of the market participants helped, and HUFONIA did not leave the interest rate corridor on any occasion during the interest reduction cycle.

Further step-outs were induced by the first and second phases of the Self-financing Programme. With the reduction of the attractiveness of the main monetary policy instrument (central bank bonds were transformed into deposits first, and their maturity was increased afterwards), the effectiveness of the base rate decreased, and the interbank interest rates were stuck in the lower half of the interest rate corridor, which increased the chance of leaving it.

Furthermore, in August 2014, after the transformation of the two-week central bank bonds into term deposits, further significant liquidity flew to the overnight interbank market, which could explain the reappearance of the interbank interest rates step-out of the interest rate corridor *(MNB [2014])*.

The last step-out occurred in March 2015. The period afterwards was characterised by higher volatility, and the interbank interest rates slowly moved away from the bottom of the interest rate corridor. On the one hand, the upgrade of the long term credit rating of Hungary by S&P on 18 September 2015[38], and, on the other hand, the making of the interest rate corridor asymmetric must have played a role in this.

The gradual removal of the two-week central bank deposit began in the last quarter of 2015, by which significant liquidity amount flew to the interbank market from the key monetary policy instrument. In September, the interbank interest rates approached the interest rate of O/N central bank credit (bottom of the interest rate corridor) on several occasions, and HUFONIA started to fluctuate around the base rate with high volatility. This phenomenon indicated more active liquidity management on the interbank market *(MNB [2016])*.

Comparing Figure 17 with the results of *Berlinger–Michaletzky–Szenes [2011]*, it can be stated that compared to the pre-crisis period, also deemed a “dormancy” period, the volatility of the daily average interest rate was significantly lower from 2012 to 2015.

Based on the above, we can say that the interest rate on the interbank market fluctuated mostly at the bottom of the interest rate corridor crossing it occasionally. Step-out of the internet corridor indicated smaller or larger difficulties on the interbank market, which were mainly related to the transformation of the monetary policy toolbox and the change in the state's credit rating.

### 3.1.4. Changes in the monthly aggregated transaction amount

The transformation of the monetary policy clearly had a more significant impact on the interbank market, which can be seen from the changes of the interest rates. If the market shocks were less reflected in the price adjustment, the quantity adjustment is worth examining in detail by all means. In addition to examining the aggregated transaction amount, I will also attempt to shed light on the structure of the quantity adjustment in Section 3.2.

[38] The previous BB rating was changed to BB+ (also not recommended for investment, speculative category) by S&P with stable outlook.

Let us first look at the changes in the aggregated volume and number of transactions in the given period for the overnight unsecured HUF loans. We have reached an important question here, namely the definition of the size of the examination window, in other words, the selection of the length of the period in which we aggregate the transactions.

The most obvious solution on the market of overnight loans would be the one-day time window. In this case, the daily transaction volumes would show fluctuations, which would completely cover the tendencies in the time series. The use of moving average could partly counterbalance this, but this type of “smoothing” the time series would lead to distortions exceeding a certain extent.

An even more powerful argument against one-day aggregation is the low activity of the Hungarian interbank market at international level. There were so few contracts in average on one day in the examined period (37 contracts) that by choosing this option, the interbank network would fall apart, it would consist of smaller or bigger separate islands, which would make the use of methodologies presented in my dissertation later, and the interpretation of the results impossible.

So it seems certain that the examination window should be selected for a period longer than one day, but the longer the period is the stronger the aggregation “conflates”, conceals diversity in data and the fewer the number of data points will be. This latter problem can be eliminated, for example, by “pushing” a time window of one quarter on every month, but in this case, approximately one-third[39] of the elementary data aggregated in every data point will match the content of the previous and the following data point.

In order to find the “optimal” solution, the literature is worth looking at. The different articles examining the interbank market are not uniform either regarding the level of aggregation over time. Some authors use a one-day time window *(León–Machado–Sarmiento [2018])*, others analyse monthly data *(Berlinger et al. [2017])*, but there are often quarterly *(Veld–van Lelyveld [2014]); Craig–von Peter [2014]; Fricke–Lux [2015])*, or even half-yearly *(Langfield–Liu–Ota [2014])* examinations, too.

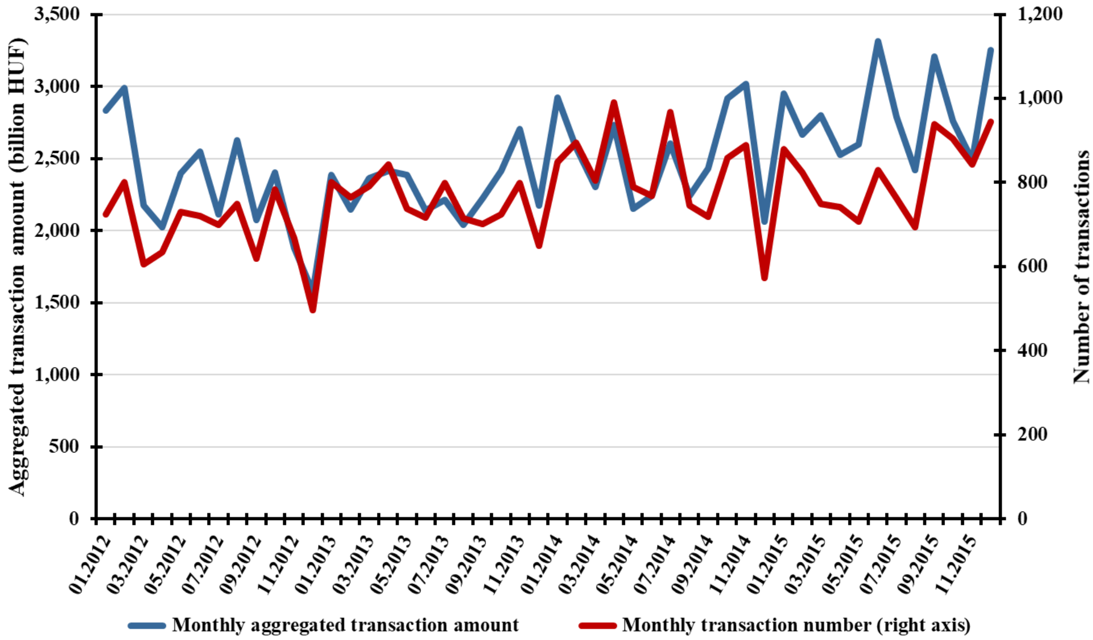
The *Berlinger–Michaletzky–Szenes [2011]* study used as a starting point for this chapter uses weekly and monthly time windows alternately. As the weekly time window is not frequent in the foreign literature, I will uniformly work with the monthly aggregation

[39] If the transactions are distributed among the different months uniformly.

level, which I will keep "pushing" on every month. By doing so, I will have 48 (monthly) data points between 2012 and 2015. The August 2015 network, for example, will consist of the sum of overnight interbank transactions initiated between 1 August and 31 August 2015.

*Figure 18:*

The monthly aggregated transaction amount of overnight unsecured interbank HUF deposit market and the monthly number of transactions (axis on the right) between 2012 and 2015




*Source: Own editing based on MNB data.*

Examining the order of magnitude of the market based on Figure 18, it can be stated that at around monthly HUF 2-3 thousand billion aggregated transaction amount (blue line and the belonging axis on the left), between 700 and 1,000 overnight credit transactions (red line secondary axis on the right) were contracted in the examined period on the Hungarian unsecured interbank market.

The monthly aggregated transaction amount and the number of transactions moved together very closely in a relatively narrow band. The two indicators separated from each other only in the first half of 2012 and in 2015; in both cases aggregated transaction amount grew more than the number of transactions.

In the first such period, the reason for this must have been the already mentioned deterioration in the Hungarian sovereign credit rating and the transformation of the central bank toolbox in the second period. One possible explanation of the phenomenon is that the banks significantly cut the limits of partners deemed less reliable due to the shocks on the interbank market. In contrast, the volume of loans extended to the best partners grew (as financing requirements still had to be satisfied from somewhere, while the central bank instruments were less and less attractive). Changes in the aggregated transaction amount exceeding the number of transactions and the scissors opening between them may point to the presence of quantity adjustment.

## 3.2. Analysis of the concentration of lending and borrowing

After examining the aggregated transaction amount, I will examine how quantity adjustment was performed structurally between 2012 and 2015. The different indicators of the concentration, such as the Lorenz curve, Gini index and the Herfindahl-Hirschman index, as well as the effective number generated from them, will help me in this.

Concentration is the focusing of the majority of the total amount (e.g. transaction amount in the present case) in few observation units (market participants) *(Hunyadi–Vita [2008a])*.

Concentration has two types fundamentally: absolute and relative concentrations. Absolute concentration is present on a market if the number of participants is very low. In this case, a large percentage of the total amount will be concentrated in few units – due to the small number of active market participants in itself. What is small and what is large multitude is difficult to define, and the literature does not give any general guidance either, but the measures of relative concentration can already be used and interpreted well if there are 30-40 active credit institutions present on the interbank market.

The volume of concentration in the relative sense can be defined in some way by the comparison of relative frequencies (one group of banks constitutes what percentage of all active banks on the market) and the relative amounts (loans granted by one group of banks in the proportion of the total market credit volume).

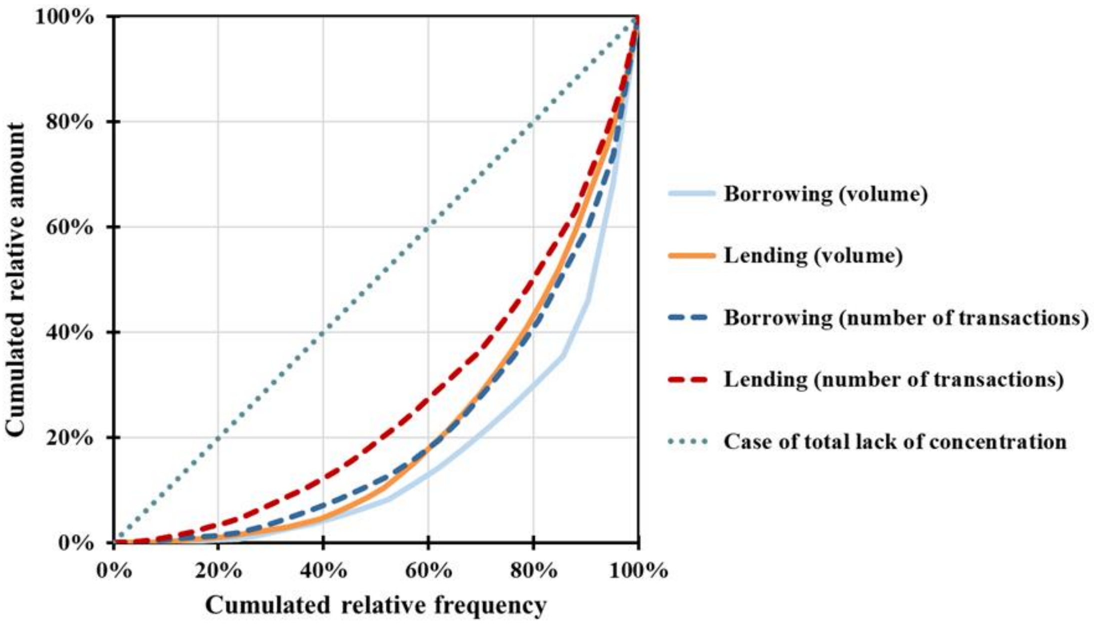
### 3.2.1. Lorenz curve and Gini index

At the beginning of the 20th century, Max Otto Lorenz American economist prepared a special chart to show the Prussian asset concentration, which was named Lorenz curve in his honour *(Kerékgyártó–Mundruczó [1998])*.

The Lorenz curve shows the cumulated relative amounts subject to the cumulated relative frequencies, where cumulation begins from the smallest observation and goes on to the larger ones.

*Figure 19:*

Lorenz curve




*Source: Own editing based on MNB data.*

The concentration of the interbank market transactions on the borrower and lender sides according to volume (continuous curves), on the one hand, and number of transactions (dashed curves), on the other hand, in December 2015[40] is seen in Figure 19. The diagonal of the square (dotted turquoise line) is the case of total lack of concentration, as the participation in the total volume and total number of transactions of the given banks is uniform. The farther the Lorenz curve is from the diagonal (and the closer it is to the lower and right sides of the square), the larger is the concentration it indicates.

According to Figure 19, taking the borrowed credit volumes as a basis, the concentration on the borrowing side (continuous light blue line) was the highest, while the lowest concentration was on the lending side with the number of granted loans taken into account

[40] The choice for the aggregate data of December 2015 was made because it is the most recent available monthly time window, and it is excellent for presenting that if two Lorenz curves intersect, then it will not be possible to determine a clear order in terms of concentration. Therefore, concentration indicators will be used to draw meaningful conclusions, and the Lorenz curve is used only for illustrative purposes here.

(dashed red line). The Lorenz curves indicated with continuous orange line and dashed dark blue line intersect each other in the chart. If two Lorenz curves intersect each other in one or several places, they cannot be compared clearly.

Different concentration indicators are worth calculating in order to eliminate this problem. Although the Lorenz curve is a very illustrative method of showing the concentration, unfortunately, it is not suitable for the examination of the dynamics over time (this is why I depicted only the last observations from December 2015). The latter's disadvantage makes the use of concentration measures necessary and justified for the Lorenz curve, too.

Gini index (*G*) is one of the indicators used most frequently to measure the degree of concentration. Its value can be defined as the quotient of the size of the area bordered by the diagonal and Lorenz curve, and the size of the area bordered by the diagonal and the axes.

$$\mathrm{G} = \frac{t_c}{½} = 2 \cdot t_c \qquad (2)$$

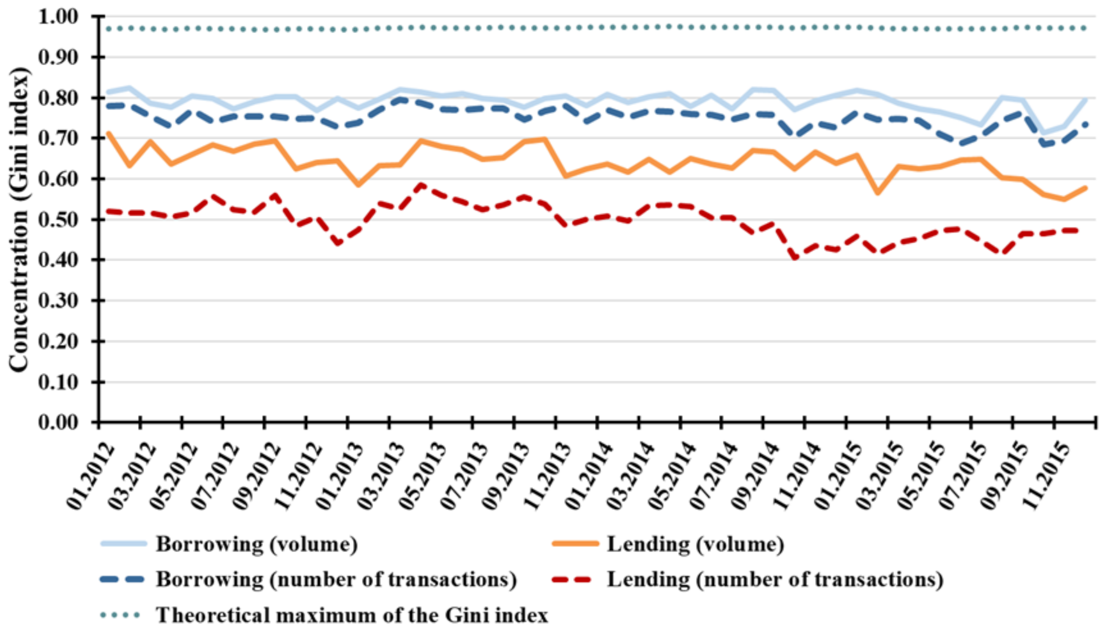
Where $t_c$ is the so-called concentration area bordered by the diagonal and Lorenz curve. The diagonal divides the square with unit-size side length into two parts. Therefore it is easy to see that the size of the area bordered by the diagonal and the axes is ½ (denominator of formula 2).

The Gini index takes its smallest value (0) when the market share of every bank is identical. This is the case of the total lack of concentration. In the case of limited number (*n*) of banks, if one bank extends all loans (or one market participant borrows all on the other side), it is seen that the value of the Gini index is $G = 1 - \frac{1}{n}$, i.e. the more participants are on the market (the bigger $n$ is), the closer the value is to 1 *(Ross [2017])*.[41]

[41] The number of active banks fluctuated between 30 and 40 in the examined period, therefore the upper limit of the Gini index is around 0.97.

*Figure 20:*

Gini index of the borrowing and lending transactions in the given months according to the amounts and number of transactions in the period of 2012-2015




*Source: Own editing based on MNB data.*

In Figure 20, we see that examining the interbank market from the lender side Gini index shows medium size concentration (values typically between 0.4 and 0.7) and strong concentration from the borrower side (values between 0.7 and 0.8).[42]

Additionally, it can be observed that regarding both the volumes (continuous lines) and the number of transactions (broken lines), borrowing is significantly more concentrated than lending, which means that a relatively small number of participants borrow the majority of interbank credits, and they do not obtain financing from individual bigger market participants, but almost every one of the market participants contributes to the maintenance of market liquidity.

[42] The precise value, from which the size of concentration is deemed strong, is difficult to define. I used the categorisation of *Harangi-Rákos [2013]* in the present case.

### 3.2.2. Herfindahl–Hirschman index and the effective number

Another index frequently used to measure concentration is the Herfindahl-Hirschman index (HHI), which can be described according to the following:

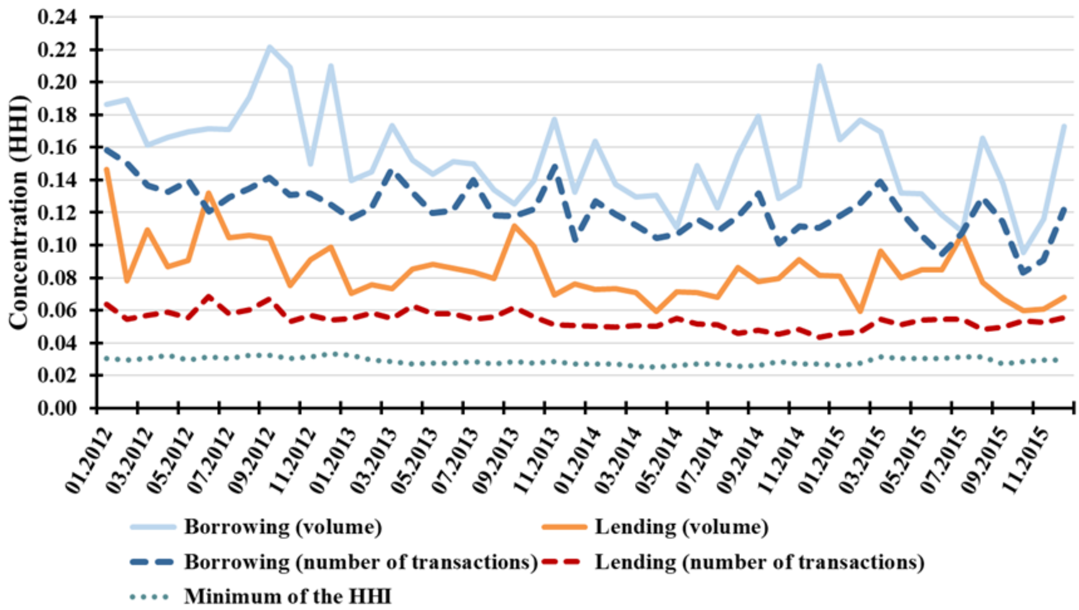
$$\mathrm{HHI} = \sum_{i=1}^{N} Z_i^2 \tag{3}$$

where $Z_i$ is the market share of bank $i$, and $N$ is the number of participants present on the market. The minimum of the index is $1/N$, when the market share of every participant is identical (total lack of concentration), the maximum of the index is 1, which indicates the presence of the highest degree of concentration (one participant owns the entire market). The lower limit depends on $N$, which means that if there is a total lack of concentration on a market, then on a market of 5 participants, we obtain ceteris paribus higher HHI value than on a market of 30 participants. Meaning that this indicator can take both the relative and absolute projections of the concentration into account simultaneously.

Additionally, the reciprocal value of the Herfindahl-Hirschman index is also a very frequently used indicator, which is known by the literature as effective number and which, if applied to the interbank market, can be interpreted as the number of active banks on the market *(Berlinger–Michaletzky–Szenes [2011])*.

*Figure 21:*

HHI index of the borrowing and lending transactions in the given months according to the volume and number of transactions in the period of 2012-2015




*Source: Own editing based on MNB data.*

Figure 21 shows the changes in the borrowing side (continuous light blue and dashed dark blue lines) and the lending side (continuous orange and dashed red lines) concentrations of the interbank market (HHI) in the given months, and the $1/N$ lower limit (dotted turquoise line).

According to the thumb rule, the market cannot be considered concentrated in HHI values under 0.15, values between 0.15 and 0.25 indicate moderate concentration, and the interbank market can be deemed highly concentrated over the value of 0.25. (U.S *Department of Justice & FTC [2010])*.[43] It means that the interbank market loans cannot be deemed concentrated (HHI values are under 0.15 every month), but the borrowing transactions show moderate concentration, especially in terms of the borrowed credit amounts (continuous light blue line).

Two phenomena can furthermore be observed in Figure 21. The first is that – similarly to measuring concentration with the Gini index – both in terms of the volumes and the number of transactions, the borrowing transactions show significantly higher concentration than the lending transactions. It means that proportionally more market participants finance fewer market participants.

The more even distribution of the lending transactions can be explained by the fact that structural liquidity surplus was typically experienced on the Hungarian interbank market in the past one and a half decades. The high concentration of the borrowing transactions derives from the partner limits and the quantity adjustment being stronger on the interbank market. Only a few large (or rather actively transacting, reliable)[44] market participants have more significant limits at their partners, limiting the number of market participants who can receive funds on the interbank market.

This result is identical with the findings of *Berlinger–Michaletzky–Szenes [2011]*; moreover, the picture is further tinged by the fact that the number of lenders is relatively stable in a crisis, while the number of borrowers drops significantly (the concentration of borrowing grows drastically).

*Minoiu–Reyes [2013]* examined cross-border interbank transactions using the exceptionally rich time series of BIS *(Bank for International Settlements)* from 1978 to

[43] It is interesting that the line was drawn at 0.1 and 0.18 values in their 1997 publication.

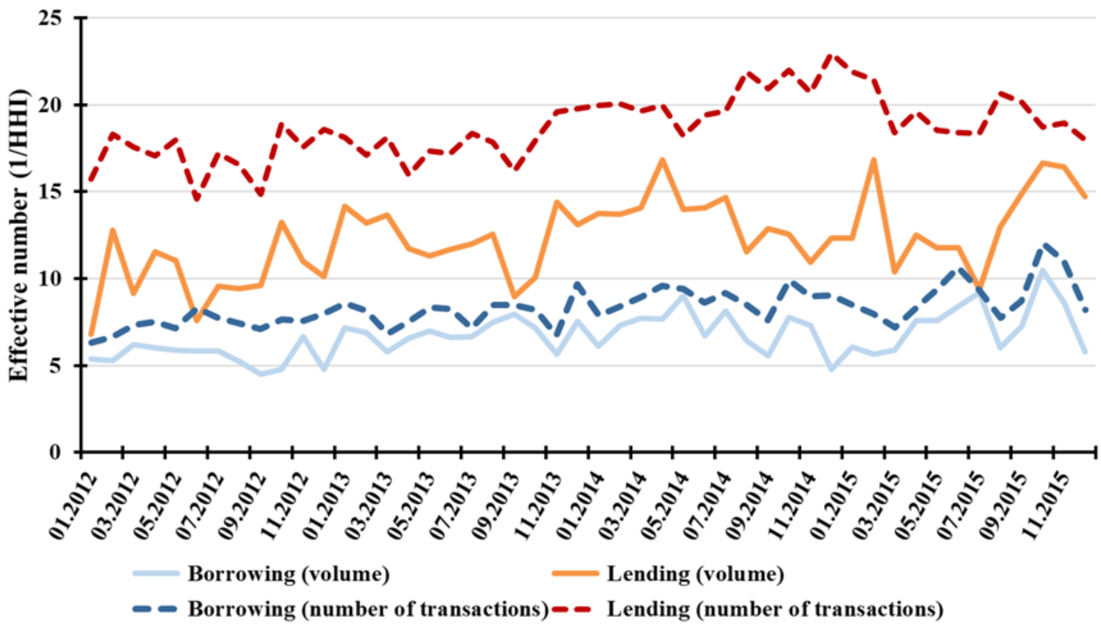
[44] The literature is not uniform in this, as I pointed to it earlier (see for example *Berlinger [2017]*).

2010, covering 184 developed and developing countries (including the Visegrad states). The network they analysed contains data for individual resident banks as aggregated at the level of countries. Their analysis of a global interbank network of states also shows clearly that the concentration of borrowing was significantly higher than that of lending throughout the 32 years under review. In addition, the authors observed increasing concentrations over time on both sides.

The effective numbers derived from the borrowing and lending HHI indicators are to quantify the average number of active banks on the two sides of the interbank market.

*Figure 22:*

Effective numbers generated on the basis of the concentration of the borrowing and lending transactions and according to the number of transactions in the period of 2012-2015




*Source: Own editing based on MNB data.*

Based on the effective numbers of Figure 22, it can be stated that the loans were granted by 10-15 banks on average [45] while there were only 5-8 active borrowing banks on the market. The same numbers were 17-21 and 7-10 respectively, based on the number of transactions.

[45] The limits are roughly the lower ($D_1$), and higher deciles ($D_9$) of the monthly effective numbers.

Another phenomenon, which is clear from Figures 21 and 22, is that the fluctuation, volatility of the volumes (continuous lines) is higher than those of the number of transactions (dashed lines).

This phenomenon can unfortunately not be verified by a formal test as the pre-proposition of F-test (aimed at the identity of the standard deviation of the two populations) is that the distribution of both populations is normal and that we have two independent samples *(Hunyadi–Mundroczó–Vita [2001])*. This latter condition is not met at all; examining the same transactions, there is a (expectedly positive and strong) connection between the volume and the number of loans granted by the given bank.

The first observed phenomenon is worth testing with the help of a formal hypothesis test. The phenomenon to be tested is that borrowing is significantly more concentrated both in terms of the volumes and the number of transactions. This assumption can be tested with a two-sample z-test for comparing expected values. According to our alternative hypothesis, the average concentration of borrowing *(B)* ($\mu_B$) is larger than the average concentration of lending *(L)* ($\mu_L$), and according to our null hypothesis, the expected value of the HHI index of lending is minimum the size of that of borrowing, in other words, formally:

$$\begin{aligned} \mathrm{H}_0: &\quad \mu_B - \mu_L \leq 0 \\ \mathrm{H}_1: &\quad \mu_B - \mu_L > 0 \end{aligned} \tag{4}$$

If we assume that the standard deviation of the two populations is limited and if we have a sufficiently large sample [46], if the null hypothesis is met, the test statistic written in

$$\mathrm{z} = \frac{\bar{B} - \bar{L}}{\sqrt{\frac{s_B^2}{n_B} + \frac{s_L^2}{n_L}}} \tag{5}$$

form is of standard distribution with good approximation, where the numerator contains the arithmetic average of the HHI indexes of borrowing and lending, and $s^2$ in the denominator indicates the variance of the different samples, and $n$ the number of sample elements *(Hunyadi–Vita [2008b])*.

[46] Sample of 48 elements can already be considered a large sample.

Based on the calculations of Table 7, the value of the test statistic is much higher than the upper critical value both in terms of the volumes and the number of transactions. It is in the critical (or rejection) range, therefore the null hypothesis can be rejected at 99% confidence level, which means that the average concentration of the borrowing transactions was significantly higher than that of the lending transactions. The p-value is extremely close to 0, so the null hypothesis can be rejected not only at 1% significance level, but also at any generally used significance level. Thereby, hypothesis *H2* (formulated in the introduction of this chapter) is successfully proven through a formal test.

*Table 7:*

Examination of the average HHI difference of borrowing and lending with two-sample z-test

| | **Volume** | **Number of transactions** |
|---|---|---|
| Sample mean of lending ($\bar{L}$) | 0.0844 | 0.0540 |
| Sample mean of borrowing ($\bar{B}$) | 0.1542 | 0.1220 |
| Standard deviation of lending ($s_L$) | 0.0178 | 0.0054 |
| Standard deviation of borrowing ($s_B$) | 0.0286 | 0.0157 |
| Sample size of lending ($n_L$) | 48 | 48 |
| Sample size of borrowing ($n_B$) | 48 | 48 |
| **Test statistic ($z$)** | **14.3331** | **28.4172** |
| **Upper critical value** | **2.3263** | **2.3263** |
| **p-value** | **0.0000** | **0.0000** |

*Source: Own editing based on MNB data.*

*Kolozsi–Horváth [2020]* also examined the concentration of interbank loans and found that by the increase of additional liquidity (the saturation of the market with liquidity), the concentration of liquidity decreases. The authors also showed that in addition to the quantity of interbank liquidity, the distribution (concentration) of liquidity also significantly affects the average interest rate. The relative price was significantly higher in the case of higher concentration (the majority of liquidity is concentrated in few banks).

Furthermore, by the increase of additional liquidity, the aggregated transaction amount of the interbank market decreased, as due to the lower relative price of liquidity, the banks were less motivated to place their liquidity surplus on the interbank market.

After the descriptive analysis of the main features of unsecured interbank overnight loans (maturity, interest rate, aggregated transaction amount) and the examination of the concentration of the market, let us explore the lending relationship between the banks. In the coming section, I will first use the fundamental measures of network theory, followed by the network models in Section 4.

## 3.3. General network features of the unsecured interbank deposit market

The idea of featuring a financial system as a network is tied to the name of François Quesnay, who, in his work in 1758, depicted the capital flows between the market participants of an economy as a network *(Nagurney–Ke [2001])*. In the centuries passed since the research of financial networks has become an organic part of the financial literature, the number of publications grew in the topic, especially in the recent years.

A network fundamentally consists of interconnection nodes (or vertices) and the connections (or links, edges) connecting them. The nodes are marked with $i = 1, 2, \ldots, N$ positive integers, which means that the number of nodes (the size of the network in other words) is shown by $N$. Edges connecting the points are marked with their endpoints, for example, edge (1, 2) establishes an interaction between vertices 1 and 2. Let us indicate the number of all existing links between the nodes by the letter $L$.

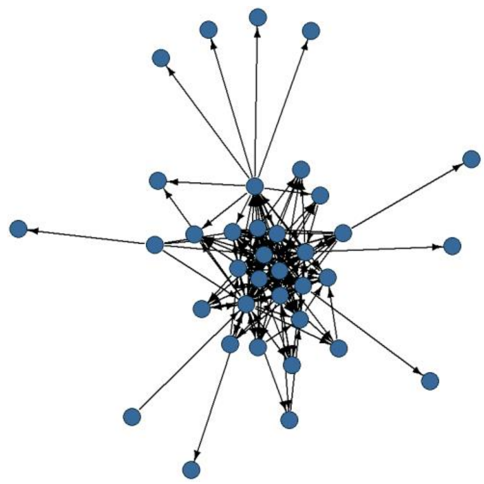
Depending on whether the direction of the connection between two nodes can be interpreted (or whether it carries additional information), there are undirected and directed networks (this latter is also called digraph). A network is undirected if every one of its edges is undirected, and we call a network directed if every link has a direction.

The unsecured interbank deposit market in the focus of my research is an excellent example of the directed network, where the nodes are the different market participants (banks), while the links between them in a given moment (or period) are the – not yet repaid – loans extended to each other. The direction of the edges is critical here, as it defines which one of the vertices connected by it is the lender and which one is the borrower. For specific analysis purposes, we can also view the interbank network as an undirected graph, where the direction of the edges connecting the nodes is not but the fact of the connection between them is crucial.

Figure 23 shows the directed network of the unsecured interbank deposit market in a grasped period [47] in overnight (liquidity type) loans. It is striking at first glance that the transactions (arrows) between the banks in the middle (turquoise disks) are very dense, while the banks on the periphery typically have only one connection.

*Figure 23:*

Directed network of the unsecured interbank HUF deposit market (March-May 2015)



*Source: Own editing based on MNB data.*

I will describe this connection system between the banks in the following. I will present the basic network theory indicators first (uniformly with the help of the markings of *Barabási et al. [2016]*), then, with the use of these – as "building blocks" – I will present the network model, with which the interbank market seen in Figure 23 can be described best.

### 3.3.1. Average degree and degree distribution

The average degree and degree distribution is a frequent element (often the starting point) of the analyses of networks. It is worth dividing the undirected and directed networks, as both the concepts and the calculations will be different in the two types at a certain point.

In undirected networks, the degree of point $i$ ($k_i$) will show the number of links of the given nodes with the other component of the network. Vertices with 0 degree are called isolated nodes in a network, while the most connected nodes are the hubs or concentrators.

[47] The selection of the period is not random, I will compare the interbank network of the same period with an interpersonal network in Chapter 6.

The latter has special significance concerning macroprudence if we wish to analyse an interbank network.

With the use of the already introduced marks, we can calculate the average degree ($\langle k \rangle$) as follows:

$$\langle k \rangle = \frac{\sum_{i=1}^{N} k_i}{N} = \frac{2\left(\frac{1}{2}\sum_{i=1}^{N} k_i\right)}{N} = \frac{2\,L}{N} \tag{6}$$

It means that the average degree in an undirected graph is double of all existing edges ($L$) divided by the number of nodes ($N$).

Considering the undirected network of the overnight transactions of the unsecured interbank deposit market, the average degree was in the range between 6 and 9 between 2012 and 2015, which means that one market participant has a live connection with 6-9 other participants on the market.

In directed networks, there is an incoming degree ($k_i^{in}$) showing the number of links pointing to nodes $i$, and there is an outgoing degree ($k_i^{out}$) showing the number of edges pointing from vertex $i$ to the other components of the graph. The total degree of nodes $i$ ($k_i$) is the sum of in-degrees and out-degrees:

$$k_i = k_i^{in} + k_i^{out} \tag{7}$$

In this case, the average in-degree $\langle k^{in} \rangle$ and the average out-degree $\langle k^{out} \rangle$ is always identical and can be calculated according to the following:

$$\langle k^{in} \rangle = \frac{\sum_{i=1}^{N} k_i^{in}}{N} = \langle k^{out} \rangle = \frac{\sum_{i=1}^{N} k_i^{out}}{N} = \frac{L}{N} \tag{8}$$

Let $p_k$ be the probability of the degree of a randomly selected point in the network being $k$. If, in line with the previously introduced marks, there are $N$ nodes in the network, the degree distribution is the histogram normalised with $N$ is:

$$p_k = \frac{N_k}{N} \tag{9}$$

where $N_k$ indicates the number of points with degree $k$ (degree-k node). Degree distribution plays a central role in network science. The form of degree distribution significantly influences the network robustness or, for example, the extent of contagion resulting from the insolvency of a market participant in a network representing an interbank market. The majority of network measures – such as the average degree of a network presented previously – can be calculated with the help of degree distribution:

$$\langle k \rangle = \sum_{k=0}^{\infty} k \cdot p_k \tag{10}$$

The links between the nodes of a network are worth structuring and placing in a so-called adjacency matrix ($\boldsymbol{A}$), to which the toolkit of linear algebra can be applied later.

Similarly to the previous practice, the presentation of the adjacency matrix is also worth dividing into undirected and directed networks. The adjacency matrix of an undirected network consisting of $N$ nodes is an $N \times N$ matrix, the value of a general $A_{ij}$ element of which is 1 if there is an edge between points $i$ and $j$, and 0 if there is no connection. It is evident that the adjacency matrix is symmetric in undirected networks, that is $A_{ij} = A_{ji}$ and there are 0 values[48] in the main diagonal $A_{ii} = 0$, as none of the vertices can have a connection with itself. The degree of node $i$ ($k_i$) is the sum of elements in the given row or column of the adjacency matrix:

$$k_i = \sum_{j=1}^{N} A_{ij} = \sum_{j=1}^{N} A_{ji} \tag{11}$$

The value of the $A_{ij}$ element of the adjacency matrix in directed networks is 1 if a link points from node $j$ to node $i$, and 0 if edge does not point from node $j$ to node $i$. In this case, we differentiate between in-degree and out-degree, which result from the following row or column sum:

$$k_i^{in} = \sum_{j=1}^{N} A_{ij} \tag{12}$$

$$k_i^{out} = \sum_{j=1}^{N} A_{ij} \tag{13}$$

[48] Depending on the purpose of the analysis, values of 1 (loops) may appear in the main diagonal, in some cases.

The concept of weighted network is worth introducing for the description of the majority of problems occurring in practice where the elements of the adjacency matrix are not 1 (to indicate connection) but show the weight of the given link *(Barrat et al. [2004])*.

### 3.3.2. Shortest paths, average path length

The definition of the distance between two points has outstanding significance in networks. In network theory, this function is fulfilled by the path's length. The path consists of sequentially connected nodes, and the path's length is the number of connections (edges) representing the path (how many steps it takes to get from one node to the other on a given path). The key characteristics of the path are the shortest paths, the network diameter, and average path length.

The shortest path between nodes $i$ and $j$ of a network – the distance of two vertices / geodesic path, in other words – ($d_{ij}$) is the path going through as few nodes as possible to link the two points. In undirected networks, the paths are "there and back", $d_{ij} = d_{ji}$ in every case. This connection does not necessarily exist in directed networks. The existence of path $i \rightarrow j$ does not guarantee the existence of path $j \rightarrow i$, and even if both exist, their distance is not necessarily the same. The shortest paths, in general are calculated from the adjacency matrix.

The network is connected if there is a path between any of its two vertices. If there is a node $i$ and node $j$, which are not connected by a path ($d_{ij} = \infty$), the network is not connected. The connected parts (subnetworks) of a disconnected network are called cluster or component. The adjacency matrix of such a network can have a block diagonal form, which means that with the exception of the squared blocks on the main diagonal, every element of the adjacency matrix will be 0 *(Auer–Joó (ed.) [2019])*.

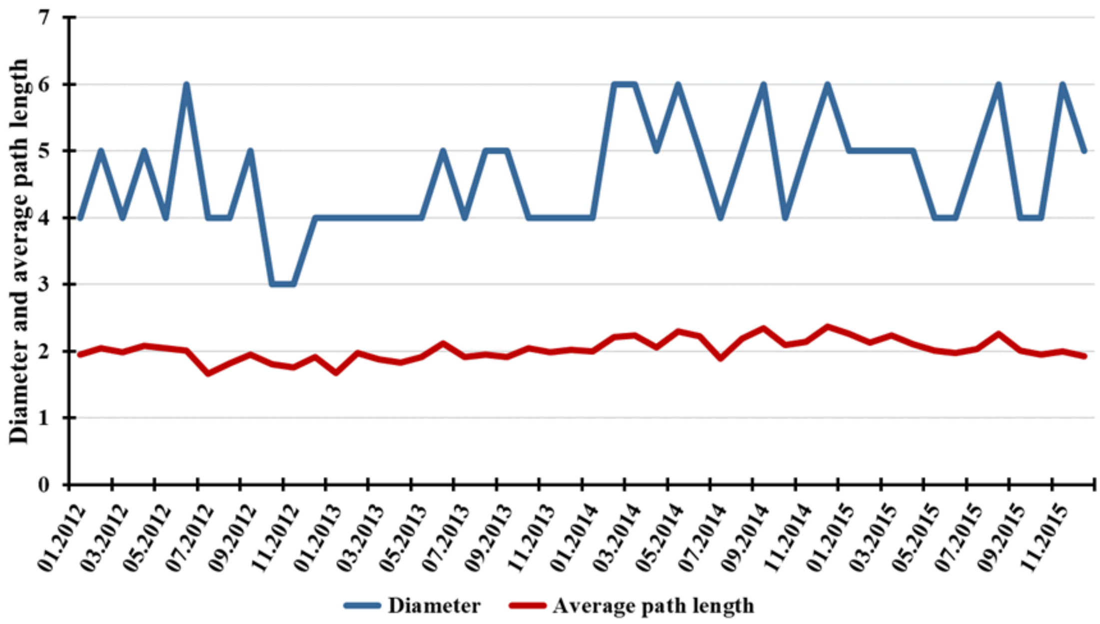
Connection, due to the termination of which a connected network may become disconnected, is called bridge. Such bridges play a key role in terms of systemic risk in most networks – and especially in financial networks –, as they can transmit post-bankruptcy contagions to otherwise separated network components.

Network diameter and average path length are often used as descriptive statistics of a network. The diameter of a network ($d_{max}$) is the biggest of the distances among every node of the network. The average path length $\langle d \rangle$ is the arithmetic average of the distances between the nodes of a network:

$$\langle d \rangle = \frac{\sum_{\substack{i,j=1,N \\ i \neq j}} d_{ij}}{N(N-1)} \tag{14}$$

*Figure 24:*

Diameter and average path length of the directed monthly networks of the unsecured interbank market for the period of 2012-2015




*Source: Own editing based on MNB data.*

Figure 24 shows that the average path length (red line) fluctuated around 2 in a relatively tight band, which means that the market participants could contact any other bank with the involvement of expectedly one participant (intermediary).

*Hausenblas–Kubicová–Lešanovská [2015]* examined the Czech interbank market from March 2007 to June 2012. According to their calculations, the average path length was similarly short, ranging between 1.9 and 2.6, and was almost perfectly in line with the values measured in the Hungarian interbank network. When analysing the Austrian interbank market, *Boss et al. [2004]* obtained a value of 2.59, also falling within the same range. A possible explanation for the phenomenon that any two players can contact each other if, on average, a single intermediate player is inserted in between them is that intermediation is strongly present in the Hungarian, Czech and Austrian interbank markets and central participants playing the role as intermediaries are able to efficiently transfer excess liquidity between two such smaller (peripheral) banks that would not lend directly to each other due to counterparty limits.

The network diameter on the Hungarian interbank market (Figure 24, blue line) was mainly in the range between 4 and 6, meaning that connection between any two market participants could be made with the involvement of maximum of 3-5 partners.

### 3.3.3. Clustering coefficient and density

Local clustering coefficient ($C_i$) is the measure of the local connection density of a network. In undirected networks, it shows the probability of an edge between two randomly selected vertices adjacent to node $i$ with degree $k_i$ (if the components are connected):

$$C_i = \frac{L_i}{k_i(k_i-1)/2} = \frac{2L_i}{k_i(k_i-1)} \tag{15}$$

where $L_i$ shows the number of links between the neighbours of degree $k_i$ of node $i$. One of the main advantages of the indicator is that it expresses the extent of clustering with values between 0 and 1. The value of the local clustering coefficient is 1 if a connection is established between every neighbour of point $i$ (its neighbours form a complete graph). The value of the indicator is 0 if there is no connection between the neighbours of node $i$ at all. The clustering coefficient of nodes with degree 0 and 1 is of course 0 (the vertex either does not have a neighbour or only has one neighbour, the connection with its own self cannot be interpreted).

The simple arithmetic average of the local clustering coefficients of nodes constituting the network exceeds the so-called average clustering coefficient $\langle C \rangle$, which shows the probability of connection between two randomly selected neighbours of an arbitrary vertex of the network:

$$\langle C \rangle = \frac{\sum_{i=1}^{N} C_i}{N} \tag{16}$$

In addition to the average clustering coefficient, another measure frequently used for the connection density of the whole of the network in undirected networks is the global clustering coefficient (or ratio of transitive triplets) ($C_\Delta$), which can be calculated as follows:

$$C_\Delta = \frac{3 \times Number\ of\ triangles}{Number\ of\ connected\ triples} \tag{17}$$

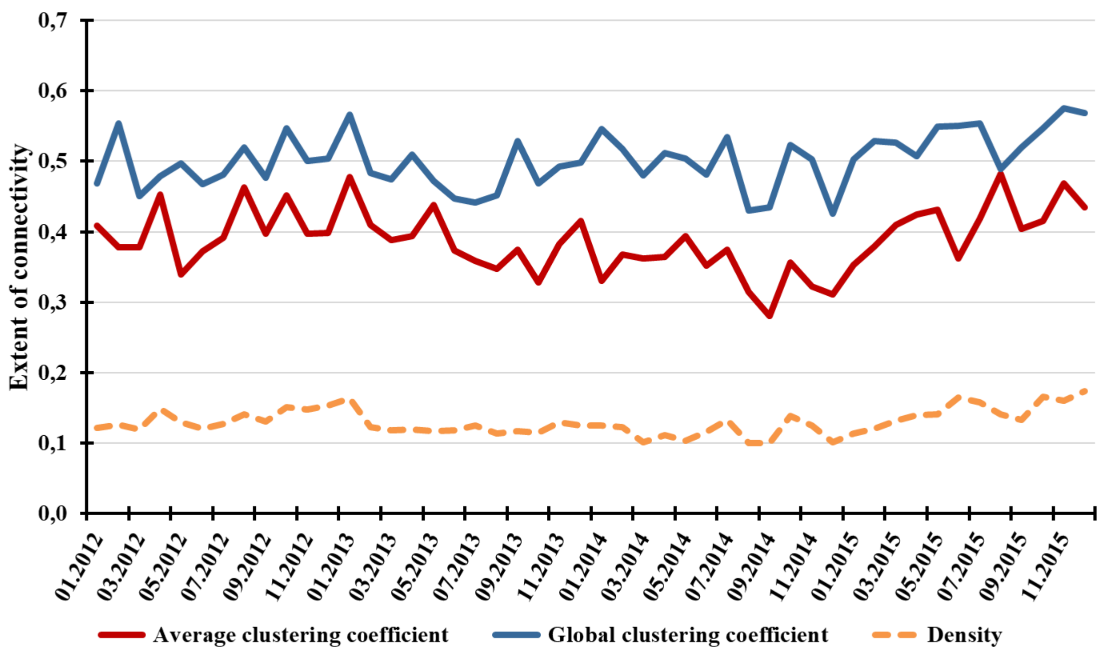
where the connected triples in the denominator indicate groups of 3 nodes with a minimum of two edges between them. If there are a total of two connections between three nodes, the triplet is called open triplet, and if the vertices are connected with the maximum three edges, the triplet is called closed triplet (in which case the nodes form a complete graph). Calculating them this way, we counted every triangle (or closed triplet) three times. The role of multiplier 3 in the numerator of the equation is to filter this multiple calculation *(Barabási et al. [2016])*.

Another widely used indicator for examining connection density is the so-called density (or connectivity), which, as the quotient of the existing and maximum possible edges of a network, gives the probability of the existence of a direct relationship between two randomly selected players *(Auer–Joó (ed.) [2019])*. In the case of a directed network, the edge density can be calculated as follows ($p$):

$$p = \frac{L}{L_{max}} = \frac{L}{N(N-1)} \qquad (18)$$

*Figure 25:*

Clustering coefficients and density of the directed monthly networks of the unsecured interbank market for the period of 2012-2015




*Source: Own editing based on MNB data.*

In Figure 25, the global clustering coefficient (blue line) fluctuated in the range of 0.45-0.55 over the period reviewed, while the average clustering coefficient (red line) typically fluctuated in the 0.3-0.45 band, which means that the probability of connection between two randomly selected partners of a participant arbitrarily selected on the interbank market is around 30-45%.

*Hausenblas–Kubicová–Lešanovská [2015]* measured average clustering values ranging between 0.35 and 0.41 in the Czech interbank market in the first half of 2012, i.e. the two regional interbank networks appear to be very similar in terms of connection density, in addition to the average path length.

Density in the network for the Hungarian unsecured interbank deposit market fluctuated in a relatively narrow range of 0.1-0.17 (Figure 25, dashed orange line). The same value for the Czech interbank market was between 0.09 and 0.19; thus the similarity between the two networks is also striking in this respect.

Figure 25 clearly shows that density for the interbank market network is always much lower than the average clustering coefficient. That is, the probability that there is a connection between two randomly selected neighbours of an arbitrary node (average clustering coefficient) is much higher than the probability that any two points are connected independently of anything else (density). In short, we could also say that despite the relatively few connections, the interconnection is high.

This may indicate that the interbank market is of a modular structure, i.e. it is built from related parts, where each part has similar motivations and functions and come into contact only through a few intermediate participants. Only in this way is it possible that an edge is less likely to exist between two randomly selected nodes than between two neighbours of an arbitrary vertex, which neighbours are interconnected within a single module.[49] Central players connecting isolated nodes have a key role to play in such a network.

Interestingly, the same phenomenon is observed in the *Minoiu–Reyes [2013]* study (mentioned above in the section on analysing concentration), where a global interbank network of states embracing 184 countries is examined in the period of 1978-2010: the clustering coefficient was higher than the density throughout the 32 years examined. At times of crises (such as the bursting of the dotcom bubble or the global financial crash of 2008), the difference between the two types of connection density significantly decreased, mainly due to a drastic fall in the clustering coefficient. This happens because, upon the

[49] Later, I will present that relationships in the interbank markets are not randomly evolved (in that case, $\langle C \rangle = p$ would be true), instead they are characterised by a kind of hierarchy.

freezing of international interbank capital flows, participants that had previously connected parts of the network separated from each other now partially terminate their previous intermediary activities.

Overall, based on the high degree of coincidence of interbank network metrics for Hungary (analysed by myself), the Czech Republic *(Hausenblas–Kubicová–Lešanovská [2015])*, and Austria *(Boss et al. [2004])*, these relatively separate markets, which are operated in different currencies and with different players involved, appear to be similar even when examined along several dimensions. This suggests that the characteristics of unsecured interbank deposit markets (no physical collateral, liquidity management as the primary goal) develop a kind of special structure, so it is worth examining the network topology of interbank markets more in-depth.

# 4. Core-periphery structure on the Hungarian interbank market

In the previous section, I presented the basic concepts and measures related to networks, with the help of which the main network models in the literature can be featured and differentiated.

In this chapter, I am looking for the answer to the following research questions:

> *What characterises the network of unsecured interbank deposit markets, and what model can be used to describe it?*
>
> *To what extent does a coreness measure adjusted by a concave weight function give better and more reliable results than the coreness measure widely used in academic literature?*

To answer these questions, I reviewed the three fundamental models essential to understand and analyse financial networks: random, scale-free and hierarchical networks. The literature calls the first one Erdős-Rényi, and the second one Barabási-Albert model in honour of their Hungarian creators.

Analysing and understanding the structure is highly important, among others, because the resilience of an interbank market depends not only on the stable liquidity and capital position of each of its constituent banks but even more so on the structure of the interbank network *(Hausenblas–Kubicová–Lešanovská [2015])*.

In the majority of the interbank networks, a so-called core-periphery structure is present, which can be considered a special type of the hierarchical network model. Following the train of thoughts in the article of *Berlinger et al. [2017]*, I will first present a discrete symmetric core-periphery model, from which I will continue with a continuous symmetric model and the so-called coreness measure calculable within its framework.

As one of the key added values of my dissertation at the end of the chapter, I will present a methodological innovation as an amended alternative of the continuous symmetric coreness measure in the academic literature.

My research hypothesis examined in the chapter is the following:

*H3:* *A coreness measure adjusted by a concave weight function allows for a better and more robust classification than before.*

## 4.1. Basic network models

We often use models in finance to understand the observed phenomena, as the observation of reality in its totality is impossible. We attempt to concentrate, systematise information and make them clear, but this way, we always see only a simplified representation of reality. The models are perfectly suitable for observation, but we must always bear in mind that our model is only a representation of reality and not identical to it. Our conclusions drawn from the model are valid only within the frameworks of the given model; therefore our assumptions must be met at least partly *(Pollák–Kocsis [2015])*.

As George E. P. Box British statistician once said: "Essentially, all models are wrong, but some are useful" *(Box–Draper [2007], p 414)*.

We need useful models – the basic models of the networks, too –, as they attempt to offer an explanation for the development of real networks and provide a specific toolkit to study the observed networks. The different network models are extremely important concerning the understanding of real financial networks. The three key models are random, scale-free and hierarchical networks.

How is a real network built or formed? Let us first have a look at its components. Let us assume to have $N$ independent nodes. Based on what principles, laws are links between vertices formed? If a new ($N+1$) vertex is formed, how is it connected to the existing network?

### 4.1.1. Random (Erdős-Rényi) networks

The first and maybe most obvious assumption is that links between nodes are random. Let us designate one $p$ real number in the [0,1] interval, and let us generate a random number of uniform distribution between 0 and 1 in the relation of every vertex $i$ and $j$. Let connection be established between nodes $i$ and $j$ if our random number thrown is smaller than the $p$ threshold value and let us not have an edge between nodes $i$ and $j$ in other cases. New components can be added to the networks upon the same principle connected to the existing points with $p$ probability.

The graph described above is a random network consisted of $N$ points with an edge between any two vertices with $p$ probability. This is the so-called $G(N,p)$ model *(Gilbert [1959])*. Random networks can also be defined with the help of $N$ nodes and $L$ randomly formed links ($G(N,L)$ model). In the description of the random network defined here, two Hungarian mathematicians Pál Erdős and Alféd Rényi have eternal merit *(Erdős–Rényi [1959]*, therefore this type of random network is also called Erdős-Rényi network in the academic literature.

A random network is really "random in type"; its constitution, the number of its edges change from realisation to realisation. The probability of having $L$ links in any realisation of a random network follows binomial distribution with $n = L_{max} = \frac{N(N-1)}{2}$ and $p$ parameters ($B(L_{max}, p)$) in undirected networks. From this, it can be proven[50] that the expected value of the links is:

$$\langle L \rangle = L_{max}\, p = \frac{N(N-1)}{2}\, p \tag{19}$$

Using the earlier formula, the average degree of a random network can be defined as follows:

$$\langle k \rangle = \frac{2\langle L \rangle}{N} = (N-1)\, p \tag{20}$$

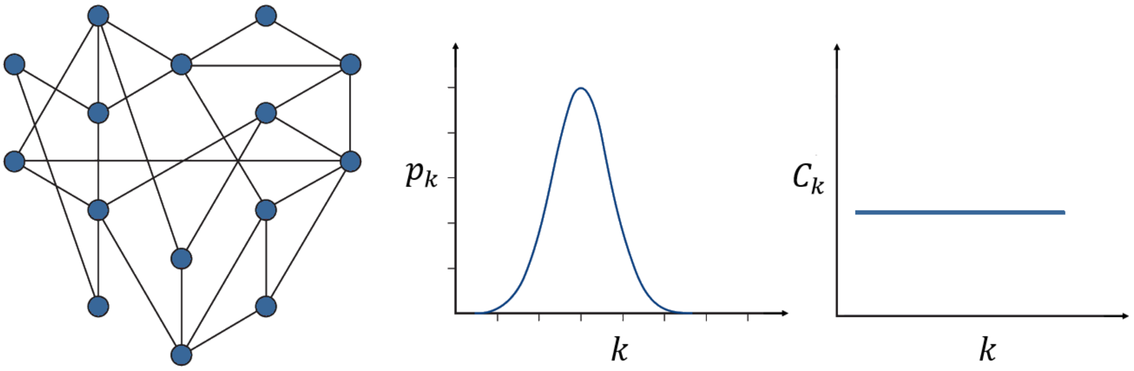
It is evident from formula 20 that in random networks, the average degree is in linear connection with $p$ probability.

Degree distribution $p_k$ in random networks follows binomial distribution (Figure 26 diagram in the middle); therefore, its precise form depends on the previously presented $p$ probability (the probability with which there is an edge between two vertices), and the number of the nodes in the network ($N$). In sparse networks, where $N \gg \langle k \rangle$ (the value of $p$ is low), degree distribution can be approximated with Poisson distribution. As opposed to binomial, the main advantage of approximation with Poisson distribution is that the first two momentums (average and standard deviation) in it only depend on $\langle k \rangle$. Despite this, in networks such as the network of the interbank market, a more precise result is obtained with the use of binomial distribution, as there can be significant differences in the relative smaller networks as opposed to the Poisson distribution. (It should be noted that real financial networks are not Erdős-Rényi networks in general.)

[50] See for example *Barabási et al. [2016]*.

*Figure 26:*

Graph, degree distribution of random network and clustering coefficient subject to the degree




*Source: Barabási–Oltvai [2004] p. 105.*

As the degree distribution in Figure 26 shows, the deviation of components in random networks containing many nodes is low. There are no huge nodes, the degree of the majority of the vertices is near the average degree ($\langle k \rangle$). The tail of $p_k$ degree distribution (degree $k$ with high value) decreases exponentially, which means that the probability of the existence of points with degree significantly differing from the average degree is extremely low *(Barabási–Oltvai [2004])*.

In random networks, the previously discussed general formula of the local clustering coefficient ($C_i$) changes and – because it is a random network – it indicates the expected number of the links between the $k_i$ degree neighbours of nodes $i$ in the numerator $\langle L_i \rangle$. In a random network, maximum $\frac{k_i(k_i-1)}{2}$ edges may be between the $k_i$ degree neighbours of vertex $i$, and $p$ is the probability that there is a connection between two adjacent points. Based on this the $\langle L_i \rangle$ expected value is the following:

$$\langle L_i \rangle = \frac{k_i(k_i - 1)}{2}\, p \tag{21}$$

Inserting this connection in the general formula of the local clustering coefficient, we can perform the following reductions:

$$C_i = \frac{2\,\langle L_i \rangle}{k_i(k_i-1)} = \frac{2\,k_i(k_i-1)\,p}{2\,k_i(k_i-1)} = p = \frac{\langle k \rangle}{N} \tag{22}$$

One of the main messages of this is that the local clustering coefficient of a randomly selected vertex is independent of the degree of the node ($k$). The phenomenon is demonstrated well by the graph on the right in Figure 26.

Additionally, it can be established that the average clustering coefficient of the entire network is identical to the local clustering coefficient:

$$\langle C \rangle = \frac{\sum_{i=1}^{N} C_i}{N} = \frac{N\,\frac{\langle k \rangle}{N}}{N} = \frac{\langle k \rangle}{N} = C_i \tag{23}$$

The main characteristics of networks observed in reality (such as degree distribution or clustering coefficient) are not similar to those of random networks *(Barabási et al. [2016])*. It is a model still used today, as random networks can serve as good benchmarks for every network: if a phenomenon observable in a real network also occurs in the random networks, its reason is randomness, and if not, it points to some deeper connection, directing principle, which leads us on to other network models (scale-free networks, for example).

### 4.1.2. Scale-free (Barabási-Albert) networks

An undirected network is scale-free if its degree distribution can be described with a power function as follows *(Barabási–Albert [1999]):*

$$p_k \sim k^{-\gamma} \tag{24}$$

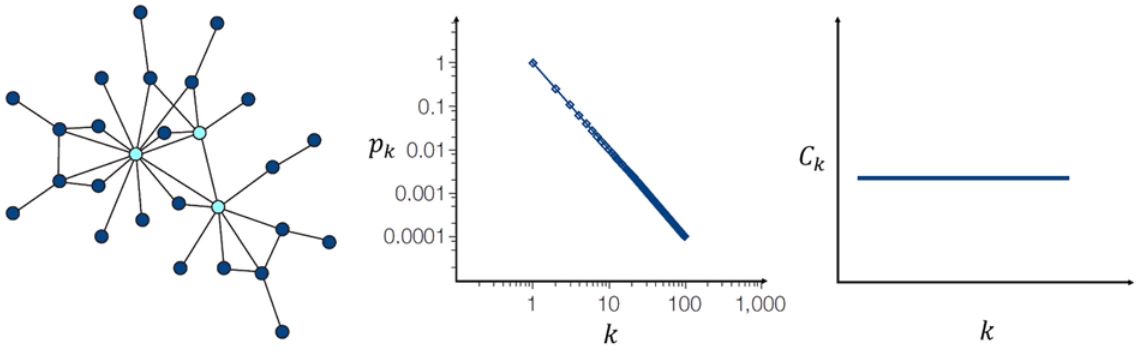
In undirected networks, the scale-free criterion can be set up both for the in-degrees and out-degrees, similarly to the previous formula.

Taking the logarithm of both sides, we can see that there is a linear connection between $\log p_k$ and $\log k$, where the slope of the line is the single (-1) of $\gamma$ degree exponent:

$$\log p_k \sim -\gamma \log k \tag{25}$$

*Figure 27:*

Graph, degree distribution of scale-free network and clustering coefficient subject to the degree




*Source: Barabási–Oltvai [2004] p. 105.*

Comparing Figures 26 and 27, it is immediately visible that in terms of the degree distribution, random and scale-free networks have completely different characteristics. Power distribution in $k$ degrees observable in scale-free networks highly exceeds the Poisson (or binomial) distribution typical of the random networks, which means that there are significantly more points with low degree in the scale-free networks. In the relatively close surroundings of the average degree ($\langle k \rangle$), the degree distribution of random networks is well over the degree distribution of scale-free networks, then the order reverses again in high degrees, the probability of nodes of high degree is much higher in scale-free networks compared to that in random networks. I indicated the hubs – playing a special role – in light blue in the graph on the left in Figure 27.

The natural concomitants of scale-free networks are the nodes of a high degree (or hubs), and it can be observed that the larger a network is, the bigger its nodes are (the connection is polynomial) *(Auer–Joó (ed.) [2019])*.

The scale-free attribute comes from physics, from the theory of phase transitions, where the power functions also play a central role. In a random network, where degree distribution approximately follows the Poisson distribution, the degree is very likely to be in the following interval:

$$k = \langle k \rangle \pm \sigma_k = \langle k \rangle \pm \sqrt{\langle k \rangle} \tag{26}$$

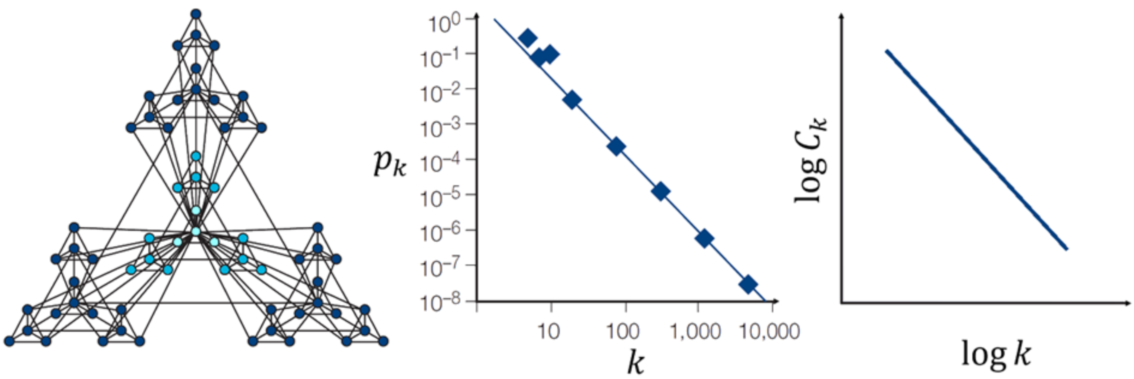
The nodes of random networks have degrees of similar "order of magnitude"; therefore we can state that the scale of a random network is the general degree $\langle k \rangle$. As opposed to this in a scale-free network, where the degree distribution follows a power function with $\gamma < 3$ degree exponent, the first momentum $\langle k \rangle$ is limited, but all other superior momentums are infinite (approaching infinity if $N$ is high). In randomly selected vertices, we cannot really estimate the degree (it can be very low or extremely high); there is no applicable internal size scale, which characteristic is called scale freeness *(Barabási et al. [2016])*.

### 4.1.3. Hierarchical networks

The so-called modularity is typical of most real, complex networks. The networks are built from connected parts, and the contained nodes have similar functions in the network in some respect, or the achievement of the same goal governs them. The vast majority of real networks are scale-free and are kept together by some central hubs, which have many edges in the network with other modules' vertices. This contradicts the isolated, modular structure of the network. Networks can be modular and scale-free at the same time *(Barabási [2013])*.

*Figure 28:*

Graph, degree distribution of hierarchical network and the logarithm of clustering coefficient subject to the logarithm of the degree




*Source: Barabási–Oltvai [2004] p. 105.*

Let us see an example of a network which is scale-free and modular at the same time. This network is structured that we first start from node 1 (from the centre of the graph on the left in Figure 28), then we take three points, which we link with each other and with the initial node (light blue dots in the middle). Then we copy the graph (module) containing 4 vertices three times and link the nodes on the edge of every new module with the component of the old module to have a network containing 16 nodes (turquoise network containing four modules). In the next step, we repeat the previous steps to have a graph containing 64 vertices.

The network built as described above contains modules resulting from the logic of the structure, and it is scale-free with some large hubs keeping the structure together. We can use the clustering coefficient to identify the hierarchical structure, as the clustering coefficient decreases inversely proportionally to the growth of $k$ (graph on the right side of Figure 28) *(Dorogovtsev et al. [2002])*.

To put it simply, an increase in the degree will be coupled with a decrease in clustering, i.e. the more connections a node has got (the more significant the central player in question is), the more it is its role to connect those who otherwise would not come into contact with each other.

In the examples illustrating the presented hierarchical modularity, the clustering coefficient depends on the $k$ degree precisely as follows:

$$C_k \sim k^{-1} \tag{27}$$

which is a straight with slope (-1) in a log-log graph (graph on the right in Figure 28) *(Barabási–Oltvai [2004])*.

The dependence of the clustering coefficient on the degree is a fundamental difference from the previously presented random and simple scale-free (Barabási-Albert) models, where the clustering coefficient was independent of $k$. The outstanding role of the nodes in hierarchical networks is to establish connection between the modules. This hierarchical modularity allows the simultaneous operation of several separate functions within one network, such as intermediation.

## 4.2. The core-periphery structure

In this section, first, a special case of hierarchical networks, namely discrete and continuous core-periphery models, which are often used in financial markets, are presented. In connection with this latter model, a new weighted version of calculated coreness measures is presented. I will use the results of our joint research performed together with Edina Berlinger and Barbara Dömötör in this Section so that I will switch to first-person plural in the wording.

The idea of a core-periphery structure first emerged in John Friedmann's 1966 book on regional development policy *(Friedmann [1966])*. Friedmann examined an economic area, which in terms of development was divided into two groups: a developed, urban centre and underdeveloped, rural areas called peripheries. The central region (core) is dynamically developing, innovative, and has significant growth potential. The growth of the backward peripheral areas lags significantly behind its centre, and its development largely depends on the demand for raw materials in the central region. Due to their high dependence, peripheral areas are attached to the core by many strands but operate completely separately from each other.

The subject of our study, i.e. the Hungarian unsecured interbank HUF deposit market, can be viewed as a financial network where nodes and links correspond to market players and lending transactions between them, respectively. *Fukker [2017]* supported the statement by empirical analyses that such a network (like most real networks) is scale-free. Similar results have been obtained for the Austrian and Czech interbank markets by *Boss et al. [2004]* and *Hausenblas–Kubicová–Lešanovská [2015]*, respectively.

*Berlinger et al. [2017]* established that, in addition to a scale-free nature, a hierarchical structure can also be observed in the market and that such structure was steadily present in the Hungarian unsecured interbank deposit market both before and after the crisis, a fact enabling the application of the core-periphery model.

### 4.2.1. Evolution of core-periphery models

The core-periphery structure consists of two distinct groups of nodes (in this case, banks). The first group is the core, which forms a complete graph; that is, any two vertices are connected by an edge. The other group, the periphery, is a set of isolated nodes not connected at all *(Borgatti–Everett [2000])*.

That is, in the case of a core-periphery structure, the part of the adjacency matrix ($\boldsymbol{A}$) containing the connections between the core actors is a block of pure 1 (except for the main diagonal, of course), and the part containing the connections of the periphery is a 0-block. Borgatti and Everett, who were among the first to apply the model, made no further requirements for the relationship between the core and the periphery.

A general adjacency matrix of a core-periphery structure is of the form

$$\boldsymbol{A} = \begin{pmatrix} CC & CP \\ PC & PP \end{pmatrix} = \begin{pmatrix} \mathbf{1} & \boldsymbol{CP} \\ \boldsymbol{PC} & \mathbf{0} \end{pmatrix} \tag{28}$$

*Craig–von Peter [2014]* also formulated requirements for the part describing the core-periphery ($\boldsymbol{CP}$) and periphery-core ($\boldsymbol{PC}$) relationship of the adjacency matrix to avoid a fragmented structure. Each peripheral player must be associated with at least one core node, i.e., there must be at least one connection (value 1) in each row of the $\boldsymbol{CP}$ submatrix of the adjacency matrix $\boldsymbol{A}$ in formula 28. Similarly, at least one value of 1 is required in each column of the $\boldsymbol{PC}$ block.

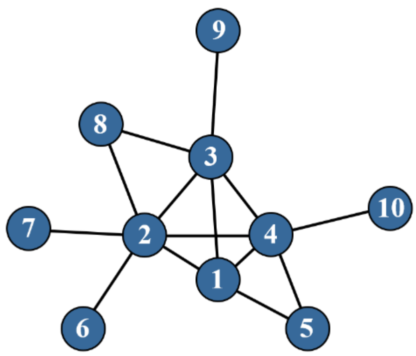
#### *4.2.1.1. Discrete core-periphery model*

Consider a schematic interbank market with 10 market participants (with numbers 1-10). Let us first consider the undirected case, where only the existence of a link between two nodes matters, not its direction. Suppose that the following adjacency matrix can describe the given market:

*Figure 29:*

An example of a core-periphery structure where the two groups of actors are clearly separated

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 4 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| 5 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |



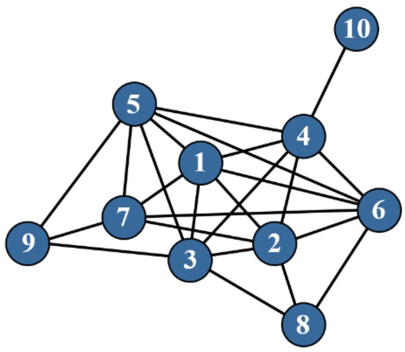

*Source: Borgatti–Everett [2000] p. 377.*

In an interbank market that can be described by the adjacency matrix shown in Figure 29, it can be clearly determined that banks marked with the numbers 1-4 form the core and banks marked with the numbers 5-10 form the periphery. In reality, the situation is not so clear, of course, so let us take, for instance, the example shown in Figure 30.

*Figure 30:*

An example of a structure where the core and periphery are not clearly separated

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 2 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 |
| 4 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |
| 5 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 6 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| 7 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| 8 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |




*Source: own edition.*

Based on the adjacency matrix of Figure 30, it is no longer possible to separate the actors of the core and the periphery as easily as in the previous example. It appears that based on previous definitions, banks 1-4 are still core, and banks 8-10 are clearly peripheral players. How could it be decided for institutions 5-7 to which group we should classify them?

*Lip [2011]* proposed a simple algorithm for separating core and peripheral actors. One of the essential characteristics of core banks is that they have many relationships, i.e. in their case, the degree is high. The higher the degree of a node, the more likely it belongs to the core. So, as a first step, let us calculate the degrees of each node and then arrange them in descending order of degrees. The degree of the node $i$ ($k_i$) is the sum of the elements in the corresponding row of the adjacency matrix (or in the corresponding column in the case of an undirected network).

$$k_i = \sum_{j=1}^{N} A_{ij} \tag{29}$$

We introduce an “error number” variable ($Z_i$) that shows the number of error points when – in descending order of degree – the node $i$[51] is included in the core. Here we consider any deviation from the ideal core-periphery structure as an error (formula 28). That is, 1 error point is the absence of a connection between two core actors, or likewise, 1 error point is the existence of a link between two peripheral nodes.

The next step is to determine the total number of connections in the network. This is half of the total number of degrees for all nodes $\sum_i k_i$ (since each connection was counted twice). If we do not include any actor in the core but classify everyone as peripheral, we make an error corresponding to the number of all connections in the network, i.e.

$$Z_0 = \frac{\sum_i k_i}{2} \tag{30}$$

By including the node of the highest degree in the core, the number of errors decreases with the degree of this node, i.e.

$$Z_1 = Z_0 - k_1 \tag{31}$$

Continuing the argument, the error score for the node $i$ is given by the following formula:

$$Z_i = Z_{i-1} + (i - 1) - k_i \tag{32}$$

Include the nodes in the core until the error number $Z_i$ is minimal (the last bank included has the smallest error number). In the example of Figure 30, this means that in addition to the nodes 1-4, which clearly belong to the core, it is also worth including 5 and 6 (rows with a light blue background in Table 8), because this is the least violation of the core-periphery model definition (everyone in the core is connected to everyone, but there are no intra-group connections in the periphery).

[51] It is important to emphasise that *i* does not (necessarily) coincide with the serial number of the node but denotes the number of vertices already included in the core (determined by the position of the given node in the order of degrees).

*Table 8:*

Separation of core and peripheral actors by *Lip [2011]* algorithm (banks included in the core have a light blue background)

| $i$ | Code of the bank | $k_i$ | $Z_i$ |
|---|---|---|---|
| 0 | | | **24** |
| 1 | **1** | 6 | **18** |
| 2 | **2** | 6 | **13** |
| 3 | **3** | 6 | **9** |
| 4 | **4** | 6 | **6** |
| 5 | **5** | 6 | **4** |
| 6 | **6** | 6 | **3** |
| 7 | **7** | 5 | **4** |
| 8 | **8** | 3 | **8** |
| 9 | **9** | 3 | **13** |
| 10 | **10** | 1 | **21** |

*Source: own edition.*

The 3 error points in the optimum can be easily identified in Figure 30. The connections 5-2 and 6-3 are missing between the banks eventually included in the core, and the 9-7 link in the periphery is the third error point.

#### *4.2.1.2. Continuous symmetric core-periphery model*

The next step in the evolution of core-periphery models is to move from the previously described discrete core-periphery model to a continuous one, where coreness is no longer measured by a binary variable 0 or 1 but by a so-called coreness measure that can assume any real number between 0 and 1. The higher the value of this coreness measure, the more the given node is assigned to the core. We can determine freely the cutoff value above which the nodes are put into the core. Thus, in a continuous core-periphery model, the issue of coreness is not black and white, but different shades of grey also appear. And the analyst can decide the critical value of the coreness measure for separating the actors of the core and the periphery.

*Boyd et al. [2010]* propose the MINRES method described by *Comrey [1962]* and *Harman [1967]* for the transition to a continuous model. This method searches a column vector $\boldsymbol{w}$ such that the so-called structure matrix $\boldsymbol{w}\boldsymbol{w}^{\boldsymbol{T}}$ best fits the given $N{\times}N$ square matrix $\boldsymbol{A}$. The algorithm finds the optimal vector $\boldsymbol{w}$ by minimising the sum of squares of the non-diagonal deviation according to formula 33.

$$SS(\boldsymbol{A} - \boldsymbol{w}\boldsymbol{w}^{\boldsymbol{T}}) = \sum_{i} \sum_{j \neq i} \left(A_{ij} - w_i w_j\right)^2 \tag{33}$$

Where $SS$ is the sum of squares, $\boldsymbol{A}$ is the $N \times N$ adjacency matrix, $\boldsymbol{w}$ is the $N$-element column vector containing the coreness measures, and $\boldsymbol{w}^{\boldsymbol{T}}$ is its transpose.[52]

In the optimisation, we first take an $N$-element vector $\boldsymbol{w}$ with arbitrary initial values between 0 and 1 and form the structure matrix as the dyadic product of $\boldsymbol{w}$ by itself. The sum of squares of the deviations of the elements of this structure matrix and matrix $\boldsymbol{A}$ gives an error term, which we can minimise by modifying the elements of $\boldsymbol{w}$. A necessary restriction is that the elements of the $\boldsymbol{w}$ can only fall between 0 and 1.

In the case of an undirected network, the components of the optimal vector $\boldsymbol{w}$ will be the coreness measures for the banks. These numbers on a continuous scale from 0 to 1 represent the subtle differences serving as the basis for classifying the banks into the core and the periphery. If the coreness is close to 1, then the bank should rather be labelled as core, whereas a bank with a coreness measure close to 0 should probably be put into the periphery.

Running the MINRES algorithm for the adjacency matrix of Figure 30, the values $w_i$ in the second column of Table 9 give the coreness measures of the banks. In the table, the double line separates the core and the periphery obtained in the discrete case by the Lip algorithm: the banks 1-6 above this line (marked in light blue) belonged to the core, and the ones 7-10 below it belonged to the periphery. In the continuous case, the coreness measures provide a much subtler distinction between the actors. A cutoff value between 0.76 and 0.86 would give the same core-periphery structure as in the discrete case.

[52] So, $\boldsymbol{w}\boldsymbol{w}^{\boldsymbol{T}}$ is the dyadic product of an $N$-element column vector by an $N$-element row vector.

*Table 9:*

The coreness measures of banks in an undirected network

| Code of the bank | $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 0.93 |
| **3** | 0.86 |
| **4** | 0.90 |
| **5** | 0.92 |
| **6** | 0.95 |
| **7** | 0.76 |
| **8** | 0.46 |
| **9** | 0.43 |
| **10** | 0.15 |

*Source: own edition.*

### 4.2.2. Properties to be fulfilled by a core-periphery measure

Now the continuous symmetric core-periphery model (described above in detail) will be examined more in-depth. For that purpose, first, four properties are defined that a properly functioning coreness measure must fulfil. These requirements are formulated everywhere at the level of economic intuition, starting from the original definition of a core-periphery structure. A core-periphery measure must fulfil the following properties:

*(1) Proper handling of pure cases.* Players that are clearly core ones must be given a coreness measure value of 1 and purely peripheral nodes a value of 0. A star structure, for example, is a simple core-periphery network where the central node alone forms the core and, therefore, a properly functioning coreness measure must assign a value of 1 to this actor, while assigning 0 to peripheral players that are at the ends of the “spokes”, being in contact exclusively with the concentrator.

Approaching it from the previously presented discrete core-periphery model, the same requirement can also be formulated by stating that, if in a core-periphery classification, Lip's algorithm gives 0 error points (this is a pure core-periphery structure, by definition), then any players classified as core ones must be given a value of 1 and any peripheral ones a value of 0. An essential cornerstone of a transition from a discrete case to a continuous one is to fix the endpoints of the value set of the continuous measure in this way.

*(2) Lip-monotony*. The result of the optimisation gives the same order as Lip's discrete case does, in the sense that the coreness measure of a player classified as core by the discrete algorithm cannot, as a result of the continuous optimisation, become lower than that of a vertex classified as peripheral; and the coreness measure of none of the nodes classified as peripheral can be higher than that of a core player. This condition, like the first, facilitates the transition from a discrete model to a continuous one. An appropriate coreness measure is expected not to be in clear incoherence with a discrete core-periphery classification.

*(3) Invariance to addition/removal.* The removal of a new node from, or the addition and connecting a new vertex to, the network should not significantly change the coreness measure of such players that the newly added node does not come into contact with, nor of such participants that have not previously been connected to the vertex removed from the network.

*(4) Robustness.* A lesser amount of "noise" placed on an adjacency matrix should modify the coreness of each player relative to each other as little as possible. In other words, the removal or addition of some connections (edges) in an existing network should, as little as possible, change the ranking of players in the network according to their coreness measures. This is especially important from a practical point of view, as one of the important uses of coreness measures is the identification of the so-called SIFIs (Systemically Important Financial Institutions). In order for a network measure to be able to perform this function effectively, it should be sufficiently stable, and the disappearance or appearance of an interbank connection should not significantly affect the ranking of banks.

#### 4.2.3. Deficiencies of the continuous symmetric core-periphery model

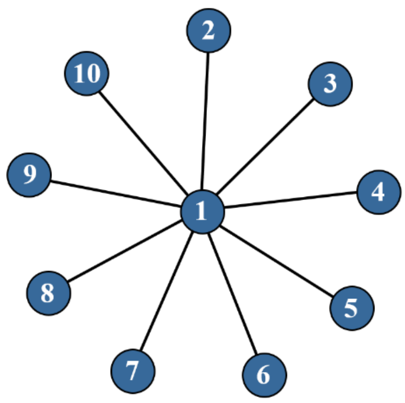
The continuous symmetric core-periphery procedure presented in subsection 4.2.1.2 cannot reliably give a satisfactory result in all cases. Next, some simple – and, by definition, perfect – core-peripheral networks will be presented and subjected to the optimisation process used in academic literature, where some elements of the coreness measure vector of $\boldsymbol{w}$ will not fulfil at least one of the four previously defined properties.

The star network can be understood as a special core-peripheral structure in which a single actor forms the core, and each peripheral vertex is associated with (and exclusively) this central node (Figure 31).

*Figure 31:*

A star network composed of a central (1) and nine (2-10) peripheral nodes

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |




*Source: own edition.*

As an illustration, we performed the optimisation known from the literature *(Boyd et al. [2010])* just presented for star networks of nodes between $N = 4$ and $N = 10$, and we can observe an interesting contradiction.

*Table 10:*

Coreness measures in star networks ($N = 4$ to $N = 10$)

| Code of the bank | $w_i$ ($N = 10$) | $w_i$ ($N = 9$) | $w_i$ ($N = 8$) | $w_i$ ($N = 7$) | $w_i$ ($N = 6$) | $w_i$ ($N = 5$) | $w_i$ ($N = 4$) |
|---|---|---|---|---|---|---|---|
| **1** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| **2** | 0.42 | 0.43 | 0.45 | 0.47 | 0.50 | 0.54 | 0.59 |
| **3** | 0.42 | 0.43 | 0.45 | 0.47 | 0.50 | 0.54 | 0.59 |
| **4** | 0.42 | 0.43 | 0.45 | 0.47 | 0.50 | 0.54 | 0.59 |
| **5** | 0.42 | 0.43 | 0.45 | 0.47 | 0.50 | 0.54 | |
| **6** | 0.42 | 0.43 | 0.45 | 0.47 | 0.50 | | |
| **7** | 0.42 | 0.43 | 0.45 | 0.47 | | | |
| **8** | 0.42 | 0.43 | 0.45 | | | | |
| **9** | 0.42 | 0.43 | | | | | |
| **10** | 0.42 | | | | | | |

*Source: own edition.*

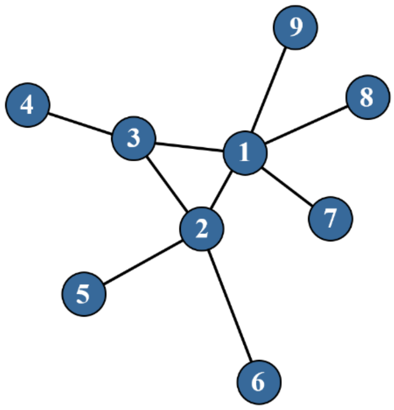
On the one hand, it is striking in Table 10 that all the (clearly peripheral) nodes associated with the central concentrator number 1 take coreness measure between 0.42 and 0.59 instead of the expected value of 0. On the other hand, as the number of nodes ($N$) increases, so does the coreness measure of the peripheral actors.

The star network was an extreme case of the core-periphery structure, so let us bring the studied network closer to the networks that occur in reality, and the next step is to look at a 9-vertex – still perfect core-periphery – structure with 3 actors forming the core and having one, two, and three peripheral nodes connected to them, respectively.

*Figure 32:*

A perfect core-periphery network

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 2 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |




*Source: own edition.*

Running the optimisation algorithm on the perfect core-periphery network of $N = 9$ nodes according to Figure 32, further anomalies can be observed.

*Table 11:*

Coreness measures of banks in a perfect core-periphery network

| Code of the bank | $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 1.00 |
| **3** | 0.89 |
| **4** | 0.27 |
| **5** | 0.31 |
| **6** | 0.31 |
| **7** | 0.31 |
| **8** | 0.31 |
| **9** | 0.31 |

*Source: own edition.*

The problem (violating criterion *(1)*) observed in the star network is that we obtained higher coreness indices for the clearly peripheral actors with sequence numbers 4-9 instead of the expected 0 value. As a new problem, we can observe that the procedure assigned a coreness measure of less than 1 to bank number 3 (to which only one peripheral player is connected).[53] This phenomenon can be further explained by the fact that although actor 3 is actively connected to the other nucleus actors, since only a single peripheral vertex is connected to it, it does not perform intermediation activity between peripheral actors. However, a clear contradiction is that the peripheral bank number 4 associated with it has a lower coreness measure than the other peripheral players, even though it plays exactly the same role in the network as, for example, bank number 5 or even number 9.

In this example, it appears that the lower the degree of coreness measure of a peripheral actor ceteris paribus, the lower the degree of the core actor it is connected to. This, in turn, contradicts the observation made in Table 10 for star networks, where the coreness measures of the peripheral actors increased with decreasing the degree of the core actor.

### 4.2.4. Improvement of the *Boyd et al. [2010]* method for continuous symmetric core-periphery networks

In order to find a solution to the anomalies mentioned above and to further develop the coreness measures in the currently used continuous core-periphery models, it is worth going down to the root of the problem, which is to be found in the calculation methodology of coreness measures.

To illustrate the problem, we refer back to the resolution of the stylised adjacency matrix by *Craig–von Peter [2014]*. From the point of view of the core-periphery structure, the core-core ($\boldsymbol{CC}$) and peripheral-periphery ($\boldsymbol{PP}$) part of the adjacency matrix are essential, i.e. the set of connections where two central or two peripheral actors come into contact with each other.

Lip's algorithm *(Lip [2011])*, previously presented for the discrete case, also penalised only in these two domains if there was no connection between two core banks or if there was a transaction between two peripheral banks. The algorithm did not (very correctly) deal with the part of the adjacency matrix describing the core-peripheral ($\boldsymbol{CP}$) and peripheral-core ($\boldsymbol{PC}$) relationship.

[53] At 0 error point (i.e. at a core-periphery structure that is perfect by definition), Lip's discrete algorithm classifies banks with serial numbers 1-3 to the core (blue cells in Table 11).

Moving from a discrete model to the use of continuous coreness measures, the squared sums of the optimisations under formula 33, in turn, include and "punish" the relationships between the core and the periphery as well. Consider, for example, a case where a strongly core entity with a coreness measure of 0.9 comes into contact with a clearly peripheral actor with a coreness measure of 0.1. Then, in the dyadic product, the square of the differences of the value 0.9 × 0.1 = 0.09 from the corresponding value 1 of the adjacency matrix will be 0.8821, which significantly alter the sum of the squares of differences to be minimised, although according to the definition of the core-periphery structure, this relationship does not matter.

To address this problem, it seems obvious that we should somehow omit core-peripheral ($\boldsymbol{CP}$) and peripheral-core ($\boldsymbol{PC}$) connections during optimisation. This is not feasible because before performing the optimisation (a priori), we do not know the coreness index of any of the actors, so we cannot separate the $\boldsymbol{CP}$ and $\boldsymbol{PC}$ parts of the adjacency matrix.

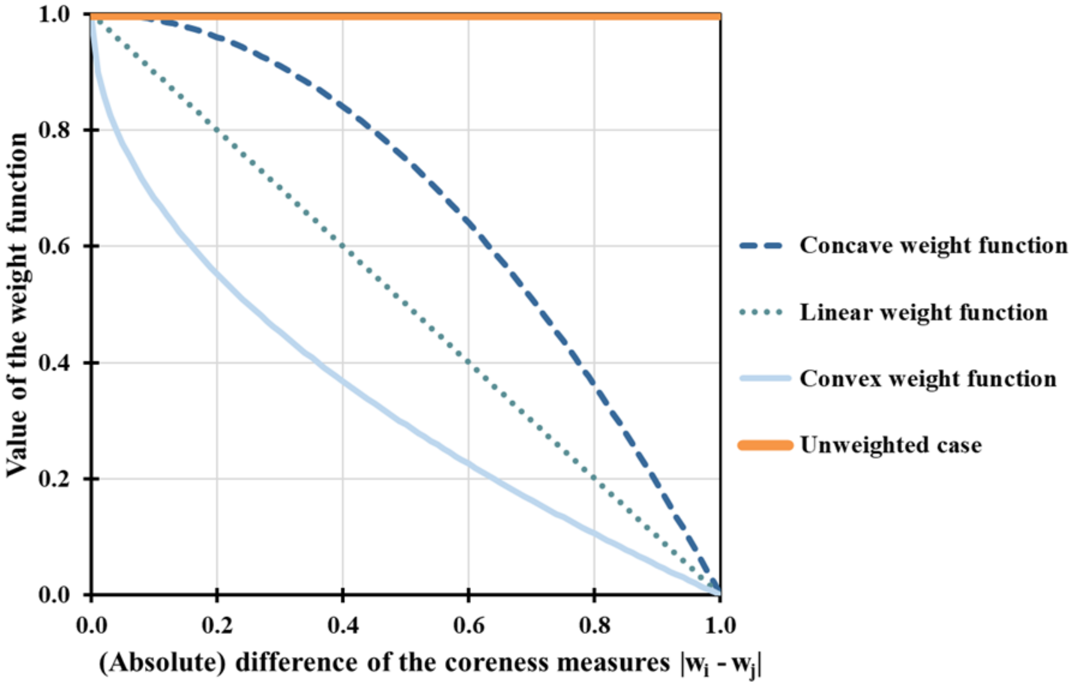
As a solution, we recommend determining $M_{ij}$ modifiers (or weight functions) between the actors $i$ and $j$ of the network which give great weight to the transactions of similar actors (core-core or peripheral-periphery), while the transactions between highly different (core and peripheral) actors are given low weights within the sum of the squares of differences.

$$\sum_{i}\sum_{j\neq i} M_{ij}\left(A_{ij} - w_i w_j\right)^2 \tag{34}$$

Formula 34 thus differs in the modification factor $M_{ij}$ from formula 33 widespread in the literature *(Boyd et al. [2010])*. The anomalies of the widely *(Langfield–Liu–Ota [2014], Fricke–Lux [2015], León–Machado–Sarmiento [2018])* used coreness model just described can be handled by introducing a modification factor $M_{ij}$ which gives more weight to the relationship $A_{ij}$ when two core players (both $w_i$ and $w_j$ are large, close to 1) or two peripheral actors (both $w_i$ and $w_j$ are low, close to 0) meet. This can be technically solved if $M_{ij}$ is a monotonically decreasing function representing the distance in the coreness measures of $w_i$ and $w_j$.

*Figure 33:*

Examples of potential weight functions




*Source: own edition.*

Figure 33 shows potential modification (weight) functions. A solid orange line indicates the unweighted case described by *Boyd et al. [2010]* (each square of a difference is given a weight of 1). With a solid light blue line, we denote a convex weight function of type[54] $1-\sqrt{x}$, which significantly punishes also a small difference in the coreness measures $|w_i - w_j|$. A dotted turquoise line shows the linear weight function, where the value of the modification factor decreases in direct proportion to the increase in the absolute difference in the coreness measures. The dashed dark blue curve is a concave weight function of type $1-x^2$, which takes into account the relationships only between relatively similar ones (core-core or peripheral-periphery) according to the coreness measures with a high weight close to 1, and increasing differences are increasingly penalised.

The latter concave weight function is best able to fulfil the function that relatively similar (core-core or peripheral-periphery) connections are given high weight, and the more significant the difference in the coreness measure of two nodes, the less the algorithm

[54] Where *x* stands for the absolute difference of the coreness measures.

will take their relationship into account in optimisation. (i.e., underweight the core-peripheral ($\boldsymbol{CP}$) and peripheral-core ($\boldsymbol{PC}$) connections).

Another argument in favour of using the concave weight function $1 - |w_i - w_j|^2$ is that it takes into account the distance of the coreness measures squared, as is customary when applying statistical methods[55] and, in addition, the original core-periphery measure in formula 33 also includes a squared deviation. Hereinafter, we will also use this, and we will understand the use of this concave weight function in the weighted case.

*Table 12:*

Coreness measures in star networks ($N = 4$ to $N = 10$) with the weighted formula

| Code of the bank | $w_i$ ($N$ = 10) | $w_i$ ($N$ = 9) | $w_i$ ($N$ = 8) | $w_i$ ($N$ = 7) | $w_i$ ($N$ = 6) | $w_i$ ($N$ = 5) | $w_i$ ($N$ = 4) |
|---|---|---|---|---|---|---|---|
| **1** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| **2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **4** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **5** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| **6** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | |
| **7** | 0.00 | 0.00 | 0.00 | 0.00 | | | |
| **8** | 0.00 | 0.00 | 0.00 | | | | |
| **9** | 0.00 | 0.00 | | | | | |
| **10** | 0.00 | | | | | | |

*Source: own edition.*

The new kind of weighted coreness measure we have introduced already gives intuitive results that satisfy criterion *(1)* for various star networks with $N$ vertices. The perfect peripheral actors are given coreness values of 0 according to Table 12, and the modified sum of squares of differences assumes a value of 0 as a result of optimisation, i.e. the structure matrix can fit the adjacency matrix perfectly with the help of the weighted formula. The fact that the new, modified measure gives a value of 0 for the sum of squares of differences for a perfect core-periphery structure shows that there is an appropriate transition from Lip's discrete model denoting the pure classification case with $Z_i = 0$ error point.

[55] Here, we may think of standard deviation, as one of the most commonly used risk measures; or linear regression, where the ordinary least squares method is used when estimating regression parameters to minimise the residual sum of squares expressing the fitness of the model *(Hunyadi–Vita [2008b])*.

In the following, let us examine the perfect core-periphery network of $N = 9$ nodes as shown in Figure 32, in which case the original, unweighted formula provided contradictory results.

*Table 13:*

Coreness measures of banks in a perfect core-periphery network with unweighted and weighted formulae

| Code of the bank | Unweighted $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 1.00 |
| **3** | 0.89 |
| **4** | 0.27 |
| **5** | 0.31 |
| **6** | 0.31 |
| **7** | 0.31 |
| **8** | 0.31 |
| **9** | 0.31 |

| Code of the bank | Weighted $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 1.00 |
| **3** | 1.00 |
| **4** | 0.00 |
| **5** | 0.00 |
| **6** | 0.00 |
| **7** | 0.00 |
| **8** | 0.00 |
| **9** | 0.00 |

*Source: own edition.*

The previously presented deficiencies of the original, unweighted model were remedied by the new, modified coreness measure; clearly core actors were given a coreness index of 1, and the pure peripheral nodes were assigned a coreness measure of 0.

Moving another step closer to real interbank networks, running on the imperfect core-peripheral network of $N = 10$ nodes in Figure 30, the modified (weighted) version of the currently used coreness measures gives the coreness values $w_i$ in Table 14. The double line still isolates the core (blue background colour) from the peripheral actors (white background) separated by the Lip discrete algorithm.

The optimisation modified by the weight function we described gave the 8-10, clearly peripheral actors a 0 coreness measure, as opposed to the values of the unweighted coreness measures scattering between 0.15 and 0.46 in Boyd’s original model. In accordance with Lip's discrete algorithm, we obtained a coreness measure of 1 for the nodes 1-6 to be included in the core.

*Table 14:*

Coreness measures of banks with unweighted and weighted formulae

| Code of the bank | Unweighted $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 0.93 |
| **3** | 0.86 |
| **4** | 0.90 |
| **5** | 0.92 |
| **6** | 0.95 |
| **7** | 0.76 |
| **8** | 0.46 |
| **9** | 0.43 |
| **10** | 0.15 |

| Code of the bank | Weighted $w_i$ |
|---|---|
| **1** | 1.00 |
| **2** | 1.00 |
| **3** | 1.00 |
| **4** | 1.00 |
| **5** | 1.00 |
| **6** | 1.00 |
| **7** | 0.73 |
| **8** | 0.00 |
| **9** | 0.00 |
| **10** | 0.00 |

*Source: own edition.*

In summary, based on the examples presented, it appears that the new weighted algorithm presented is able to more sharply separate core actors from the periphery. In accordance with criterion *(1)*, clearly core actors get a value of 1, and pure peripheral nodes get a coreness value of 0. We only get a value between 0 and 1 where actors can really be considered "transitional" (such as the case of bank number 7 in Table 14).

### 4.2.5. Robustness check of the new, modified coreness measure

Based on criterion *(4)* as defined above, we will now examine the robustness of the unweighted coreness measure described by *Boyd et al. [2010]* and the new coreness measure we have introduced. We will do this by adding a certain amount of noise to the adjacency matrix and examining how much the weighted methodology changes the coreness measure of each node relative to the original (unweighted) case. We consider it to be a more robust coreness measure, in which case a small amount of noise changes the order of the network actors ranked according to the coreness measure less.

According to the Basel principles laid down in 2013 *(BCBS [2013b])*, the Financial Stability Board designates Global Systemically Important Banks (G-SIBs) on an annual basis. The designation process is based on a multi-dimensional scoring system[56] and, at the end of that process, the 30 credit institutions having the highest scores are classified

[56] The G-SIB scoring system and its impacts on the behaviour of Global Systemically Important Banks are covered in detail in Sub-chapter 7.2.

into the G-SIB category. Due to the designation logic ($n$ banks with the highest score are selected by the Financial Stability Board), it is essential for the indicators determining the central players in an interbank market (such as the coreness measure) that random noise should influence the ranking of players as little as possible. This is why the criterion of robustness is defined based on the variability of sequence.

The change in order can be quantified by Spearman's rank correlation coefficient ($\rho$), which tells the strongness and direction of the linear relationship between two variables measured on an ordinal scale (rankings according to the coreness measures) on a range from -1 to +1, as follows *(Hunyadi–Vita [2008a])*:

$$\rho = 1 - \frac{6\sum(R - R^*)^2}{N(N^2 - 1)} \tag{35}$$

where $R$ denotes the rankings according to the coreness measures obtained as a result of the original optimisation, and $R^*$ denotes the rankings according to the optimisation obtained with the “noisy” relationship matrix, and $N$ denotes the number of actors in the network.

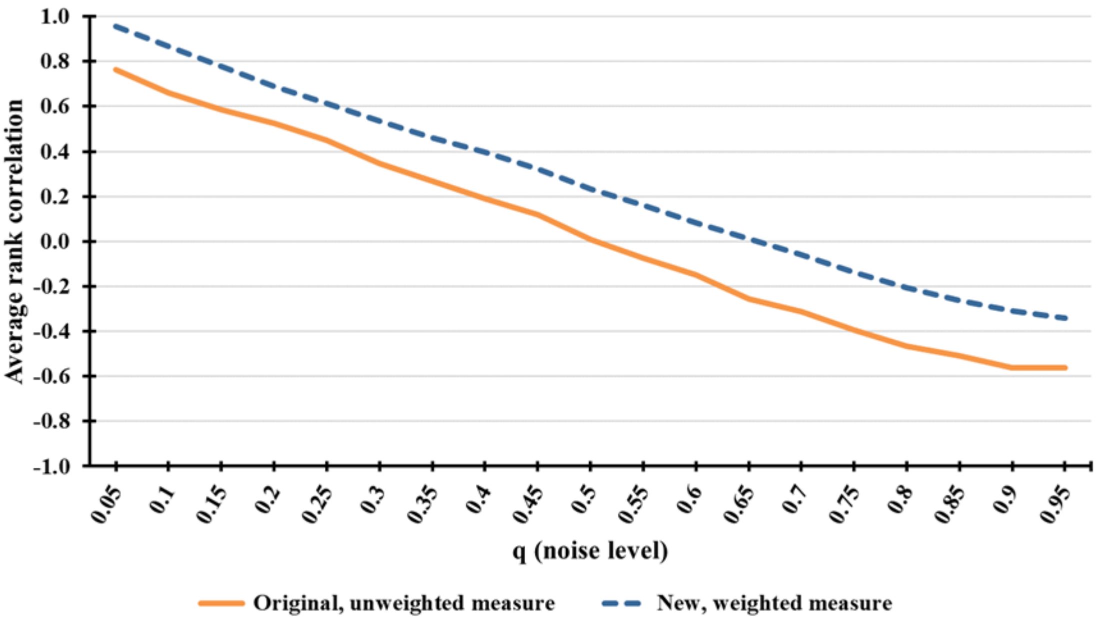
In the case of the examined problem, it frequently happens that the coreness measures of two banks are the same, and thus their places in the order are the same, too. These are called fractional ranks, and we assign a simple arithmetic average of the ranks to each node that they would receive in the ranking without matching on their position.

In terms of robustness testing, it is also essential to clarify precisely the “noise” mentioned earlier. We apply the following algorithm: each element of the adjacency matrix (in an independent manner) is changed with a certain probability $q$. Where there was previously a connection between two actors, there is a probability that this connection will disappear, and where there was no edge between two vertices, it will be there. This probability $q$ is from now on referred to as the noise level.

We performed a simulation for the perfect core-periphery structure of Figure 32 and looked at the rank correlations between the $\boldsymbol{w}$ coreness measures vectors obtained during the simulation for 1000-1000 modified (“noisy”) relationship matrices at different noise levels between 0 and 1. Finally, we took the arithmetic mean of the 1000 rank correlation coefficients and repeated it for different noise levels.

*Figure 34:*

Average rank correlations as a function of noise level for a perfect core-periphery structure




*Source: own edition.*

Figure 34 shows that the new type of weighted coreness measure is more robust, with the average rank correlation between coreness measures calculated for the initial and the noisy adjacency matrices being higher at all $q$ noise levels. The values of the figure are especially interesting at the lower noise levels because if we modify the original relationships a little, we expect robust coreness measures to change their order as little as possible.

Using a hypothesis test concerning the difference between two population means, we will examine below the extent to which differences between average rank correlations obtained at different noise levels are considered significant. Thus, we can test the statement that the average rank correlation is significantly higher in the case of the new modified type of measure ($\mu_M$) than in the original unweighted case ($\mu_U$).[57] The null hypothesis states that the average rank correlation obtained with the original measure is at least as high as in the new case calculating with the modification factor.

[57] This will be the alternative hypothesis.

That is, formally:

$$\begin{aligned} &\mathrm{H}_0: \quad \mu_M - \mu_U \leq 0 \\ &\mathrm{H}_1: \quad \mu_M - \mu_U > 0 \end{aligned} \tag{36}$$

Assuming that the standard deviation of the two studied populations is finite, then in case the null hypothesis is valid, and there is a large sample,[58] then the following test statistic will be of standard normal distribution, with a good approximation:

$$\mathrm{z} = \frac{\bar{M} - \bar{U}}{\sqrt{\frac{s_M^2}{n_M} + \frac{s_U^2}{n_U}}} \tag{37}$$

where the difference of the arithmetic averages of rank correlations is found in the numerator, and $s^2$ denotes the variances of individual samples, and $n$ denotes the number of sample elements *(Hunyadi–Vita [2008b])*.

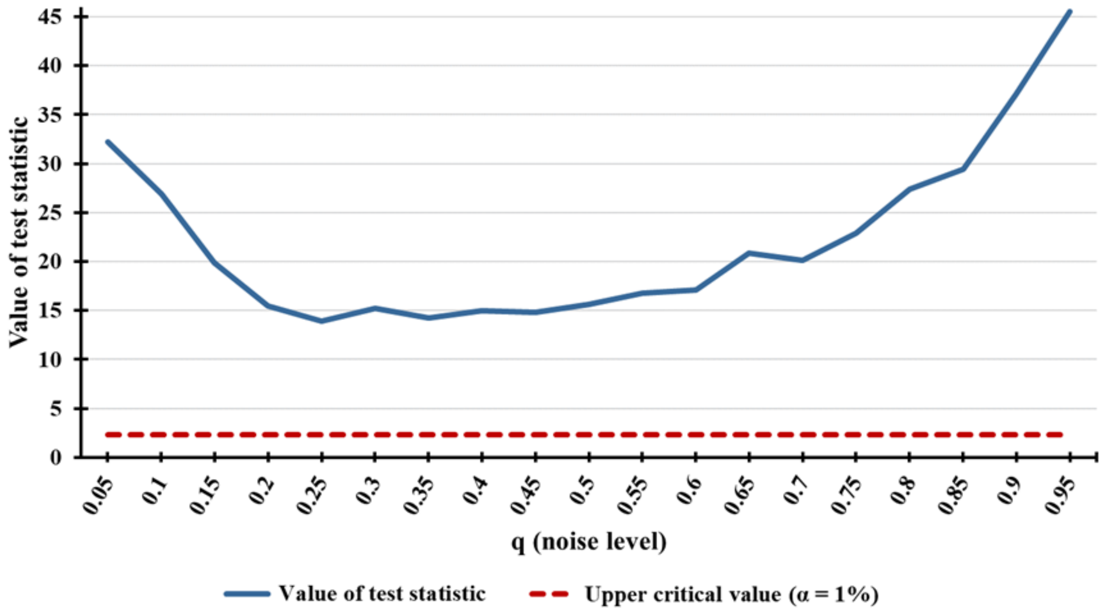
The (upper) critical value of the right-hand-side test, at a significance level of 1%, is 2.33, a value compared to which the value of the test statistic is much higher at any $q$ noise level (solid blue line in Figure 35). That is, based on the simulated 1000-element samples, the null hypothesis can be rejected at 99% confidence level,[59] i.e. the average rank correlation in the case of the new weighted measure is significantly higher than in the case of the original method found in the academic literature. That is, the modified coreness measure defined by us is more robust.

[58] The examined 1000-element simulation can be considered a large sample.

[59] p-values are extremely close to 0 everywhere, so the null hypothesis can be rejected not only at 1%, but at any commonly used significance level.

*Figure 35:*

Values of the test statistic of the hypothesis test for the differences of average rank correlations at different noise levels in the case of a perfect core-periphery structure



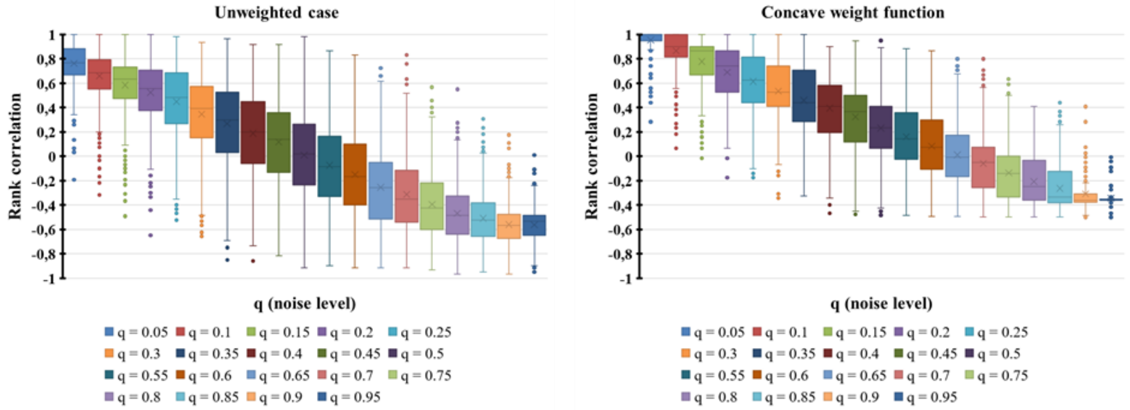

*Source: own edition.*

The mean replaces with a single value and masks the variance present in the 1000-1000 rank correlation distribution. On the other hand, robustness also means that the new weighted measure produces not only higher but also less dispersed correlations. The main features of the total distribution of the rank correlations at some $q$ noise levels can be visualized, for example, with the help of a box plot.

The bottom of the boxes is the first quartile of realised rank correlations ($Q_1$), the top is the third quartile ($Q_3$), and the dividing line within the box is the median. The protrusions (whiskers) below or above the box are up to one and a half times the height of the box. Values beyond this can be considered outlier values and are indicated by separate dots in the figure.

*Figure 36:*

Box and whiskers diagrams of rank correlations as a function of noise level for a perfect core-periphery structure




*Source: own edition.*

As shown in Figure 36, not only is the weighted measure better than the original unweighted in terms of average rank correlations, but the variance of each realised rank correlation is also smaller.[60] This can be deduced visually, for example, from the height of each box in pairs (this is the so-called interquartile range), which is smaller for all $q$ noise levels in the weighted case.

The robustness test just presented was also performed on the imperfect core-peripheral structure of $N = 10$ nodes according to Figure 30.

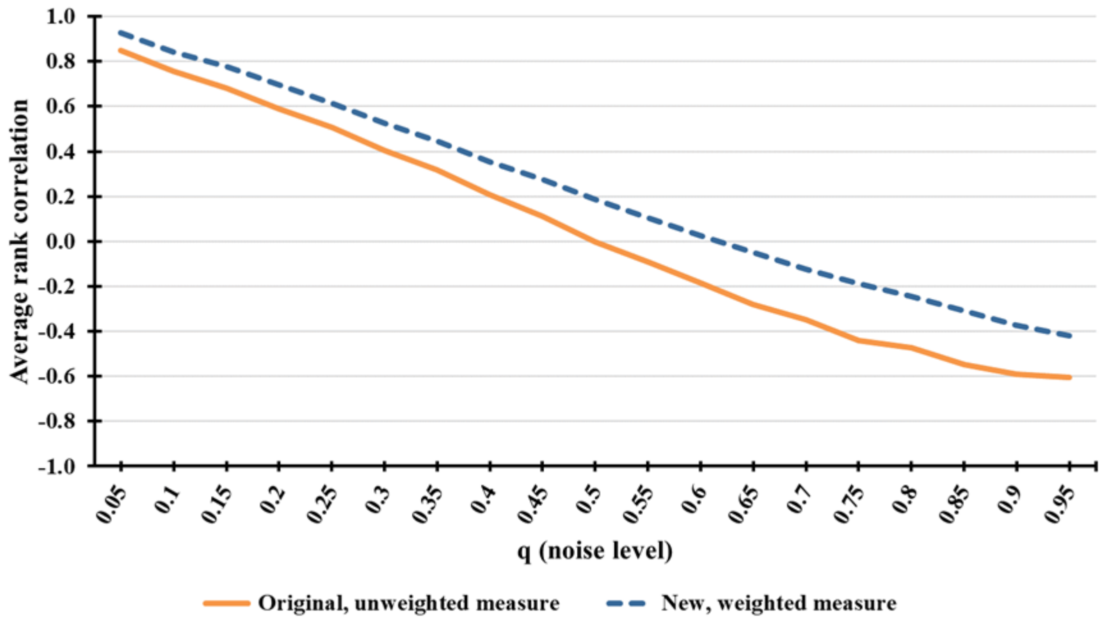
We obtained results similar to the previous ones, the new type, weighted coreness measure examining the average rank correlations being more robust at all $q$ noise levels.

A formal test concerning the difference between two population means in the case of this imperfect (but approximately perfect) core-periphery network shows similar results to previous ones.

[60] Unfortunately, differences in standard deviations cannot be verified by a formal test here, as the precondition to an F-test aimed at this is that the examined rank correlations in samples have a normal distribution and that the samples are independent of each other *(Hunyadi–Mundroczó–Vita [2001])*. The latter condition of independence is certainly not satisfied due to the logic of the simulation.

*Figure 37:*

Average rank correlations as a function of noise level for an imperfect core-periphery structure

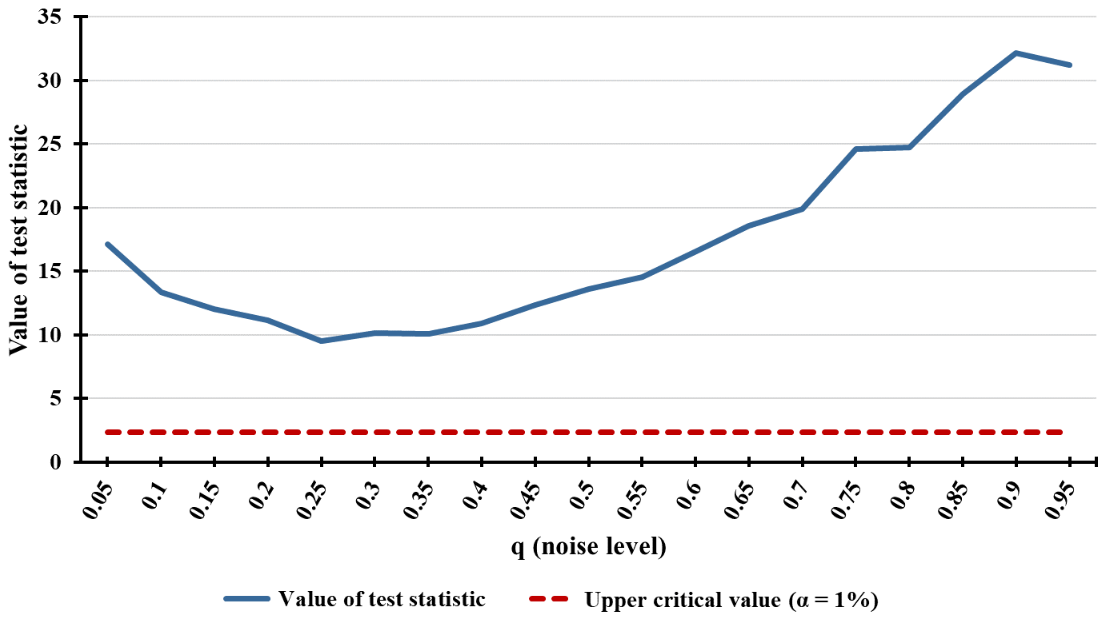



*Source: own edition.*

The critical value at a significance level of 1% is 2.33 (red dashed line in Figure 38), compared to which the value of the test statistic is higher at each noise level (solid blue line). Here again, the modified coreness measure proposed by us is more robust than the original unweighted one at all commonly used significance levels. In addition, as in the previous perfect core-periphery network, here also, not only average values but also variance is lower within the distribution of rank correlations obtained as a result of simulations.

*Figure 38:*

Values of the test statistic of the hypothesis test for the differences of average rank correlations at different noise levels in the case of a non-perfect core-periphery structure



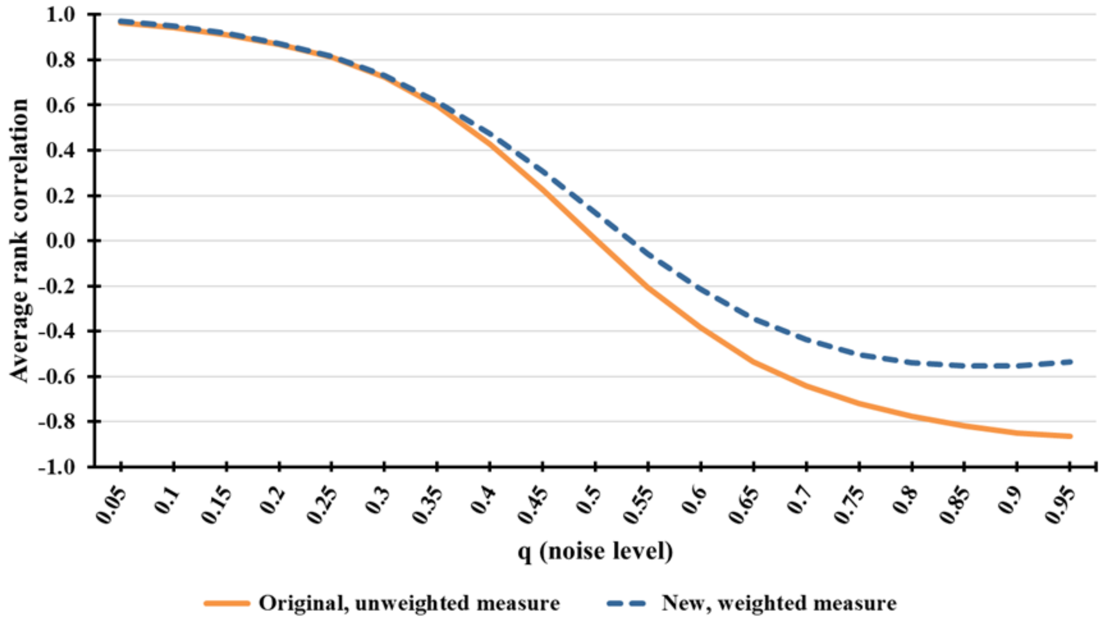

*Source: own edition.*

After using stylised networks, we also used real interbank transactions as presented in subsection 3.1 for making a comparison between original and weighted coreness measures.

The analysed undirected network includes unsecured interbank credit transactions concluded in March, April and May 2015. During this period, 36 active banks (participating in at least one transaction) were present in the market, and a total of 147 contacts were established between them. The time window is not randomly selected, as it coincides with the network to be analysed and compared with an interpersonal loan market in Chapter 6.

*Figure 39:*

Average rank correlations as a function of noise level for a real interbank network



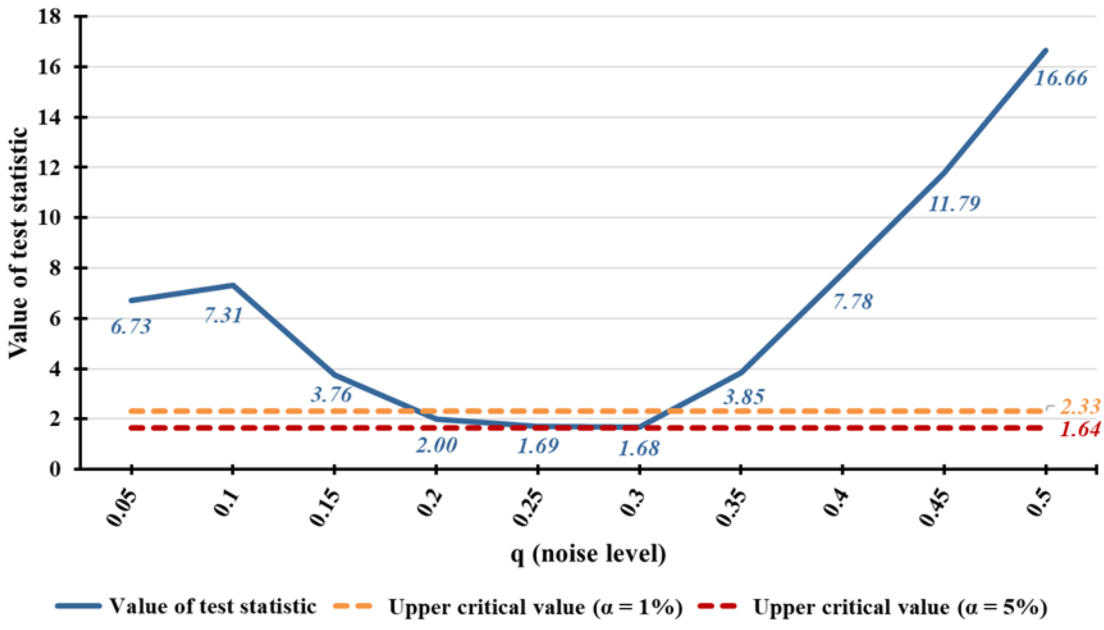

*Source: own edition.*

Although it is no longer visible to the naked eye on the real interbank network based on the 1000-element simulation (Figure 39), it is still true that average rank correlations in case of the new weighted coreness measure are higher at any $q$ noise levels than in the original case calculated without weighting, i.e. the modified metric we introduced is more robust even on a real network. In comparison with the results obtained for the previously presented perfect, or nearly perfect, stylised core-peripheral networks (Figures 34 and 37), it seems that the more different the network from the perfect core-peripheral structure and the more "errors" contained in it, the lower the difference in robustness of coreness measures calculated in the two ways. This phenomenon is especially noticeable at really significant, low noise levels.

In a similar way as in the previous stylised examples, we carried out a formal test concerning the difference between two population means for the real interbank network in order to examine whether the average rank correlations calculated from results obtained by using the new type of modified measure are higher than previously at the commonly applied confidence levels of 95% and 99%.

*Figure 40:*

Values of the test statistic of the hypothesis test for the differences of average rank correlations at different noise levels in the case of a real interbank network




*Source: own edition.*

At a significance level of 5% (dashed red line in Figure 40), the new weighted coreness measure we introduced produces higher average rank correlations than previously at all noise levels. Also, at a significance level of 1% (dashed orange line), it is true that, at the really important, low-level of noise, the new modified measure is more robust than the unmodified one, and only at noise levels of 0.2-0.3 was it observed that the value of the test statistic (solid blue line) was slightly lower than the upper critical value, 2.33, corresponding to $\alpha = 1\%$.

In summary, in addition to eliminating the anomalies of the original Boyd coreness measure described in section 4.2.3, the new type of weighted core-periphery measure presented by us appears to be significantly more robust than the unweighted measure for both the examined stylised core-peripheral structures and the real interbank network. The latter result is also of key importance because core-periphery indicators' main function is to identify systemically important banks, which requires the greatest possible stability of the ranking established by the measure. With this, hypothesis *H3*, as formulated in the introduction, is accepted.

At this point, however, it should be noted that, in the real (already noisy) network examined, although the new weighted indicator is significantly more robust in statistical terms, the deviation from Boyd's original coreness measure is much smaller than what was observed in case of pure or nearly pure core-periphery structures.

# 5. The profit of intermediation in the Hungarian unsecured interbank deposit market

The essence of the core-periphery model presented in the previous chapter is intermediation, where core banks provide a kind of intermediation service between peripheral participants who do not transact directly with each other. As these are for-profit institutions, business logic and also academic literature *(Matthews–Thompson [2005], Goyal–Vega-Redondo [2007], Babus–Hu [2017], Veld–Leij–Hommes [2020])* suggest that this service is provided by core banks for making profits.

In the following, the volume of this type of intermediation activity is examined based on empirical data; and an estimate is provided for the amount of profits to be achieved by providing intermediation services.

In this chapter, based on unsecured interbank transactions in the period of 2012-2015, I attempt to answer the following research question:

> *To what extent was the intermediation activity present in the domestic unsecured interbank deposit market between 2012 and 2015, and what was the magnitude of profit generated by intermediaries?*

My line of thought is started with the intermediation role played by the broader financial intermediation system in the economy, in which banks have faced a number of challenges in recent decades. Financial innovators have started to discuss a fundamental economic question, namely whether financial intermediaries are still needed in the 21st century. In the first section, I briefly present fintech solutions and companies that are considered to be the flagships of the sector.

Then, specifically relevant to interbank markets, I attempt to synthesise (and organise into a single common framework) such reasons that academic literature offers for explaining that the presence of intermediaries is essential, especially in the interbank market.

Finally, I review the academic literature on core-periphery networks, where authors are unanimous in their view that intermediation is strongly present in the interbank market and brings significant profits to central players doing it.

After discussing the academic literature, I analyse the Hungarian unsecured interbank overnight deposit market in terms of profits generated by intermediaries. First, using the detailed interbank transaction database described in Chapter 3, I analyse changes in the importance of intermediation activities (volume of intermediation) each year between 2012 and 2015.

Then I present that the amount of profits generated by intermediaries cannot be determined precisely even with the help of an exceptionally detailed database that includes all transactions; however, the maximum amount of profits of intermediaries can be calculated.

In this chapter, I examine, in line with the research question, the following hypotheses:

*H4:* *Intermediation activities in the Hungarian unsecured interbank deposit market are of significant volume.*

*H5:* *In the Hungarian unsecured interbank deposit market, the main motivation of intermediation activity is to make profits.*

In Chapter 6, the results obtained in this section will serve as an important starting point and chain of thought for comparing interpersonal and interbank markets.

## 5.1. Is there a need for traditional financial intermediaries at all?

One of the main functions of the financial intermediation system, which has developed over the last centuries and is constantly evolving, is to link savers and economic actors with a lack of liquidity. In parallel, securities-based financing has developed (especially in Anglo-Saxon countries) where participants with surplus funds and actors lacking funds can contact directly.

Attributable to a rapid technological development taking place at the end of the 20th century and in the 21st century, supply and demand can directly find each other at even lower transaction costs and in easier and more efficient ways through specific – primarily online – platforms, a trend leading to the emergence or strengthening of direct channels in several markets.[61]

Among the most significant innovations of the 21st century, blockchain technology should be highlighted. The technology enables information to be stored and managed in a completely decentralised and unalterable way. Although, from an IT point of view, blockchain technology has many other advantageous characteristics (such as automation

[61] Here we can also think of innovations further away from the financial markets, such as Airbnb or Uber.

and anonymity *(Kadocsa [2018])*), what is emphasised for the purposes of this thesis is that it is being decentralised, a feature which raised the idea that it may not be necessary to use a reliable central player, i.e. an intermediary, to carry out a transaction.

*Csóka–Herings [2018]* and *[2021]* have shown that bilateral settlements between banks can be as effective as central clearing.

The question of whether there is a need for traditional financial intermediaries at all in our increasingly digitising, modern world has been raised by many over the past decade and a half, including the founders of Revolut, TransferWise, Robinhood, LendingClub, or Zopa (former) startups.

Banks, as financial intermediaries, offer a whole range of investment and financial services to their clients. Banking is highly costly due to, among other things, multiple regulations and high operating expenses, which is reflected in the pricing of various services, so some (or all) of these costs are passed on to customers in order to operate profitably. Due to the high degree of regularisation of the banking sector, opening an account, requesting a bank card or even disabling a card is time-consuming and relatively complicated. Due to the costly operation of the banking business, it is expensive to open and maintain a foreign currency account; transaction costs are high and bid-ask spreads are wide in foreign exchange transactions.

In response to these problems, Revolut was founded in 2015 in the UK. Revolut is a prepaid card company that offers its cardholders the possibility to open foreign currency accounts, exchange currencies even at the interbank rate, and cheap and fast foreign currency transfers. Registration and application are fast and online; the card can be disabled at the touch of a button using a mobile application. The range of these services was expanded in 2017 with cryptocurrency transactions, in 2019 with trading in other securities (such as shares), and since 2020, the company's customers can manage all their bank accounts in one place through the app *(revolut.com [2021])*. The launch of these latest services was made possible by the fact that in 2018 Revolut obtained a European banking license through the Lithuanian Financial Supervision Authority, and then also received a license in Hungary for cross-border banking services related to deposit collection *(MNB [2020f])*.

TranferWise started with similar services as Revolut in 2011. It aims to enable the customers to exchange currency and transfer money quickly, significantly reducing transaction fees without other hidden costs *(transferwise.com [2021])*. TransferWise and Revolut are thus trying to gain customers and market from banks by bypassing the traditional financial intermediation system, and providing service within a less regulated framework, at a much lower operating cost. Of course, this was soon recognised by banking regulators as well, so, as we have seen in the case of Revolut, they are increasingly faced with the same set of rules as traditional banks. On the customer side, there is a clear need against the financial service providers to have a physical presence (office) in each country, which increases customer confidence in the service providers. So, it seems that as these fintech companies grow, they are increasingly beginning to resemble a traditional bank and face the same cost-increasing factors (e.g., regulatory expectations, physical branches) as their traditional competitors.

The last decade has brought similar developments in investment as in the area of other financial services. Robinhood was founded in 2013 in the United States with the goal of making investment portfolio construction, securities transactions easily accessible to everyone and without trading commissions. Through a mobile application, one can trade stocks, cryptocurrencies, ETFs or even options free of charge, with no minimum restrictions on the parameters of transactions *(robinhood.com [2021])*.

In the past, the hegemony of banks in lending seemed irresistible. The beginning of the 21st century brought a change in this aspect as well, and peer-to-peer lending appeared. To this end, online platforms have been set up, which can provide loans to borrowers at lower interest rates than banks and offer lenders a high-yield investment on the other hand.

The first such platform (and the market leader in Europe ever since) is Zopa, launched in the UK in 2004. In 2018, Zopa applied for a supervisory license to continue operating as a credit institution. Zopa finally received a full banking license in June 2020 and significantly expanded its range of services offered to the customers *(zopa.com [2021])*.

The best known and globally leading peer-to-peer platform is LendingClub, which was founded in 2006 in the United States. In 2020, LendingClub acquired a Boston-based financial institution, Radius Bank, with 3 million customers. The acquisition was completed in 2021, but as early as 31 December 2020, LendingClub permanently shut down its peer-to-peer lending platform and set itself the new goal of becoming the first public American neobank *(lendingclub.com [2021])*.

The above examples show that the role of financial intermediaries has been questioned in several areas in recent years. Many startups have started with the goal of offering a solution to a given problem cheaply and quickly in a narrow market segment, bypassing the traditional banking system and taking advantage of online operations. These examples show that as these companies developed and progressed in their life cycle, they faced the limitations and cost-increasing factors of the traditional banking sector. And at some point, they were forced to apply for banking licenses, and they were partially integrated into the traditional financial intermediation system.

Thus the answer to the question raised at the beginning of this sub-chapter is that banks are presumably needed. Having seen these examples, one’s intuition may be that the establishment and current operation of credit institutions represent an “equilibrium” point that has evolved as a result of a natural process, as companies starting from completely different positions and applying innovative approaches are heading – through different paths – towards the same state.

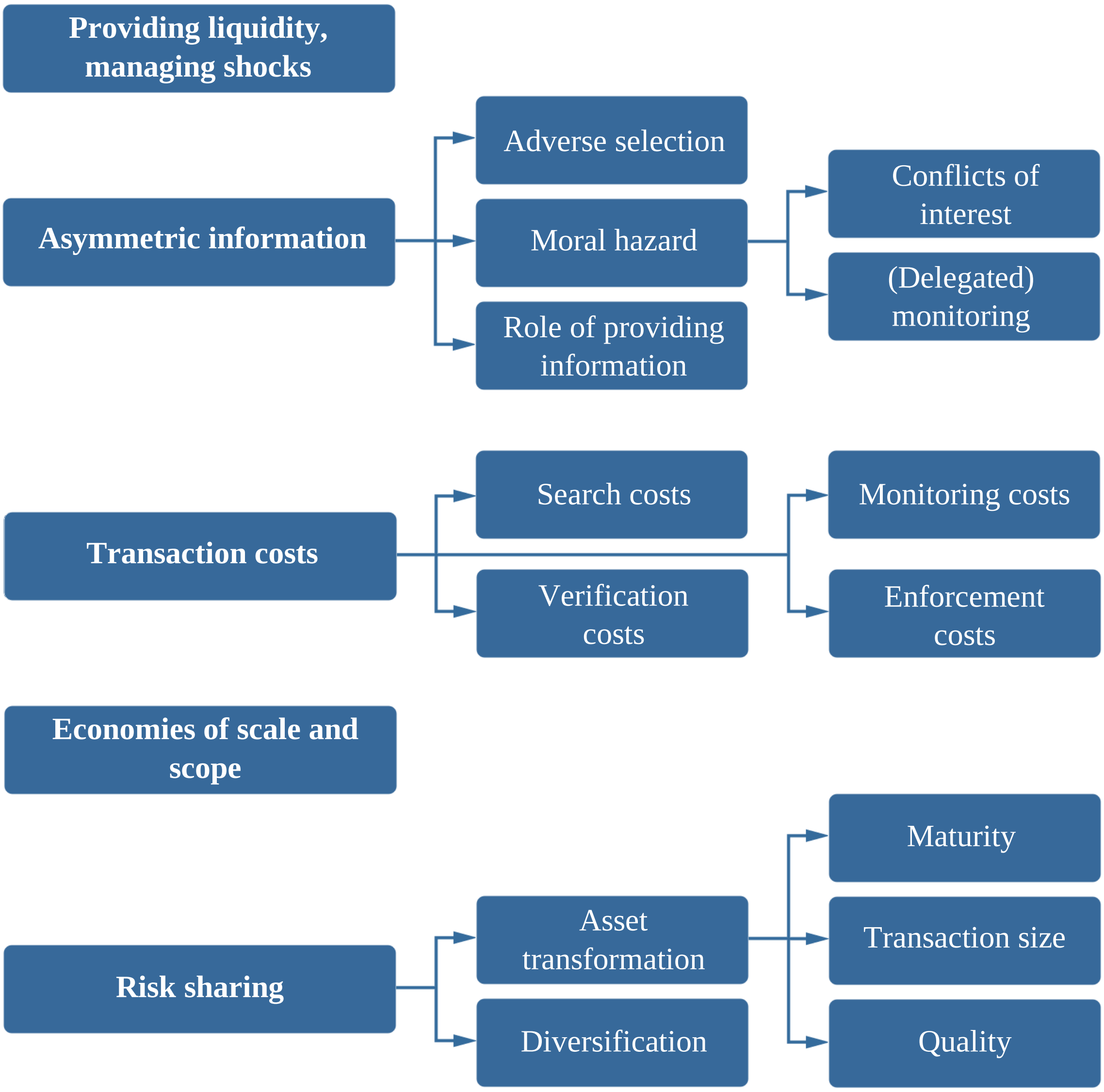
Contrary to the above examples, the role of intermediaries and the importance of their activities in the unsecured interbank deposit market is unquestionable, even in the 21st century.

## 5.2. Why is the need for financial intermediaries?

Financial literature has in recent decades attached special attention to the question of why financial intermediaries or, more narrowly, banks are needed in an economy. The questions of why intermediation has evolved in the interbank market and what beneficial effects intermediary activities have on the network as a whole are much less researched areas.

*Figure 41:*

Why is the need for financial intermediaries? – summary chart




*Source: own edition.*

In many respects, parallels can be drawn between the role banks and the financial intermediation system play in the economy and the role core intermediary participants play in the interbank market. In the next section, I collect (and include in an extended and unified framework) intermediary functions relevant to the interbank market as covered in academic literature; and I attempt to answer the question of why is the need for central intermediary players in the interbank market, i.e. why even intermediaries themselves need intermediaries.

***Role of providing liquidity and allocating funds***

As perhaps the most important driver of the interbank market, liquidity is discussed in detail in sub-chapter 2.1 above in my thesis. One of the essential functions of intermediaries is to provide liquidity, which is the "lifeblood" of the whole market. Market participants are constantly exposed to liquidity shocks, so they must have sufficient liquid assets to handle them.

In the presence of intermediaries, the smoothing out of liquidity discrepancies requires less liquid assets from market participants in terms of total volume than in a situation where each bank would have to resolve them individually. This type of system-level savings allows financial actors to make money through financial intermediation, i.e. by providing liquidity *(Matthews–Thompson [2005])*.[62]

***Reducing an asymmetric information situation***

This issue is approached from one of the most general and comprehensive perspectives by *Mishkin–Serletis [2020]*. An *asymmetric information* situation is present in credit markets when the borrower naturally has more information about a given credit transaction (his own solvency and readiness to pay) than the lender. The lack of information raises two issues for the provider of funds: one issue before the transaction and another issue after that.

The phenomenon of *adverse selection* arises before lending, and it essentially means that borrowers with the highest credit risk, who are the most likely to default, are the most active in seeking credit options. In the absence of intermediaries capable of reducing asymmetric information situations in the market, adverse selection may result in a state where participants with excess liquidity decide not to lend. Otherwise, good debtors who are currently struggling with a lack of liquidity will not receive funding.

*Moral hazard* arises after a loan has been granted,[63] and it essentially means that a borrower may engage in conduct (low effort, extravagant investments, etc.) that, from the lender's point of view, is undesirable ("contrary to good morals"), which may reduce the likelihood of the repayment of the loan. The presence of moral hazard may also lead to a state where those with surplus funds do not dare to lend funds, and thus, in addition to

[62] This issue is addressed in more detail in Sub-chapter 5.3 below.

[63] *Matthews–Thompson [2005]* mentions that the problem of moral hazard may arise even before granting a loan, if a participant applying for a loan tries to describe the transaction in a better light than it really is.

bad debtors, even the best debtors cannot receive credits. Adverse selection and moral hazard arising due to asymmetric information situations may be a serious obstacle to the development of a well-functioning market. The presence of intermediaries may help alleviate these problems through an efficient acquisition and processing of information, the development of appropriate contractual incentives, and the development of advanced systems for screening (adverse selection) and monitoring (moral hazard).

*Freixas–Rochet [2008]* highlights that lenders constantly monitor their partners due to asymmetric information situations and the presence of moral hazard. This type of monitoring activity represents an incentive for actors to build long-term relationships, which can reduce moral hazard. In the interbank market, one can also observe that long-term relations are formed between banks (and dealers); and some participants prefer each other in their lending activities (this is the phenomenon of the so-called *preferential lending* present in unsecured interbank markets).

Under the approach of *Saunders–Cornett [2015]*, intermediaries are essentially "agents" entrusted by smaller participants to carry out delegated monitoring activities and to acquire information about other market participants, as their primary tasks. Compared to many small clients, large financial intermediaries can significantly reduce average monitoring costs (economies of scale). Additionally, they perform monitoring activities also more efficiently, as they can employ the most competent employees who have monitoring skills. In addition, delegated monitoring solves the "free-rider" problem that arises when some smaller players rely on each other to acquire information and do monitoring activities. Thus, intermediaries can improve the efficiency of monitoring (quality) and reduce costs (quantity) at the same time.[64]

*Diamond [1984 and 1996]* examines three possible cases in his studies: (1) there are no monitoring activities, (2) small investors monitor debtors directly, and (3) an intermediary carries out delegated monitoring activities. Using a model, he demonstrates that, in the first case, if players do not carry out any monitoring activities at all, then it will be inefficient due to defaulted loans (low repayments). In the second case, direct monitoring leads to extremely costly and duplicate monitoring. Clearly, delegated monitoring is the

[64] In addition to monitoring, economies of scale is relevant to many other lending-related tasks (such as obtaining and processing information, preparing good contracts, or even screening).

most effective, whereby an intermediary is able to reduce monitoring costs to the lowest possible level by diversifying the loan portfolio.

*Bodie–Merton–Cleeton [2009]* also highlight a resource allocation function fulfilled by the financial intermediation system, by presenting the issues of moral hazard and adverse selection as a kind of incentive problem. Compared to the authors discussed earlier, the new element is the financial intermediation system's role in providing information. The various interest rates, for instance, the average interest rate on interbank unsecured loan transactions, is a crucial market information, and any change in them is an essential signal to economic actors.

In past decades, the most commonly used interbank rate used to be LIBOR,[65] which became infamous in the wake of the manipulation scandal that erupted in 2012. In addition to LIBOR, similar processes have taken place in relation to the EURIBOR. On 4 December 2013, the European Commission established that leading central participants of the interbank market had manipulated the EURIBOR and the yen LIBOR by operating a cartel, in connection which fines totalling around € 1.5 billion have been levied. According to the report, the interest rate manipulation had involved eight market participants: Barclays, Deutsche Bank, Société Générale, RBS, UBS, JPMorgan, Citigroup, and RP Martin *(European Commission [2013])*. The eight banks listed are, without exception, large, central participants acting as intermediaries in the interbank market. The scandal is an excellent demonstration of the fact that large, central network players have a significant impact on interbank interest rates, and their function of providing information will increase their importance compared to other market participants.

In connection with the role of providing information, *Saunders–Cornett [2015]* step out of the study of the (narrowly defined) functions of financial intermediaries and present their impact on the entire financial intermediation system and the national economy as a whole. Financial intermediaries (and the interbank market) have a crucial role in the proper functioning of the transmission mechanisms of monetary policy. One of the most important channels of monetary policy, the interest rate channel, is able to exert its effect,

[65] Using the past tense here is adequate because LIBOR was phased out after the scandal and was replaced by other interbank interest rates such as SOFR *(Secured Overnight Financing Rate)*, SONIA *(Sterling Overnight Interbank Average Rate)*, or SARON *(Swiss Average Rate Overnight)*.

and influence the behaviour of real economic actors, precisely through the interest rate evolving in the interbank market.

***Reducing transaction costs***

In addition to post-lending monitoring costs, *Matthews–Thompson [2005]* provide a list of various transaction costs, in the reduction of which intermediaries have a key role to play. An example is *search costs*. In the absence of intermediaries, an underfunded participant would need to find a partner willing to lend the required amount with the appropriate maturity, obtain information about the partner to be involved in the transaction, and negotiate and finalise the contract. *Verification costs* also arise, as the lender has to evaluate borrowers' offers. *Enforcement costs* are incurred by the lender if the debtor fails to perform in accordance with the terms of the contract or breaches any of its clauses.

***Economies of scale and scope***

*Mishkin–Serletis [2020]* mentions the phenomena of *economies of scope* and *conflicts of interest* as the main reasons for the evolution and legitimacy of financial intermediation. In general, as financial intermediaries provide a range of financial services to their clients, they can reduce costs by using information obtained from providing one of their banking products to some of their other services. This is what the academic literature calls economies of scope, or more narrowly, *information reusability (Greenbaum–Thakor–Boot [2019])*. An excellent example of this is the Hungarian interbank market, where one can access HUF liquidity both on the unsecured and repo markets. Information about a partner obtained in one of the markets can be used in another market.

Although there may be several benefits to a bank due to economies of scope, this beneficial aspect may also lead to conflicts of interest and thus appear on the cost side. Conflicts of interest fall into the category of moral hazard and arise when a financial institution has multiple objectives (interests) at the same time, which sometimes conflict with each other. The more services are provided by a given participant, the higher the likelihood of these conflicts of interest occurring. Conflicting and competing interests may lead to the concealment of certain information or the provision of misleading information. The existence of conflicts of interest due to poor-quality information (or downright misleading information) may worsen asymmetric information problems and thus contribute to market failures.

Due to its importance on the market, an intermediary is able to reduce per-unit transaction costs by taking advantage of *economies of scale*. Low transaction costs allow financial intermediaries to provide liquidity to their clients more efficiently *(Mishkin–Serletis [2020])*.

***Facilitating risk sharing***

Lower transaction costs also contribute to more efficient *risk sharing* by intermediaries. Intermediaries can achieve risk sharing through asset transformation on the one hand and diversification on the other.

*Saunders–Cornett [2015]* elaborate on their asset transformer function in detail: intermediaries can bridge the gap between lender and borrower preferences that differ in terms of maturity *(maturity intermediation)* or transaction size/nominal value *(denomination intermediation)*. With regard to the unsecured interbank deposit market, intermediaries can perform maturity transformation to a lesser extent (as transactions are typically aimed at providing liquidity, and thus maturities differ only slightly), but they can increase efficiency in terms of transaction size (usually, a smaller player's surplus funds alone can only to a small extent meet a larger player's credit needs).

In addition to transformation in terms of transaction size and maturity, *Freixas–Rochet [2008]* also identify *quality transformation*. This latter term means that an intermediary can achieve a better risk-return combination usually than direct financing can. For example, in the interbank market, a smaller peripheral participant with surplus funds can lend such funds to a large core participant at a lower risk than to another peripheral participant directly (there are no significant differences in yields in the interbank market, as price adjustment is less significant and quantity adjustment dominates there). Quality transformation is also related to asymmetric information because larger intermediary actors tend to have more information.

*Table 15:*

Functions of intermediaries in the academic literature

| | Bodie–Merton–Cleeton [2009] | Greenbaum–Thakor–Boot [2019] | Matthews–Thompson [2005] | Mishkin–Serletis [2020] | Saunders–Cornett [2015] |
|---|---|---|---|---|---|
| Providing liquidity, managing shocks | X | X | X | X | X |
| Asymmetric information | X | X | X | X | |
| - Adverse selection | X | X | X | X | |
| - Moral hazard | X | X | X | X | |
| ○ Conflicts of interest | | | | X | |
| ○ (Delegated) monitoring | | X | X | | X |
| - Role of providing information | X | | | | X |
| Transaction costs | | X | X | X | X |
| - Search costs | | | X | | |
| - Verification costs | | X | X | | |
| - Monitoring costs | | X | X | | X |
| - Enforcement costs | | | X | | |
| Economies of scale and scope | | X | X | X | X |
| Risk sharing | X | X | | X | |
| - Asset transformation | | X | X | X | X |
| - Diversification | | X | | X | |

*Source: own edition.*

Table 15 summarises the functions mentioned in individual sources of academic literature (marked with an X in the given cell). In this subsection, mainly the intermediary functions collected by the authors listed in the table have been synthesised and interpreted relevant to interbank market intermediary activities specifically.

## 5.3. Core-periphery model and intermediation in the literature

The line with the thought of *Matthews–Thompson [2005]* presented before – namely, that intermediation has financial benefits – is continued now by examining the positive benefits of intermediation activities for intermediaries performing it in core-periphery networks. With this introduction discussing academic literature, we can link the core-periphery structure present in interbank markets with intermediation activities and their regularly mentioned benefit, namely profits generated by intermediaries.

The interbank market is an over-the-counter (OTC) market where there is no central counterparty (clearing house), but participants enter into bilateral transactions directly with each other. Unlike the stock market, where everyone is equally well informed about the available orders, the participants of the interbank market do not necessarily transact at the best available conditions, as individual banks often ask for quotes from only a few partners. There is a cost of finding the best offer (the right partner) that contributes to the development of intermediary activity in OTC markets *(Duffie–Gârleanu–Pedersen [2005])*.

I presented in Chapter 4 that financial markets can be characterised by a hierarchical structure, in which two groups of actors can be distinguished: (1) the core formed by extremely closely related, frequently transacting banks; and (2) a periphery with a rare network where the banks do not lend directly to each other. In this core-periphery structure, core banks act as intermediaries between the periphery banks, who, for some reason, are unable or unwilling to transact directly with each other.

Examining social networks, *Goyal–Vega-Redondo [2007]* built a model where actors exchange information or goods with each other, and each exchange (or relationship) generates some kind of "benefit" for participants. In the model, the actors are influenced by various incentives, one of which results in their willingness to enter as a mediator between two actors, because there is some advantage to this. In the absence of capacity constraints on the number of connections, this kind of incentive creates a so-called star network[66] as an equilibrium. Similarly, the star structure led to an optimum in the model of *Hojman–Szeidl [2008]*, who explained all this by the fact that the establishment of new network connections is costly and the associated benefits are of decreasing amount. There is a single central actor in such a star network, grouped around all other nodes, and transacting exclusively with that concentrator vertex. This central actor, as an intermediary, handles all transactions alone and enjoys significant benefits.

[66] The star network is described in detail in Sub-chapter 4.2.3 of my thesis.

Although the above paper of *Goyal–Vega-Redondo [2007]* is about social networks, we can undoubtedly find interesting similarities with the interbank market. Banks are encouraged by their interest rates on overnight lending to disburse their excess liquidity, and for a given amount of profit (whether in cash or through social capital), intermediation also develops naturally. The equilibrium state (star network) mentioned in the study can be understood as an extreme core-periphery structure in which the core is composed of a single actor.

Moving from social networks to financial networks, *Babus–Hu [2017]* examined the dynamics of trading in over-the-counter markets. They presented the key role of the informal network between traders in the smooth functioning of the market. In this type of market, intermediation is also strongly present, for which intermediaries receive a fee. Similar to the research of *Goyal–Vega-Redondo [2007]*, the star network has been studied in detail. Compared to other typical network topologies, it has been found that for large networks, the star network has the highest compensation received for intermediation. The central player in the star structure receives a significant reward in return for its activities.

Applying their model to the Dutch interbank market of about 100 financial institutions, *Veld–Leij–Hommes [2020]* also found that the benefits of intermediation are significant, for which the core, multi-connected (larger) banks compete. The isolation of peripheral banks from each other allows core players to further increase their central role through their intermediary activities. The profits made through intermediation increase the size of the core players, thus conserving their central role in the market. So the size gap between the core and peripheral players increases further.

As we have seen, the academic literature is unique in the opinion that in a core-periphery network, such as the interbank market, intermediation activity is significant and profitable. Consequently, intermediation ensures significant benefits to central actors. In the following, I investigate the magnitude and the benefits of intermediation activity in the Hungarian interbank market between 2012 and 2015. There have been no studies in the literature to measure intermediary profits in the interbank market to the best of my knowledge.

## 5.4. The importance of intermediation

I will perform an analysis on the database of transactions presented in detail in Chapter 3, by focusing again on interbank transactions concluded solely for liquidity management purposes, i.e. overnight loans, which account for 91% of unsecured interbank deposit market transactions. A significant difference compared to previous methods is that data is now aggregated on an annual rather than a monthly basis.

Previously, a significant advantage of monthly data – in addition to its direct comparability with literature – was that it was able to smooth out monthly seasonality,[67] making it possible to examine the effects of central bank measures aimed at transforming individual monetary policy tools. However, annual seasonality is also common in the interbank market; for instance, December is a special month for interbank liquidity, partly due to a sharp increase in demand for cash as a result of Christmas and partly due to a much higher number of bank holiday than average, creating difficulties in managing the liquidity position *(Antal et al.[2001])*.

Now, my purpose is specifically to provide a long-term estimate for volumes of intermediation activities and the magnitude of interbank intermediary profits, net of one-off effects. For this purpose, annual aggregation is more appropriate, as it can smooth out not only monthly but also annual seasonality.

### 5.4.1. Annual transaction volumes in the unsecured interbank market

First, I would like to show a comprehensive picture of the magnitude and annual changes of the annual transaction amounts prevailing in the market to serve as a benchmark for the later estimated profit of intermediation. The magnitude of the overnight transactions and loan volumes in the market and the general dynamics of the transactions are summarised in Table 16.

[67] Generated, for example, by the Treasury Single Account described in section 2.3.2, or various tax payments.

*Table 16:*

Size and volume of the Hungarian unsecured interbank deposit market (2012-2015)

| | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|
| Sum of the transaction volume (million HUF) | 27,625,252 | 27,602,445 | 30,203,019 | 33,762,722 |
| Number of transactions | 8,225 | 9,042 | 9,844 | 9,817 |
| **Average size of a transaction (million HUF)** | **3,359** | **3,053** | **3,068** | **3,439** |
| **Median of the transactions' volume (million HUF)** | **2,000** | **2,000** | **2,000** | **2,000** |
| Number of active banks in the market | 39 | 39 | 41 | 43 |
| **Average transaction volume (per institution, million HUF)** | **708,340** | **707,755** | **736,659** | **785,180** |

*Source: Own editing based on MNB data.*

The aggregate transaction volume increased dynamically in the period under review, rising from HUF 27,625 billion in 2012 to approximately HUF 33,763 billion in 2015. This was mainly due to the increase in the number of transactions. The ratio of the total transaction volume and the number of transactions gives the average transaction size, which fluctuated in the range of HUF 3-3.5 billion.

Because the size of the transactions showed significant variance (there are multiple outlier values in the data series), a median that is less sensitive to outliers, is a more appropriate metric to quantify a typical transaction size. The typical transaction volume (the median) was HUF 2 billion in each year examined.

At the beginning of the period, 39 banks were active in the market, and by 2015 this number had reached 43. Here, I considered as active any bank that took or granted at least one O/N unsecured loan in the given year. Of course, the market participants were also very different in terms of the volume of transactions. There were participants that participated in only 2 transactions during the period under review, and some participants granted or took out more than a thousand unsecured loans. In parallel with the aggregate transaction volume, the average transaction volume per bank also increased in the 4 years under review, from HUF 708 billion to HUF 785 billion.

### 5.4.2. Volume of intermediation

In the previous section, I outlined typical lending volumes observed in the Hungarian unsecured interbank deposit market. In the next step, let us examine the question of how much of the credit volumes observed in the market can be linked to intermediation activities.

Let $L_{i,t}$ denote the face value of bank $i$ lending and $B_{i,t}$ the face value of bank $i$ borrowing on day $t$. The volume of intermediation for bank $i$ ($I_{i,t}$) – being overnight transactions – is the minimum amount taken or given, on every single day $t$. This amount is supposed not to serve the institution's daily liquidity management directly.

$$I_{i,t} = min(L_{i,t}; B_{i,t}) \tag{38}$$

$I_{i,t}$ is the amount that the bank $i$ merely flows through itself on day $t$, the net liquidity position[68] at the end of the day would remain unchanged without this common part of borrowing and lending. Table 17 shows the total volume of the lending amount and the volume of intermediation during the period examined.

*Table 17:*

Intermediation in the Hungarian unsecured interbank deposit market (2012-2015)

| Year | Total volume of lending amount (million HUF) | Total volume of intermediation (million HUF) | Rate of intermediation |
|---|---|---|---|
| **2012** | 27,625,252 | 3,835,564 | 13.88% |
| **2013** | 27,602,445 | 5,308,237 | 19.23% |
| **2014** | 30,203,019 | 6,984,471 | 23.13% |
| **2015** | 33,762,722 | 8,513,659 | 25.22% |
| **2012-2015** | **119,193,438** | **24,641,931** | **20.67%** |

*Source: Own editing based on MNB data.*

Table 17 shows that the intermediation activity was significant in the market and grew dynamically during the investigated period: the intermediated volume increased from 13.88% in 2012 to double in the next three years, to 25.22%, as a percentage of total loan

[68] A strict requirement for banks operating in Hungary is that the balance of their settlement account at the end of the day cannot be negative at the close of VIBER. The missing liquidity is be obtained from other domestic or foreign banks, or the Government Debt Management Agency or the Central Bank of Hungary *(Kolozsi–Horváth [2020])*.

volume. We can also see a very significant intermediation activity of over 20% (20.67%) in the average of the examined 4 years. With this, hypothesis *H4* (as formulated in relation to the volume of intermediation activities in the introduction to this chapter) is confirmed.

I also examined, broken down by banks, the volume of intermediation in relation to their lending activity. Table 18 shows the banks with the highest intermediation volume, which exceeds by more than 15% their lending activity over the entire period.

*Table 18:*

Intermediation activity of the Hungarian banks

| Code of the bank | 2012 | 2013 | 2014 | 2015 | 2012-2015 |
|---|---|---|---|---|---|
| **14** | 20.03% | 25.80% | 26.84% | 22.72% | **23.85%** |
| **10** | 0.00% | 13.86% | 29.47% | 31.37% | **22.54%** |
| **11** | 14.12% | 15.56% | 20.12% | 17.13% | **16.80%** |
| **12** | 0.26% | 0.17% | 8.49% | 43.27% | **15.16%** |

*Source: Own editing based on MNB data.*

I received similar results for the single banks, as in the case of the whole market.

## 5.5. Estimation of the intermediary profit

The calculation of the intermediation profit is not straightforward, even with the most detailed transaction database. To illustrate this, I present a simple example, then give an estimation using volume-weighted interest rates, and finally determine the maximum of the intermediation profit.

Consider the following table as an example, in which the transactions of the fictive bank number 31 on 8 August 2015[69] are listed with 5 different partners:

[69] Due to the non-public nature of the database, the table does not contain real data; it is for illustration only (for example, 8 August 2015 and 9 August 2015 fell on Saturday and Sunday, respectively).

*Table 19:*

Transactions of the fictive bank number 31 on 8 August 2015

| Code of the data provider (borrower) bank | Code of the partner (lender) bank | Size of the transaction (million HUF) | Effective date | Expiry date | Interest rate |
|---|---|---|---|---|---|
| 31 | 78 | 6,000 | 08.08.2015 | 09.08.2015 | 1.2% |
| 31 | 62 | 4,000 | 08.08.2015 | 09.08.2015 | 1.0% |
| 52 | 31 | 5,000 | 08.08.2015 | 09.08.2015 | 1.5% |
| 55 | 31 | 7,000 | 08.08.2015 | 09.08.2015 | 1.4% |
| 67 | 31 | 2,000 | 08.08.2015 | 09.08.2015 | 2.0% |

*Source: own edition.*

In the example, bank 31 borrowed a total of HUF 10 billion[70] and granted a loan of HUF 14 billion, so it was a net lender of HUF 14 – 10 = HUF 4 billion. The volume of intermediation is $I$ = min (10, 14) = HUF 10 billion in the present case, this amount was only flowed through the institution and was not served the handling of its own liquidity need or surplus, assuming that the time horizon of liquidity management is 1 day.

Suppose we want to determine the profit achieved through intermediation in the given example. In that case, we have a simple task on the borrowing side, the HUF 10 billion borrowing is equal to the intermediated amount, the cost of which is 1.2% (per annum) for HUF 6 billion and 1% (per annum) for HUF 4 billion.

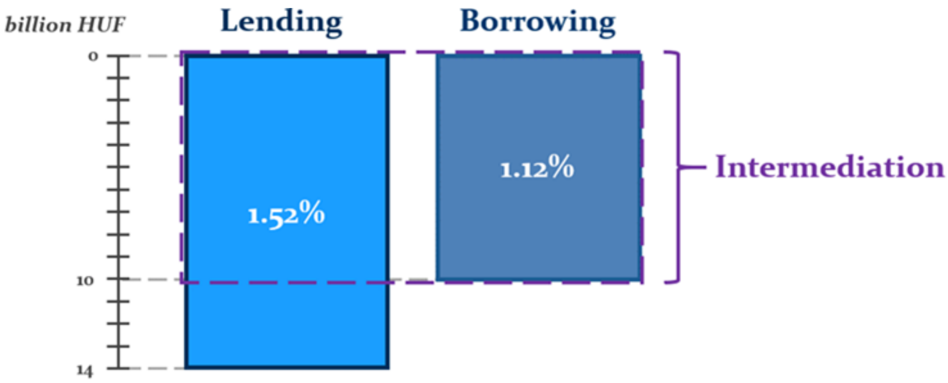
Regarding the lending side, on the other hand, the calculation is not so obvious at all. Based on the transaction data, it is not possible to determine what amounts and at what interest rates are connected to the HUF 10 billion part of the loan of HUF 14 billion.

One possible solution to the problem is to determine the volume-weighted average interest rate and suppose that the HUF 10 billion intermediated lending had an average interest rate. Figure 42 illustrates the estimation of intermediation profit applying a weighted average interest rate.

[70] Data providers are the borrowing banks in all cases.

*Figure 42:*

Profit of intermediation applying weighted average interest rates




*Source: own edition.*

Generalizing the method mentioned above, the calculation of the intermediary profit ($\pi$) for bank $i$ on day $t$ is

$$\pi_{i,t} = I_{i,t} \cdot \frac{{r^L}_{i,t} - {r^B}_{i,t}}{360} \tag{39}$$

where ${r^L}_{i,t}$ and ${r^B}_{i,t}$ are the weighted average (annual) lending and borrowing rates, respectively, and $I_{i,t}$ stands for the volume of intermediation of bank $i$ on day $t$. I rescaled the annual interest rate into daily return by dividing by 360, as the money market ISDA standard suggests *(ISDA [1998])*.

Table 20 shows the estimated intermediary profit for each period, calculated with a weighted average interest rate. It can be observed that the trading profit achieved is stable; it seems that some central (core) players were very active in terms of intermediation activity. The institutions with the highest profits were banks 14, 10, and 8. The highest annual intermediary profit in the period was HUF 12,326,309, which was achieved by bank No. 10 in 2015. Given that intermediation accounted for a very significant proportion of total unsecured money market interbank activity of about 25% on average this year, the profit of intermediation even in the most profitable case is less than 0.007% of the average intermediated amount, which appears to be extremely low.

*Table 20:*

Annual intermediary profit of the 5 most profitable bank, using weighted average interest rates (in HUF, 2012-2015)

| Code of the bank | 2012 | Code of the bank | 2013 | Code of the bank | 2014 | Code of the bank | 2015 |
|---|---|---|---|---|---|---|---|
| 14 | 5,438,569 | 14 | 8,885,388 | 14 | 9,796,580 | 10 | 12,326,309 |
| 8 | 1,370,261 | 8 | 2,968,322 | 10 | 9,182,167 | 14 | 8,894,802 |
| 9 | 1,240,140 | 5 | 2,006,445 | 27 | 2,380,703 | 8 | 3,293,590 |
| 11 | 823,156 | 10 | 1,403,091 | 5 | 2,076,897 | 224 | 1,682,088 |
| 28 | 653,130 | 4 | 1,389,937 | 8 | 1,313,410 | 27 | 1,586,501 |

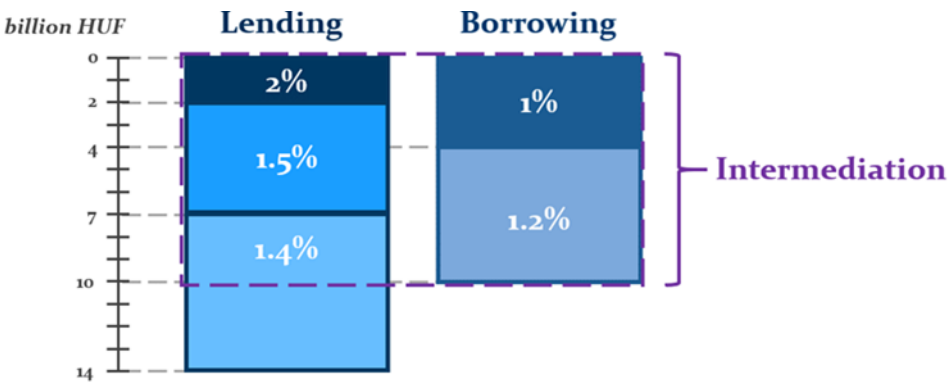
| Code of the bank | 2012-2015 |
|---|---|
| 14 | 33,015,339 |
| 10 | 22,911,567 |
| 8 | 8,945,584 |
| 5 | 5,387,705 |
| 27 | 5,103,906 |

*Source: Own editing based on MNB data.*

The calculation with a weighted average interest rate is a possible estimation method; it is impossible to determine the exact intermediary profit. From the detailed transaction data, however, the upper limit of the intermediary profit can be calculated.

*Figure 43:*

Estimation of the maximum of intermediary profit




*Source: own edition.*

All we have to do is to sort the transactions in descending order of interest rate on the lending side and in ascending order on the borrowing side for a given day and for a given market participant, so we assume the most favourable conditions for the intermediary's profit. Figure 42 illustrates this in the example of the deals of bank 31 (based on Table 19).

By assigning the most favourable loan conditions to intermediation, we can estimate the highest intermediation profits that were possible. In the case the maximum intermediary profit calculated in this way is similarly neglectable compared to its volume, then we can state that the data do not confirm the size effect of *Veld–Leij–Hommes [2020]*, which considers the intermediation activity to be a factor explaining the size differences between the banks.

*Table 21:*

Maximum of intermediary profit per year of the 5 most profitable bank
(in HUF, 2012-2015)

| Code of the bank | 2012 | Code of the bank | 2013 | Code of the bank | 2014 | Code of the bank | 2015 |
|---|---|---|---|---|---|---|---|
| 14 | 7,104,979 | 14 | 11,518,968 | 10 | 13,241,457 | 10 | 18,322,149 |
| 8 | 1,595,672 | 8 | 3,513,793 | 14 | 12,348,553 | 14 | 11,966,128 |
| 17 | 1,501,493 | 10 | 3,349,139 | 5 | 2,533,435 | 8 | 3,889,060 |
| 9 | 1,455,364 | 5 | 2,606,725 | 27 | 2,494,583 | 17 | 2,703,278 |
| 6 | 1,017,924 | 4 | 2,031,664 | 8 | 1,758,547 | 224 | 1,756,806 |

| Code of the bank | 2012-2015 |
|---|---|
| 14 | 42,938,628 |
| 10 | 34,912,745 |
| 8 | 10,757,072 |
| 17 | 7,580,785 |
| 5 | 6,742,121 |

*Source: Own editing based on MNB data.*

Table 21 shows the maximums of potentially available intermediary profit in each period. Based on these, we can draw two important conclusions. On the one hand, it can be observed that the ranking among the banks changed only minimally compared to the weighted average interest rate estimate (Table 20), i.e. in terms of intermediary profit, the order seems robust to the chosen estimation methods.

On the other hand, we can state that, as expected, this method resulted in higher profits everywhere, but no increase in magnitude occurred. The maximum intermediary profit achieved by one bank for one year was only HUF 18,322,149 in the period under review, which, similarly to the case calculated with the weighted average interest rate, was achieved by bank number 10 in 2015.[71] This amount is very low and – presumably – not

[71] It is notable that the highest annual intermediary profit of 18.3 million HUF (~60,000 EUR) was barely 0.0005% of the HUF 4,035 billion unsecured exposure of the bank No. 10 as a lender.

sufficient even to cover the direct costs of the activity (dealers' salaries, provision of necessary IT infrastructure).

Thus, it seems that interesting results – contradictory to academic literature – are achieved, because HUF 18 million in profits from intermediation is far from the order of magnitude that could significantly increase the size of bank number 10 (presumably a core bank).

Another exciting result of the research can be presented through the case of bank No. 12, which had little intermediation activity until 2014, but it was the most active in the interbank market with its exceptionally high activity rate of 43.27% in 2015. In addition, it did all this with a loss of HUF 4.3 million. Why did a for-profit institution increase its intermediation activity so dynamically when it generated such a loss? This finding is not in line with the theory of *Veld–Leij–Hommes [2020]* on the effect and mechanism of intermediary benefits.

One of the most fundamental thoughts of finances is that risk and yield go hand in hand; higher return can be achieved (in the long run) by assuming a higher risk. Due to the unsecured deals and large volumes, the participants in the interbank deposit market run outstandingly high risks.

I presented in the previous chapter that the annual intermediation profit of the banks is negligible; moreover, in some cases there is even intermediation loss. This means that the market participants do not perform intermediation activity (which is additional to their own liquidity management) to achieve profit. However, if they do not do it for money, what rational explanation can there be for “free” daily services amounting to billions or even tens of billions of forints?

According to literature, there are basically three possible motivations behind intermediation activities: (1) making profits through intermediation *(Matthews–Thompson [2005], Veld–Leij–Hommes [2020]);* (2) selfless, philanthropic assistance *(Caudell–Rotolo–Grima [2015])*; or (3) risk sharing based on reciprocity *(Laczó [2015])*.

As shown above, the main motivation for intermediaries in the interbank market is not profit-making. As a huge risk is posed by the unsecured nature, as characteristic to interbank markets, therefore, selfless, philanthropic assistance cannot be the main driver either, and altruism is mainly a feature of social networks. *(Caudell–Rotolo–Grima [2015])*.

By a process of elimination, we can assume that the main motivation of intermediaries in the unsecured interbank deposit market is risk sharing. Risk sharing, in this case, means that one bank makes a loan to another so that when it encounters a lack of liquidity later, then the previously assisted partner should reciprocate it. Individual liquidity shocks affect individual market participants at different times and to different extents, which allows participants in the interbank market to operate such kind of insurance scheme based on reciprocity. Intermediaries, therefore, do not carry out their activities for making profits, but for the "security" they can enjoy by belonging to the community of the interbank market. With this, hypothesis *H5* about the main motivation of intermediation is rejected.

# 6. Comparison of the interbank network with the network of an interpersonal loan market

In the following, a comparison is made between a small network representing interpersonal lending relations in a village of Borsod county, which is inhabited mainly by Roma people, and an unsecured interbank deposit market. In both markets, participants lend funds to each other without any financial collateral, and the purpose of transactions is liquidity management. Thus, the two markets are very similar in terms of their most important characteristics, but the players and the transactions concluded are completely different.

It is worth examining whether any change is observed in network characteristics if the basic functions of two networks are the same, but liquidity management is placed in a context completely different from the set of formalised rules used by banks' office buildings, namely, in an underdeveloped village inhabited mostly by the poor and driven by informal rules.

As explained in detail in previous chapters, the key to the core-periphery structure in unsecured interbank deposit markets lies in intermediation. And the fact that intermediation is significantly present in interbank markets is shown through volumes of intermediation activities in Chapter 5. A level of intermediation similar to the level observed in interbank markets is difficult to imagine at first in interpersonal markets, as this would mean in practice that the poor, who are exposed to extreme liquidity shocks, would lend funds to someone by being aware that they themselves will need to borrow at the end of the month. So, intuition suggests that, although the basic functions of the two networks examined are the same, the two networks differ significantly due to a lack of intermediation and significant differences in transactions and participants.

A comparative analysis is followed by an examination of the main motivation behind intermediation activities carried out (presumably to a lower extent) in interpersonal lending markets. A study by *Caudell–Rotolo–Grima [2015]* is briefly presented, which also focuses on the network of informal loans in a lagging region. The authors found that the main motivation for lending is altruism, where the rich benevolently help the poor. Hypothesis *H7* was formulated in line with their findings.

The research questions examined in that chapter are as follows:

> *What are the main similarities and differences between the unsecured interbank deposit market network and that of interpersonal loans in a disadvantaged village with a majority Roma population?*
>
> *Are there intermediation activities present in the interpersonal lending market, and what is the main motivation for granting loans?*

In line with the research questions, the following hypotheses are examined:

*H6: The network of the examined interpersonal loan market differs significantly from the Hungarian unsecured interbank deposit market network.*

*H7: The main motivation for transactions in the interpersonal loan market is selfless, philanthropic assistance provided by the rich to the poor.*

I will use first-person plural in this chapter, as I will build on the results of our joint research performed together with Edina Berlinger, Márton Gosztonyi and Dániel Havran.

## 6.1. Formal and informal networks

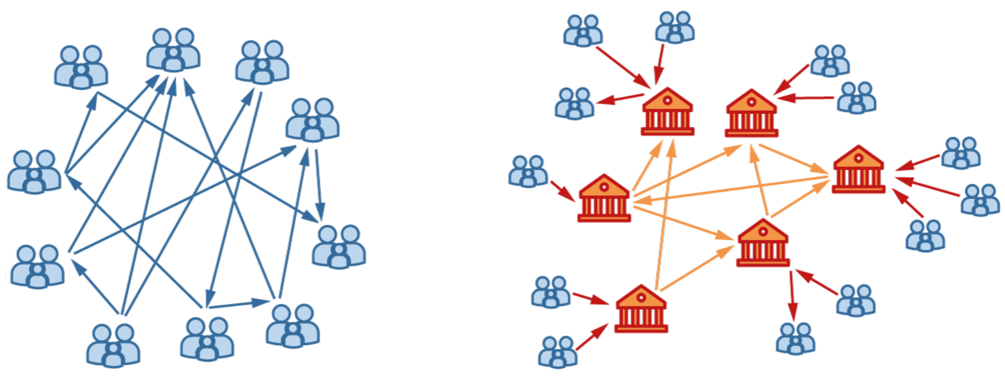
Examining underdeveloped regions, the issue of financial inclusion is often in the foreground as it is a necessary (but not sufficient) condition of social and economic catch-up *(Allen et al. [2016])*. Bank services have a defined hierarchy in the sense that higher-level services – such as loans, insurances or asset management – can only be used if the person has a bank account, knows and uses the electronic payment and may have securities account to manage part of their savings. The totality of these bank services will be understood as formal bank services in the following.

A significant part of the households living in underdeveloped settlements do not even have bank accounts; therefore they are completely excluded from the formal bank services. In his PhD thesis titled "Jugglers of Money: Financial Surviving Strategy of Low-income Families and a Story of a Participatory Action Research" *(Gosztonyi [2018])*, Márton Gosztonyi presented how these families living in extreme poverty manage their finances. We took the findings and database of this study, to which a series of interviews was added as our starting point in this chapter.

The research mentioned above revealed that the incomes of the poor families were highly uncertain and cyclic, causing extreme liquidity shocks to them. We cannot say that underprivileged households are not financially aware and do not plan their budget. On the contrary, they are the masters of operating their complex risk management systems. They have developed and used many informal tools every day. One of them, the informal[72] market of interpersonal loans set up in small village communities, where the households extend interest-free loans to each other directly (on the left in Figure 44), plays a key role.

*Figure 44:*

Structure of the interpersonal loan and interbank deposit markets



Interpersonal loan market Interbank deposit market

*Source: own edition.*

Figure 44 illustrates the fundamental structural differences between the interpersonal and the interbank loan market. The blue pictograms depict households, the buildings with red outlines represent banks, and the arrows symbolise the financial transactions.

As opposed to the interbank deposit market, in the system of bank services (on the right in Figure 44), the private persons are connected to their banks through their bank accounts, and the credit institutions provide them with the necessary liquidity as a professional intermediary (red arrows). At the same time – on the next level of liquidity management –, the banks manage their established aggregated liquidity position on the interbank market (orange arrows). It is a process precisely regulated in every detail; the transactions are contracted on the interbank market by highly trained professionals who perform their work based on strict regulations, prepare regular reports and monitor the market continuously *(Allen–Babus [2008]; Homolya et al. [2013])*.

[72] The word “informal” is used as a complementary of the previously presented “formal” word for every transaction, which is outside the above mentioned formal bank services. In this sense, the informal loans lack the usual formalities of the bank services (concluding a loan contract, for example) and are mostly based on an oral agreement between two private persons.

## 6.2. About informal interpersonal networks in general

The previous chapters showed that the interbank market is a thoroughly developed area of finance and network science both from theoretical and empirical sides. Detailed and large databases are at the disposal of the researches by which the use of sophisticated quantitative methods in examining interbank networks is possible.

Interpersonal lending between the members of small communities is also a widely researched topic in the literature, but for the lack of detailed databases, the analyses are performed mostly with qualitative methods. Informal lending has been examined in several developing countries of the world, for example, in China *(Allen–Qian–Qian [2005]; Allen–Qian–Xie [2019])*, India *(Banerjee–Duflo [2011]; Tsai [2004])*, Vietnam *(Barslund–Tarp [2008])*, Thailand *(Karaivanov–Kessler [2018])*, Ethiopia *(Caudell–Rotolo–Grima [2015])* or in Kyrgyzstan *(Angioloni et al. [2018])*.

Considering the person of the lender and the borrower, informal lending comes up in the academic literature in many forms. The loan, for example, can be extended by a small company to an employee working there *(Xie–Yang–Zong [2019])*, by private persons to small businesses *(Selmier [2018])*, and by private persons to each other *(Hu [2007])*. This chapter will expressly focus on liquidity loans between private persons (or households, in a wider sense).

*Gosztonyi [2017] and [2018]* examined lending between households in an underdeveloped small Hungarian village with participatory action research, to which questionnaires and interviews were added. The main peculiarity of the research is that the author lived in the researched village for a year and a half. During this time, he established an intimate trust relationship with the locals and created a rich and well-documented interpersonal loan database.

*Table 22:*

Comparison of the interpersonal loan and the unsecured interbank deposit markets

| Viewpoints | Interpersonal loan market | Interbank deposit market |
|---|---|---|
| **Features of the entire market** | | |
| Asymmetric information | present | present |
| Risk management | they continuously monitor each other (informal monitoring), ratings, partner limits | developed monitoring and early warning systems, ratings, partner limits |
| Key motivation of the transactions | liquidity management | liquidity management |
| Type of the managed risk | asymmetric, focus is on obtaining funds | asymmetric, focus is on obtaining funds |
| Presence of intermediation, hierarchy | present, they lend and borrow at the same time | present, they lend and borrow at the same time |
| Key motivation of the intermediation | operation of an insurance scheme based on reciprocity[73] | operation of an insurance scheme based on reciprocity |
| Rules on the market | informal rules | detailed, formal rules |
| Reporting obligation | none | regular, daily |
| **Features of transactions** | | |
| Collateral behind the credit transaction | there is no financial collateral, there is social capital | there is no financial collateral, there is social capital |
| Transaction size | few thousand forints | billions of forints |
| Frequency of liquidity demand | typically in every two weeks or monthly | daily or more frequent |
| Typical maturity | 2 weeks | 1 day |
| Interest rate | none | low |
| **Participants** | | |
| Competence of the participants | uneducated, disadvantaged individuals | highly qualified, professional traders |
| Criteria of partner selection | individual preferences | other factors (e.g. interest rate) added to individual preferences |
| Geographical location | the participants physically live nearby | the participants are physically far from each other |
| Emotional impacts | borrowing is accompanied by a sense of shame, giving feels good | none |

*Source: own edition based on Gosztonyi [2018].*

[73] For a detailed explanation of this, see Sub-chapter 6.5 below.

Based on *Gosztonyi [2017] és [2018]* descriptions and results, the market of interpersonal loans can be compared with the interbank market. We were surprised to experience that the two markets were similar in several aspects. Table 22 presents the comparison of the two markets from different points of view. We highlighted the similarities (or rather more similar features) in blue and showed the differences in red.

Information asymmetry, i.e. the difficulty of the lender to judge the repayment ability and willingness of the partner in real-time, is present in both markets. This raises the possibility of adverse selection and moral hazard in both cases, which the participants on the interbank market attempt to mitigate with the operation of developed monitoring and early warning systems.[74] Based on the interviews, people on the interpersonal loan market also watch each other continuously, and they run a surprisingly well-developed informal monitoring "system".

The key motivation of the loans is liquidity management in both markets. The banks have the regulatory obligation (and it is also their elementary interest) not to have negative balances at VIBER closure, while the households attempt to have the funds necessary to cover their expenses.

It is also a characteristic of both markets that the participants run asymmetric risks in the sense that obtaining funds is the biggest problem; a smaller difference is that while the placement of liquidity surplus is also a consideration on the interbank market, it is not the key motivation of the lending on the interpersonal market.

One of the key motivations of intermediation[75] is to maintain an insurance system based on reciprocity, where helping the participant presently struggling with liquidity difficulties is the interest of the entire market. As the lender and borrower roles change often, most of the participants try to help because later they may suffer from the lack of liquidity.

The main difference between the two markets is that while the interbank market operates under detailed, formal (written) rules and protocols, the interpersonal market is entirely informal, often without any trace of the transactions in writing. Related to this, the

[74] On the basis of interviews with portfolio managers and dealers, *Szűcs–Váradi [2014]* found that Hungarian market players generally prefer simpler methods and indicators when managing risks.

[75] The main motivations of participants acting as intermediaries are explored in more detail in Sub-chapter 6.5 below.

participants on the interbank market report their transactions to MNB in detail every day, while there is no central participant on the interpersonal market to collect data, and therefore we may not even receive information on every transaction.[76]

Turning our attention from the market to the features of individual transactions, there is no financial collateral behind the transaction on either market. Although they are unsecured in the traditional sense, these transactions in reality, in our opinion, have significant security backing them, which is social capital. *Putnam [1993]* identifies social capital with community networks and trust. For the lack of financial collateral, trust relationships in themselves are capable of functioning as collateral on both markets when granting a loan *(Portes–Landolt [2000])*.

The size of the transactions is orders of magnitude larger on the interbank market, and demand for liquidity may occur far more frequently or even several times a day (while it generally occurs every two weeks or monthly on the interpersonal market). The typical maturity on the unsecured interbank deposit market is 1 day, while it is 2 weeks on the interpersonal market. The transactions are always interest-free on the latter, while there is interest on the interbank market, but its size is small. In Chapter 5, I proved with calculations that the banks did not perform their mediation activity in the hope of profit.

Regarding the participants of the markets, there are almost only differences there. On the interbank market, highly qualified professionals manage liquidity, while the participants on the interpersonal market are mostly uneducated *(Gosztonyi [2018])*. Individual preferences (*preferential lending*) play a role in the search for partners on both markets; however, the interest rate generally makes the decision among the requested offers on the interbank market. Trading on the interbank market is performed virtually (through online interface or occasionally by telephone), therefore the distance between the participants does not matter, while the participants on the interpersonal market transact personally and live close to each other in general.

The issue of emotions related to lending is a consideration of outstanding importance. This is not an issue on the interbank market; the traders do not mind the entity from which they take out a loan or to which they grant one. As opposed to this, interviews confirmed

[76] We will see later that the density of the interpersonal network is much lower than that of the unsecured interbank market. One of its reasons could be that we are not aware of every transaction.

that borrowing is accompanied by a sense of shame and giving feels good on the interpersonal market.

Based on Table 22, we can say that while several differences are spotted at the levels of the transactions and the participants, the markets are very similar. It makes sense (and it is also relevant) to compare the key network measures and structures of the interpersonal loan and the unsecured interbank deposit markets.

## 6.3. Database used for the analysis

The participatory action research took place in the period between June 2014 and September 2015, during which financial survival strategies of low-income families were investigated in a small rural village in a disadvantaged region of Hungary *(Gosztonyi [2018])*. The research included 171 structured surveys related to 159 households covering nearly two thirds of the population representative for the whole village.

The questions of the surveys were categorised into two main blocks. The first part asked 13 network-oriented questions concerning (1) search for employment, (2) receiving information and giving advice, (3) housework and voluntary common work, (4) neighbours and friends, (5) smaller and bigger loans, (6) mental help, (7) family and relatives. The second part of the questionnaire covered the incomes and expenses of the household and the local frameworks of borrowing and lending.

Based on answers given to the (5) part of the first block, we analysed the interpersonal loans with the following questions:

*Q9:* To whom do you *lend* a smaller amount (1-2 thousand forints, transportation, food)?

*Q10:* From whom do you *borrow* a smaller amount (1-2 thousand forints, transportation, food)?

*Q11:* From whom do you *borrow* a larger amount (20-30 thousand forints)?

As the survey was conducted between 15 May and 24 June 2015, the relevant lending period is the period between March and May 2015.

We transformed individuals into households based on their addresses, and we considered only the households having at least one link to the others. We defined a common category for households outside the village having 38 in-degrees (borrowing) and 0 out-degrees (lending) corresponding to neighbouring villages (70%), other cities in the county (25%), and outside the county (5%). However, for the sake of consistency, these extra nodes not participating in the survey were excluded from the analysis. As *Q9* had a different direction (*lending*) than *Q2* and *Q3* (*borrowing*), when aggregating data, first, we transposed the adjacency matrix of *Q9*, then took the maximal value of the three adjacency matrices corresponding to *Q9*, *Q10*, and *Q11*. Thus, we got the intra-village network represented by an aggregate adjacency matrix[77] $\boldsymbol{H_{ij}}$ for 159 households (nodes) and 283 transactions (edges) between them.

We used the detailed interbank transaction database presented in Section 3.1 in connection with the unsecured interbank deposit market. Aggregating all reported transactions initiated in March, April, and May of 2015, we produced an adjacency matrix for the interbank deposit market $\boldsymbol{B_{ij}}$ (containing 1 if bank $i$ borrows from bank $j$, and zero otherwise) which comprehends 36 banks (nodes) and 198 transactions (edges).

As a result, we have two adjacency matrices representing the interpersonal ($\boldsymbol{H_{ij}}$), and interbank lending ($\boldsymbol{B_{ij}}$) markets, which are parallel snapshots reflecting comparable market structures.

*Table 23:*

Typical loan conditions

| | **Interpersonal loan market** | **Interbank deposit market** |
|---|---|---|
| **Amount** | 2 thousand HUF | 2 billion HUF* |
| **Maturity** | 2 weeks | 1 day* |
| **Interest rate** | 0% | 1.8%* |

* Mode of the distribution

*Source: own edition based on participatory action research, interviews and MNB data.*

Table 23 shows the typical loan conditions in the different markets. In the interpersonal market, loan amounts are one million times lower, maturities go typically until the next month, and there is no interest rate at all. The following section contains the detailed network related comparisons.

[77] containing 1 if household $i$ borrows from household $j$, and zero otherwise

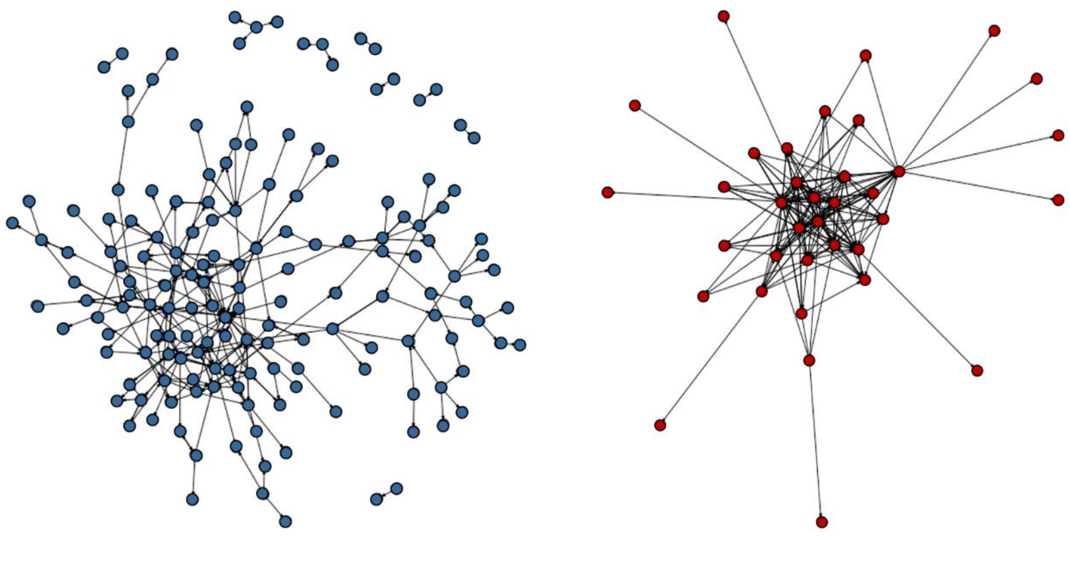
## 6.4. Comparative network analysis

To the best of our knowledge, except for the previously mentioned study by *Caudell–Rotolo–Grima [2015]*, there is no previous study to describe the network structure of informal interpersonal lending among poor people. However, the network structure of the formal capital markets – as I presented it in the previous chapters – is an intensively researched area.

Figure 45 shows the directed networks of interpersonal and interbank credit markets. The circles indicate the different market participants, and the arrows show the credit transactions (connections) between them. Compared to the interbank network, the interpersonal network contains more nodes and edges and is not fully connected. As mentioned before, interpersonal data were survey based on voluntary disclosure, while the mandatory daily reports ensure the completeness of existing connections on the interbank market. There is a significant density difference between the two networks (the density of the interbank network is much higher), which may have been (partly) explained by the differences in data collection.

*Figure 45:*

Networks of interpersonal and interbank lending markets (March-May 2015)



Interpersonal loan market Interbank deposit market

*Source: own edition.*

Although both networks exhibit a core-periphery structure at first sight, the interpersonal network seems less concentrated. The central lender in the interpersonal network is the mayor of the village who lends needy households out of his pocket regularly

(19 households in this period), and there is a central borrower, a poor Roma family (having 11 in-degrees). In the interbank network, there are no central points like these (the Central Bank of Hungary is serving as the lender of last resort, but it is not included in the network), here, an exclusive club of the biggest and most reliable banks plays the central role in the middle of the graph composed of the most attractive trading partners for the others *(Allen–Babus [2008]; Craig–von Peter [2014]; Veld–Leij–Hommes [2020]; Fricke–Lux [2015])*.

In the next part, we will first present the basic characteristics of the two networks and analyse the structure of the network more deeply with the help of the degree distributions and the clustering coefficients.

### 6.4.1. Basic network characteristics

Table 24 summarises the basic characteristics of the two networks. Based on the comparison, it can be stated in general that the interpersonal network has more edges, but it is 16 times less dense than the interbank market. Calculating basic reciprocity and transitivity measures, the interbank market seems more interlinked.

*Table 24:*

Basic network characteristics of interpersonal and interbank lending markets

| | Interpersonal loan market | Interbank deposit market |
|---|---|---|
| Nodes | 159 | 36 |
| Edges | 283 | 198 |
| Density* | 0.01 | 0.16 |
| Reciprocity** | 0.13 | 0.35 |
| Transitivity*** | 0.13 | 0.56 |
| Reciprocity / Density | 11.32 | 2.19 |
| Transitivity / Density | 11.33 | 3.50 |
| Diameter | 15 | 5 |
| Average path | 5.92 | 2.04 |
| Average degree | 1.97 | 5.5 |

[*] Number of actual edges divided by the number of potential edges.

[**] Probability that two connected nodes are linked in both directions (in a directed graph).

[***] Probability that two neighbours of a given node are also neighbours.

*Source: own edition based on participatory action research, interviews and MNB data.*

However, it is easy to see that larger density leads to proportionally larger reciprocity and transitivity; so, larger reciprocity and transitivity of the interbank market can be due to its larger density. We adjust for this difference by dividing reciprocity and transitivity by density. Measured by this ratio, the interpersonal lending market is significantly more reciprocal and transitive, reflecting the importance of social capital within the local community. The interpersonal network is also more extended, the diameter (the distance between the two farthest nodes in the largest component) is 15 (as opposed to which it is 5 on the interbank market), and the average path length is around 6 (as opposed to approx. 2), which is a typical value in social networks like internet, e-mail, and scientific co-authorship *(Barabási [2016], Table 3.2.).*

In directed graphs, it is worth analysing out- (lending) and in- (borrowing) degrees separately. The results are shown in Table 25.

*Table 25:*

Analysis of in-degrees and out-degrees

| | Interpersonal loan market | Interbank deposit market |
|---|---|---|
| Maximum of in-degrees (borrowing) | 11 | 24 |
| Maximum of out-degrees (lending) | 19 | 14 |
| HHI of in-degrees (borrowing) | 144 | 707 |
| HHI of out-degrees (lending) | 756 | 460 |
| Mode of in-degrees | 0 | 0 |
| Mode of out-degrees | 1 | 1 |
| Median of in-degrees | 1 | 2 |
| Median of out-degrees | 1 | 4 |

*Source: own edition based on participatory action research, interviews and MNB data.*

The central lender plays the dominant role on the interpersonal market (highest out-degree = 19), while the borrower plays the dominant role on the interbank market (in-degree = 24). The HHI (Herfindahl–Hirschman index) on the interpersonal loan market shows a much higher value for the lenders than for the borrowers, meaning that proportionally few households finance many borrowers, while the opposite is true on the interbank market.

One possible explanation is that available liquidity is tight on the interpersonal loan market, which means that only a few households can afford lending to others. In contrast, in the previous chapters, I pointed out that the Hungarian unsecured interbank deposit market typically had a structural liquidity surplus. Liquidity available in the system is sufficient in normal market circumstances (not including crisis situations), but due to the significant size of the partner risk, the lenders prefer a small group of large, reliable and transparent borrowers when they place their liquidity surplus.

The two markets are similar because most of the market participants do not extend loans at all, and on the other side, the majority of them borrow from one single partner. The difference of the medians may point to the degree distribution on the interpersonal loan market being less oblique, which means that nodes of higher degrees are less frequent.

We categorize nodes into three disjoint groups: *(1) borrowers* who only borrow; *(2) lenders* who only lend; and *(3) intermediaries* who borrow and lend at the same time. The shares of different players are presented in Table 26 for both markets.

*Table 26:*

Share of different types of players

| | Interpersonal loan market | | Interbank deposit market | |
|---|---|---|---|---|
| | **number** | **share** | **number** | **share** |
| Borrowers | 25 | 16% | 2 | 6% |
| Lenders | 58 | 36% | 12 | 33% |
| Intermediaries | 76 | 48% | 22 | 61% |
| **Sum** | **159** | **100%** | **36** | **100%** |

*Source: own edition based on participatory action research, interviews and MNB data*.

In both markets, most players are intermediaries. Borrowers are the fewest in number (16% and 6%, respectively), which shows the insurance nature of this market. If a player only takes out loans, it cannot work in the long run because, after a while, that player will find it more difficult to get funds. On the other side, the motivation for participants who only lend funds is to ensure that they can access funds later, should they be struggling with a lack of liquidity. The similar proportions reflect the fact that, in line with the results in Table 24, the internal structures of the two markets are very close to each other.

### 6.4.2. Existence of hierarchy in the examined networks

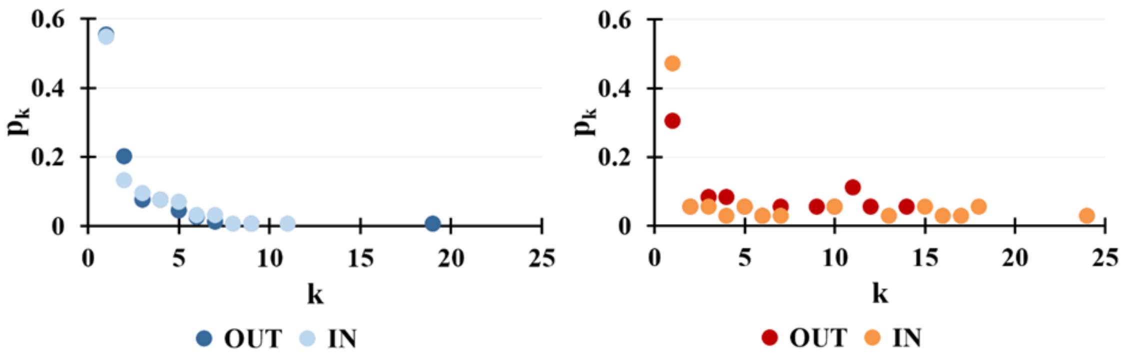
Previously, in Section 4.1, I presented in detail the three fundamental models known in network science: random (Erdős-Rényi), scale-free (Barabási-Albert) and hierarchical networks. The clustering coefficient is independent of the degree in the former two cases, while the clustering coefficient decreases inversely proportional to the increase of the degree (graph on the right in Figure 28).

It means that in a hierarchical structure, central players with more degrees tend to interconnect those ones who are not communicating with each other directly.

Figure 46 presents degree distributions where out- and in-degrees ($k$) of different vertices are on the *x* axis and their frequency ($p_k$) is on the *y* axis.

*Figure 46:*

Degree distributions of interpersonal and interbank lending markets



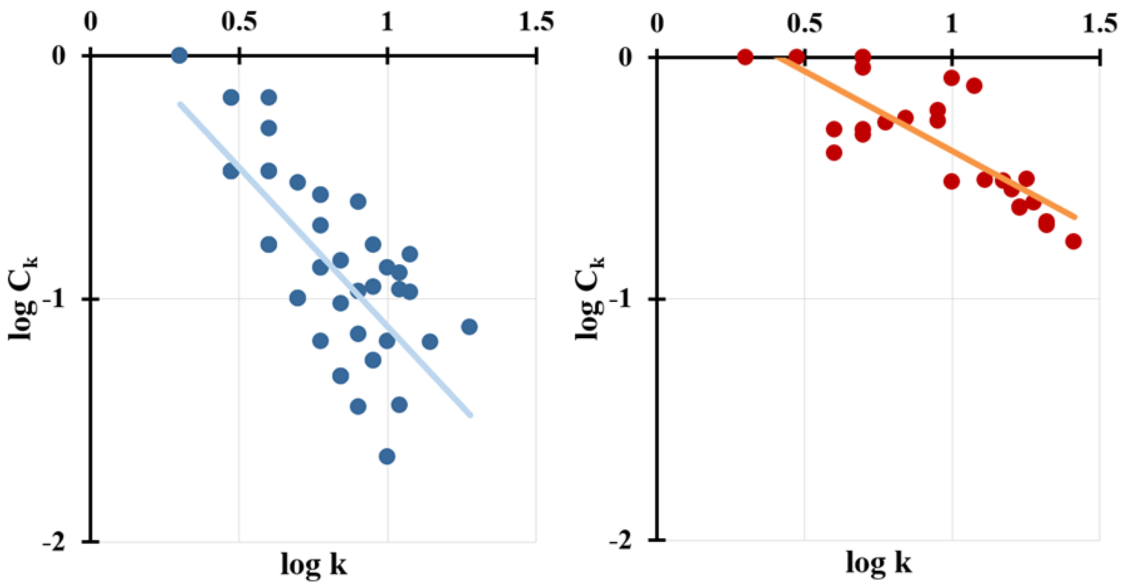

Interpersonal loan market Interbank deposit market

*Source: own edition.*

The charts show that out- and in-degrees tend to be lower and less disperse in the interpersonal market.

*Figure 47:*

Clustering coefficients and degrees on a log-log scale




Interpersonal loan market Interbank deposit market

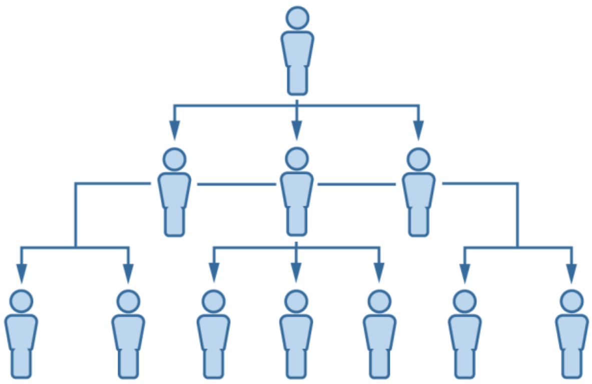
*Source: own edition.*

Calculating local clustering coefficients for all the vertices and plotting them against the total degree on a log-log scale, we get Figure 47. The point clouds and the linear trends fitted on them show that the connection between the clustering coefficient and the degree is closer to the horizontal on the unsecured interbank deposit market. The interpersonal market is more hierarchical as the slopes of the best-fitted lines are -1.3 (interpersonal) and -0.7 (interbank).[78]

Figure 48 may help to understand the phenomenon. In a hierarchical organisation, higher-level players are interlinked with more and more players (all their inferiors and their counterparts), and they tend to interlink separate hubs. For example, in a large corporation, employees in the marketing and the finance departments do not communicate directly, only via their directors connected by the CEO. The more this feature holds for a network, the more it is considered as hierarchical.

*Figure 48:*

Schematic chart of a hierarchical organisation



*Source: own edition.*

In the case of the interpersonal network we investigate, hubs are mainly constituted by families (for example, cousins, grandparents living on different addresses) tending to communicate through their central market participant, for example, by active and caring housewives or godfathers having lots of connections both within the family and outside. Friendship and neighbourhood may also shape the hierarchical structure seen in Figure 47.

[78] Note that the difference in densities cannot explain this result because densities influence both clustering coefficients and degrees proportionally.

Thus, the similarity of the examined unsecured credit markets is verified by examining them from several aspects, so hypothesis *H6* (as formulated in the introduction to this chapter) can be rejected.

## 6.5. The main motivation of intermediaries in interpersonal lending markets

As previously presented, as in interbank markets, a large number of intermediaries are present also in the informal lending network of those living in underdeveloped regions with such intermediaries among them who – in addition to managing their own liquidity – are willing to step in between two players not directly in contact with each other. In addition, poor households tend to lend funds even if consequently they themselves may have to borrow funds up until the end of the month. In the following, we seek an answer to the question: what can the main motivation be for intermediaries in the interpersonal lending market?

As mentioned earlier for interbank markets, three possible motivations can be imagined: (1) making profits through intermediation; (2) providing selfless, philanthropic assistance; or (3) risk sharing based on reciprocity.

Chapter 5 of my thesis presents that – contrary to a statement often recurring in the academic literature – the Hungarian unsecured interbank market is not driven by a pursuit of profits. There, with for-profit institutions present, philanthropy, or selfless help to another bank by taking risks, is out of the question, so I came to the conclusion that intermediaries in interbank markets carry out their activities in order to maintain a reciprocal insurance scheme in the spirit of risk sharing.

Turning to the network of interpersonal loans of the disadvantaged, profit as a possible motivation can immediately be ruled out, as transactions are interest-free in all cases. However, when examining sentient individuals and their communities, philanthropy may be raised as the main driving force, where the richer selflessly help their fellow human beings in a more difficult situation.

*Caudell–Rotolo–Grima [2015]* studied the effects of exogenous shocks (weather) on the network of informal loans of the Sidama ethnic group in the South-Western part of Ethiopia. The authors found that the main motivation for lending is altruism, where the rich benevolently help the poor.

In contrast to a complete anonymity of the interbank market, thanks to questionnaires and interviews in the interpersonal lending market, detailed information is available not only on lending relations, but also on the main parameters of individual households. This information and sociodemographic characteristics can help identify the main motivation for interpersonal intermediation.

Examining information available on households that make up the nodes of the interpersonal network, we came to the conclusion that the most important differentiator of households in terms of lending is their income situation and ethnicity.

As a first step, we divided households into poor households and richer ones[79]. For this, the per capita income for each household was calculated according to OECD guidelines *(OECD [1982])*, by assigning different weight factors to each family member (a weight factor of 1 to the primary bread-earner adult; 0.7 to any additional employed family member; and 0.5 to any unemployed adult or child in the family).

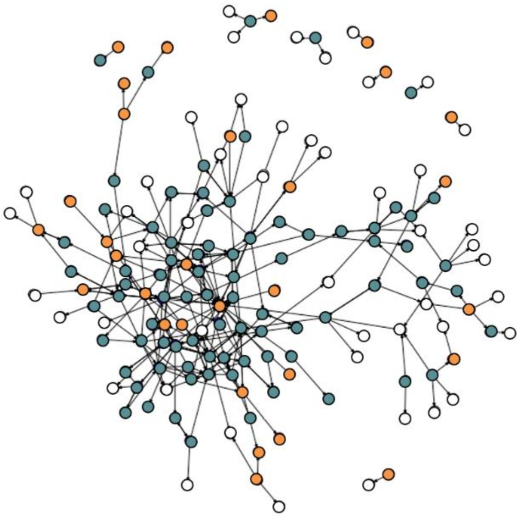
The relative poverty threshold in Hungary in 2015 was approximately HUF 70,000. Households with a per capita income below this relative poverty threshold were classified as poor, and those with higher incomes were considered (relatively) rich. In the village examined, 75% of households fell into the former group, and only 25% lived above the poverty threshold, which illustrated the extremely disadvantageous situation of those living there.

Figure 49 shows the positions of poor households (blue) and rich ones (orange) in the interpersonal lending market (no information was available on the income situation for households marked with empty circles).

[79] It is worth noting here that the category "rich" refers to the fact that a given household has an income above the relative poverty threshold.

*Figure 49:*

Network of interpersonal loans of households, broken down into poor households (blue), rich ones (orange), and those with unknown income (empty circles)



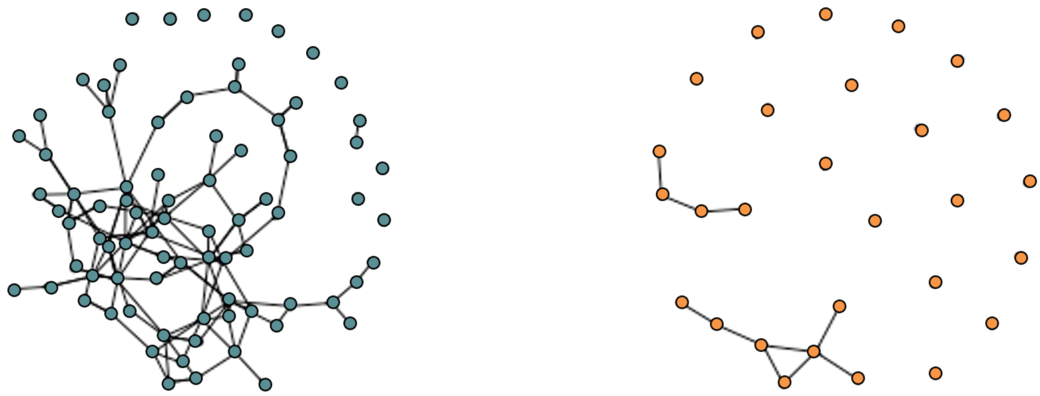
*Source: own edition.*

Figure 49 shows that central participants with many contacts in the network typically live below the relative poverty threshold (except for the central participant who has the most contacts, who is the mayor of the village), and these – primarily poor – central households maintain a much denser network of contacts than the richer ones.

In Figure 50, in order to illustrate the phenomenon more clearly, lending relations between the poor (left graph) are separated from those between the rich (right graph).

*Figure 50:*

Sub-networks of poor households (blue) and rich ones (orange)



*Source: own edition.*

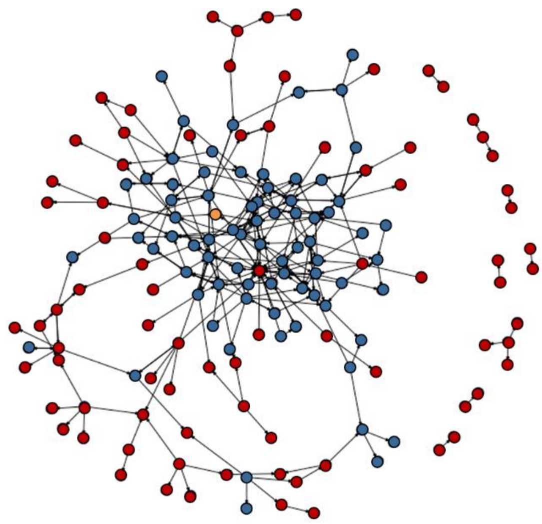
Thus, it can be established that, while lending activities are low among richer households, poor families develop a dense system of informal lending relationships, helping each other in dealing with liquidity shocks. Central participants carrying out intermediation activities are typically those with incomes below the relative poverty threshold, and poor households provide the majority of loans to each other. Loans from the rich to the poor are rare; so it can be stated that the main motivation for intermediation is not selfless, philanthropic assistance, but – like in the interbank market – risk sharing. Thus, exciting results are obtained, contradicting the study of *Caudell–Rotolo–Grima [2015]*, on the basis of which, the last hypothesis, *H7* is rejected.

Households in the most challenging situations operate an insurance scheme based on reciprocal assistance. As part of the community, they are willing to lend, knowing that, should they find themselves in a difficult financial situation later, they can count on the support of their peers.

In addition to the income situation of households, the network of interpersonal loans is worth examining based on another interesting dimension: ethnic composition. In the questionnaire survey, 51.9% of the surveyed households declared themselves to be Roma and 47.9% to be non-Roma (one household was of mixed ethnicity). Roma households are typically more populous than average and more likely to live below the relative poverty threshold. Figure 51 shows the ethnic structure of the network of interpersonal loans.

*Figure 51:*

Network of loans of Roma households (blue), non-Roma ones (red) and mixed ones (orange)

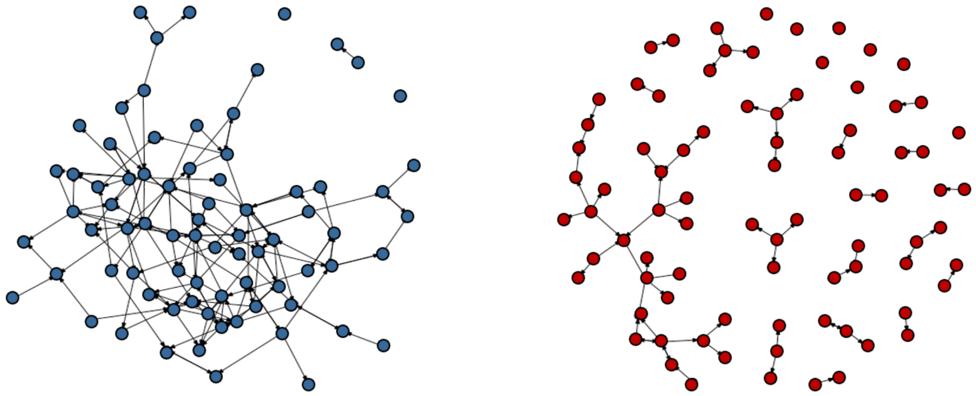


*Source: own edition.*

As Figure 51 clearly illustrates, the network of informal loans of the Roma is extremely densely intertwined with connections, while the sub-network of the non-Roma is sparse and disintegrating. Roma households, therefore, play a key role in maintaining the informal credit market in the village and in managing liquidity shocks collectively.

*Figure 52:*

Sub-networks of Roma households (blue) and non-Roma ones (red)



*Source: own edition.*

The sub-networks in Figure 52 show that vulnerable Roma households, mostly living in deep poverty, effectively operate a dense "safety net" based on risk sharing and help each other with liquidity management. The Roma have a significant amount of social capital through close family ties, friendships and neighbourhood relations.

Overall, therefore, it can be established that similarly to the interbank market, a strong presence of intermediation activities is found also in the examined interpersonal lending market, where intermediaries are typically poor, Roma households, whose main motivation is risk sharing. Roma households, mostly living below the relative poverty threshold, operate an insurance scheme based on reciprocity to deal with extreme liquidity shocks they may face, which is an "ecosystem" where intermediaries represent the essential links of the chain.

## 6.6. Further possible research directions

To conclude this chapter, some exciting further research directions are highlighted to shed light, to my hopes, on some further aspects of unsecured lending networks. In addition to the interpersonal loan market, the described connections and patterns on other analogue, unsecured credit markets would also be worth examining in the future.

In Section 5.1, I mentioned LendingClub and Zopa, the two largest and best-known peer-to-peer (*P2P*) lending platforms as examples. The fundamental idea of P2P lending is that by pairing the borrowers and lenders, loans can be extended to the borrowers at low operating costs at interest rates better than the conditions offered by the banks on the one side, and higher profit can be promised to the lenders on the other side.

Considering its type – similarly to the interbank and the above presented interpersonal loans –, the market of P2P loans is also unsecured, but the preparation and analysis of the entire network of the market is unfortunately not possible. The reason is that data are only available on the borrowers (anonymously) and on the extended loans on these platforms. In the absence of defining the lenders (the partner), the network of this credit market cannot be prepared.

The other problem regarding comparability is that the purpose of the lenders on the aforementioned P2P credit markets is not liquidity management, and they are most likely motivated by the profit, they consider the granted loan a profitable investment. There is no “ecosystem” providing liquidity based on reciprocity (due to for example, anonymity), as the market of interbank loans presented in my thesis or the market of the interbank loans of the underdeveloped rural settlement. Due to the investor approach, the lenders on the market of P2P credits strive for higher diversification (the spreading of risks); they perform a huge number of transactions while they typically grant low loan amounts to the different applicants. In the LendingClub, for example, the minimum loan amount to extend is $ 25, and the website encourages every investor to establish a granular portfolio *(lendingclub.com [2021])*, which, due to its character – even if a complete transaction database was available –, would result in a type of network different, for example, from the network of the unsecured interbank market.

Another analogue “market” to be examined is the network of – typically short-term and unsecured – debts between companies. These data are not available publicly; the supplier relationship system of the Hungarian businesses could be built from the regular VAT returns managed by the National Tax and Customs Administration of Hungary.

*Borsos–Mérő [2020]* modelled the spreading of shocks in the interbank market network in their study based on this database with real economy feedbacks added. They examined these feedbacks through the supplier relationship system of companies, to which, based on the VAT returns, they took every commercial relationship between Hungarian businesses with tax content exceeding annual € 3000 into account for the period between 2014 and 2017.

*Borsos–Stancsics [2020]* prepared the descriptive type analysis of the same supplier network database between companies (and added the ownership connections of the businesses), in which they primarily examined the spreading mechanism of contagion in the network and separated different homogeneous economic groups from each other.

The first – and only – ones to have access to NAV data for research purposes to date are the *Borsos–Mérő [2020]* and *Borsos–Stancsics [2020]* authors. The use of the database established and cleaned by them for network science purposes offers several unexploited opportunities, in my opinion.

# 7. Possibilities for utilising research findings

As I analysed networks of markets systematically, from a bird's eye view in my thesis, the results presented could be most beneficial for regulatory authorities. I examined two separate, yet in many respects similar networks: the unsecured interbank deposit market and the interpersonal loan market of disadvantaged households. Accordingly, I formulate my policy recommendations in relation to these two groups in this section.

## 7.1. Recommendations in connection with the interpersonal loan market

First, the results of a European study involving disadvantaged individuals are presented to complement the results discussed above on informal interpersonal loan markets, thus providing an opportunity to formulate some relevant policy recommendations.

In 2011, a project called SIMS *(Social Innovation and Mutual Learning on Micro-Saving in Europe)* was launched with the support, among others, of the European Commission, aimed at encouraging disadvantaged low-income individuals to make savings and to improve their financial awareness *(Guisse–Gilles [2013])*.

From Hungary, a total of 239, mostly Roma participants started the project, and 123 of them completed it. Now, by connecting to the interpersonal network research presented above, I will describe the operation of the programme in Hungary based *Aldehi–Gilles–Bernat [2013]* by presenting the main lessons learned from it.

Three savings programmes were launched to encourage disadvantaged people to save regularly and increase their financial awareness. Two of the programmes were collective savings programmes, with participants establishing a fund of joint savings and deciding together who can borrow from it and in what order.

Under the third programme, individual savings accounts (*Individual Development Accounts, IDA)* had been opened for participants. Mentors asked everyone first to determine an amount they could set aside each month. The essence of the savings scheme was that the amount of savings was doubled for those who had been able to save a pre-determined amount (which was at least HUF 2,000) on a monthly basis for at least eight months during the ten months of the experiment. In addition, participants were also required to attend related training on finance and energy-saving opportunities. Now I summarise the results of this experiment that are important from the aspect of my thesis.

Even the recruitment of applicants had been difficult, as it had been challenging to convince people that the programme was real and reliable. Building trust was a key issue for achieving that participants join the programme and stay in it. A crucial factor in this was that mentors had long been living as part of the local community in disadvantaged settlements, and they had been known to participants. They helped dispel participants' doubts and find solutions to their problems by maintaining their motivation throughout the programme.

Despite their efforts, the churn rate in the IDA programme (based on individuals savings) was extremely high, 67%, while a much lower proportion of participants, only 5% and 23%, respectively, quitted prematurely the other two community-type programmes.

By the end of the programme, there was a significant increase in the proportion of those who had a bank account and a savings account; however, they could not become more conscious in planning their expenditures. Only 6% of them monitored their bank accounts regularly, and the proportion of those who prepared a detailed budget for themselves at the end of the programme was even lower, although this was an integral part of the training.

In the case of collective schemes, participants were ready to take out loans and to provide loans. The results showed that saving and borrowing can be effectively combined in a community where people trust each other. The secret of success is to be found in collectivity: in an established community of trust, members of the community are willing to help each other, because in this way they will also have someone to rely on should they get into trouble later.

Although the individual savings account (IDA) product offered by far the most favourable return, the highest drop-out rate was still documented. One of the main reasons for this was that, unlike the other schemes, it was a program for individuals, where participants were not motivated by a community.

The other problem was that the annualised return of more than 100% on accumulated savings was only available if a pre-determined amount was set aside for 8 months. In many cases, the pre-determined goals were too ambitious, which a significant number of participants could not keep up with.

The third reason for the failure of the IDA program was that it offered no possibility for providing credits to partners who were experiencing unexpected financial difficulties.

The last problem was the rigidity of the product. In theory, participants could not have access to their accumulated savings before the end of the program, unless by quitting from it. Please note that the original rules were relaxed by some of the mentors in consultation with the organisers (it was possible to withdraw money from the account a few times, or to omit a month, or to change the monthly savings amount to suit the needs of a household). Without such easing, the dropout rate would probably have been higher than 67% *(Aldehi–Gilles–Bernat [2013])*.

***Social capital is more valuable than the most promising individual savings product***

Based on the SIMS experiment presented above, two important recommendations can be made. One of them is that, among the disadvantaged Roma, belonging to the community is more important than individual interest. If someone saves money, they prefer to lend it to an acquaintance, thus contributing to the operation of the previously mentioned reciprocal insurance scheme, because in this way they can, as part of the community, count on the help of the community, should a subsequent liquidity shock arise. This "financial safety net" is more valuable to most poor people than an individual savings product with a risk-free return of more than 100% per annum (approximately HUF 16,000). In other words, it may not be worthwhile to strongly encourage people living in deep poverty to save individually; the effectiveness of programs aiming for that is likely to be low *(Berlinger [2020])*.

***Disadvantaged people can successfully manage liquidity shocks they encounter, so the path leading to their rise is not primarily through the development of their financial awareness***

Another recommendation that is worth considering is related to financial awareness. One of the most common development paths in lagging regions is to improve the financial awareness of those living in deep poverty, to show them the importance of savings and to increase their financial literacy *(Klapper–Lusardi–van Oudheusden [2015]; Grohmann–Klühs–Menkhoff [2018])*. *Gosztonyi [2018]* describes the poor as "the jugglers of money" who masterfully manage their liquidity shocks and operate their versatile informal risk management systems in a very conscious way. In other words, the reason for their disadvantaged status is not to be found primarily in their lack of financial knowledge; it would be worthwhile for policy makers to take this into account when formulating development paths.

## 7.2. Recommendations concerning the interbank market

Interbank market regulations are sharply separated (in academic literature and also by regulatory authorities) into a macro-prudential (systemic) and a micro-prudential approach (related to individual credit institutions, separately). In connection with the former, lightning-fast contagion following the bankruptcy of Lehman Brothers in 2008 and the ensuing global financial crisis highlighted the importance of managing systemic risk.

***The new type of weighted coreness measure allows a better and more robust classification of core and peripheral banks than earlier***

The Basel III regulation – by requiring the identification of systemically important financial institutions – officially made systemic risk part of international banking regulations. Systemically important players are selected based on various measures, of which coreness measure is discussed in detail in my thesis. My first recommendation is that, in light of the deficiencies of the current coreness measure, it is worth considering the application of its modified version presented in Sub-chapter 4.2 to identify central (core) banks. Using the new weighted coreness measure, a better classification of core and peripheral banks can be achieved than earlier.

***Strict individual liquidity requirements for credit institutions may result in a less resilient interbank market***

Examining the micro-prudential side of banking regulations, the new system of requirements having been introduced since the global crisis of 2008 raises the issue of over-regulation. Since the entry into force of Basel III, banks have been facing very strict liquidity rules, obliging players to maintain their own liquidity positions flawlessly. One of the most important elements of the new rules is the *Liquidity Coverage Ratio* (LCR), which requires institutions to have sufficient liquid assets of high quality to cover a 30-day outflow of funds following a severe stress situation *(BCBS [2013a])*. Thereby, regulators oblige each bank individually to manage its liquidity continuously and rigorously.

As a result of current micro-prudential regulations, which are stricter than the previous ones, banks are turning inwards and primarily focus on their own liquidity positions, having less room for manoeuvre in providing temporary support to other partner banks, a fact deteriorating the efficiency of the interbank market. Individual-level (micro-prudential) regulations may therefore be at odds with ensuring systemic (macro-prudential) liquidity *(Berlinger [2020])*. My second recommendation is that the current regulation, which has a strong focus on liquidity management at the individual level, should be reviewed from that aspect in order to balance micro- and macro-prudential interests.

Based on data from the 27 largest Polish banks, *Smaga et al. [2018]* examined the effects of simulated endogenous shocks on a dynamically changing interbank market network. Their results confirm the line of thought just presented. They established that the interbank market has a kind of stabilising function, which is the weakest when banks have to meet all regulatory requirements. Measures regulating banks' individual liquidity are not able to stabilise the interbank market at the systemic level. It is common for regulators to decide on easing individual liquidity requirements in response to a crisis, but the authors argue that these tools should rather be used as preventive tools to forestall the outbreak of a systemic crisis.

***The introduction of G-SIB scores restricts Globally Significant Core Banks in their intermediation activities, a fact that severely weakens the efficiency of interbank markets***

Another new element of Basel III is the inclusion of the macro-prudential approach in banking regulations, which requires that systemically important banks, the failure of which could cause serious damage to financial markets, must receive special treatment. According to the Basel principles laid down in 2013, the Financial Stability Board designates *Global Systemically Important Banks (G-SIBs)* annually *(BCBS [2013b])*.

Now, 30 such institutions have been identified, facing additional prudential requirements and rigorous supervision. First, the Financial Stability Board sets up subgroups within G-SIBs, where banks are required to maintain an additional capital buffer ranging from 1% to 3.5%, depending on their respective ratings.[80] Secondly, global systemically important banks must meet standards concerning *Total Loss-absorbing Capacity (TLAC)*[81]. Since the beginning of January 2019, they have been required to possess TLAC

[80] Currently, the highest capital buffer rate is 2% and there are three banks in this subgroup, Citigroup, HSBC and JP Morgan Chase.

[81] this is a requirement related to capital and such funds that may be involved in case of resolution

instruments to be involved in a potential resolution corresponding to 16% of the value of their risk-weighted assets, a ratio to be increased to 18% from 2022 *(Kovács–Marsi (ed.) [2018])*. Thirdly, G-SIBs are faced with higher supervisory rigour concerning their risk management functions and internal controls *(FSB [2020])*.

G-SIB scores are based on a predefined system of indicators that examines the systemic significance of banks according to five dimensions. These dimensions include the size of an institution, its embeddedness (interconnectedness) within the financial system, its substitutability, the extent of its global (cross-jurisdictional) activities, and the complexity of its activities. In determining the final score, the five aspects are taken into account with equal weight (20%).

The criterion of interconnectedness penalises interbank activity through a higher G-SIB score associated with a growth in the amount of interbank loans granted and in the number of partners, thus weakening the intermediation activity, though it is vital for the market. In other words, according to the current logic of banking regulations, large banks receiving special treatment from the aspect of systemic risk must meet the strictest conditions, and they constitute the core of interbank markets, and their task is to ensure liquidity on the market as a whole through their intermediation function.

After mentioning epoch-making Hungarian scholars – Dénes Kőnig, Pál Erdős, Alfréd Rényi, Albert-László Barabási and Réka Albert – in my thesis above, now I summarise the thoughts of Credit Suisse's world-famous investment strategist, Zoltán Pozsár,[82] about the effects of Basel III on the behaviour of banks *(Pozsár [2019])*.

Before the crisis in 2008, US banks' reserve accounts at the Fed had been allowed to have a negative balance temporarily due to ongoing liquidity operations. In this way, the Fed had extended a kind of "daylight overdraft" to each bank, and banks had been allowed to settle such credits and smooth out their liquidity positions at the end of the given day.

Under the LCR requirement introduced by Basel III, banks are required to maintain such amount of liquid assets at all times that may be required in the event of a 30-day severe stress situation. Banks are required to keep this type of liquidity reserve either in their

[82] On 16 September 2019, a very severe market crash, referred to as a "repocalypse", took place in the United States, followed by a complete freeze on the interbank repo market for a time. Interest rates in the repo market, which had been fluctuating around 2%, jumped to 10% in minutes. Zoltán Pozsár predicted this event in advance.

reserve accounts with the central bank or in government securities. Such part of their liquidity reserve that covers their intra-day liquidity needs must be kept in their reserve accounts with the central bank. Under this new system, banks' reserve accounts with the Fed cannot have a negative balance even during the day. Only excess reserves above the required reserves can be placed as a loan with other players, a circumstance reducing the room for manoeuvre in managing liquidity for all participants and significantly decreasing the excess liquidity of the entire interbank market.

In the system has evolved, the bank with the largest excess reserves – JP Morgan – functions as a kind of *"lender of next-to-last resort"*, as its excess liquidity provides a crucial part of the shock-absorbing capacity of the interbank market. Thus, the ceasing of this next-to-last resort can easily put the entire interbank market in a difficult position. On 16 September 2019, this was the case when JP Morgan purchased approximately $ 350 billion in government securities from a significant portion of its excess reserves and stopped its interbank lending activities. Without the largest market player, the interbank repo market was frozen in a short time, an event that has gone down in economic history as the "repocalypse".

The reason for JP Morgan's withdrawal of interbank liquidity, the fact leading to the eruption of the event, is also connected to the new Basel regulations. The above-mentioned global systemically important banks (G-SIBs) are required under regulations to maintain a significant amount of additional capital. As this excess capital significantly reduces the profitability of G-SIB institutions, these capital requirements provide an incentive for participants to reduce their scores (and thus to restructure their balance sheets on an ongoing basis). And scores allocated to participants will limit their room for manoeuvre in deciding what to do with their excess liquidity.

When a large bank's G-SIB score is too high, the obvious solution is for it to buy government securities from its excess liquidity. This is exactly what happened to JP Morgan in September 2019, a situation leading to a decline in interbank liquidity and the collapse of the market ultimately.

Another factor significantly influences the G-SIB score of the largest players and thus their reactions on the interbank market, namely the stock market. In late 2018, there was a significant general fall of 20% on the stock market in the United States. As U.S. banks typically have significant equity exposures, the fall in stock prices in the last quarter of 2018 reduced the riskiness of their asset side through the contraction of their risky portfolio of shares, which temporarily led to more room for manoeuvre due to a decline in their G-SIB scores. In 2019, however, this process reversed rapidly, and there was a huge rise in stock prices, leading to a dramatic increase in G-SIB scores. To avoid the excess capital requirement, JP Morgan, and other large banks that were in the same boat, invested their excess reserves in low-risk assets (typically US government bonds). With this move, a large proportion of the US interbank market's excess liquidity and thus shock resistance disappeared.

In the light of the events of 2019, it is clear that efforts made under Basel III to reduce systemic risk prompted global systemically important banks to manage their G-SIB scores continuously. As shown earlier, the interbank market (normally) is an insurance scheme based on reciprocity between participants and helps manage liquidity shocks affecting the banking system. The system as a whole – owing, in part, to the beneficial activities of intermediaries – is able to absorb external shocks more effectively than in a situation where it is up to individual participants to solve it alone.

However, as a result of the recently introduced rigid micro-prudential rules, banks are turning inwards and focus primarily on their own liquidity positions, having less room for manoeuvre in providing temporary support to other partner banks, a fact deteriorating the efficiency of the interbank market *(Berlinger [2020])*. In light of this, my second recommendation is that it would be worthwhile to formulate more flexible liquidity requirements for credit institutions. I consider systemic risk management to be very important, but tying the hands of key banks may lead to significant distortions and may reduce the efficiency of the market in eliminating liquidity shocks.

The problem is made worse by the fact that, as a result of the single G-SIB scoring system, market events and external shocks, such as stock market fluctuations, induce major market participants to enter into transactions in the same direction, a situation that could lead to the amplification of shocks affecting the interbank market and the disappearance of intermediaries.

***Attractive monetary policy instruments tend to reduce the efficiency of the interbank market***

In Sub-chapter 2.2.4.2 above, the interest rate corridor was presented as an essential element of central bank toolkits. It was explained that, in the case of a wide interest rate corridor and less attractive monetary policy instruments, interbank interest rate volatility generally increases, which is undesirable for the efficiency of monetary transmission, but at the same time encourages market participants to be more active in the interbank market. In this way, the reciprocal insurance scheme of the interbank market can operate more efficiently.

The last decade of Hungarian monetary policy has been characterised by the fact that, in the event of major market shocks, the central bank almost immediately "switched the interbank market to manual control" with the help of a favourable interest rate central bank instrument. This happened most recently in connection with the coronavirus crisis when on 1 April 2020, the MNB decided to announce tenders for one-week deposits at the base rate regularly *(MNB [2020b])*. The purpose of this move was to place the banking system's liquidity into deposits at the base rate. In the lack of detailed data, I cannot judge whether such a step was necessary, but it is certain that, thereby, the central bank temporarily weakened the efficiency and smooth operation of the interbank market.

My fourth suggestion is that it is worthwhile to use particularly attractive monetary policy instruments temporarily and for a short period only because, if this becomes the primary tool for managing market participants' liquidity on a permanent basis, it could cause significant long-term damage to the operation of the interbank market. In a turbulent global macro environment, a well-functioning, active interbank market is critical to eliminate liquidity shocks, and monetary policy must consider this when reshaping its toolbox.

*Vodová [2014]* simulated the potential effects of a severe interbank crisis of confidence in the banking sector in the Visegrad countries. According to Vodová's model, of the four Visegrad countries, the vulnerability[83] of the Hungarian interbank market is the highest, but the Polish market would also be severely affected by a crisis of confidence. In contrast, the Czech and Slovak interbank markets are much more resilient to liquidity shocks. In the light of Vodová's research results, it would be particularly important to strengthen the interbank market in Hungary.

[83] Vulnerability is understood by the author as the severity of the effects on the banking sector of stress during a potential crisis of confidence.

***The key to a well-functioning interbank market is: trust***

Finally, I would like to discuss tools to use for handling an interbank market crisis and strengthen the interbank market's resilience to liquidity shocks.

*Hryckiewicz [2021]* examined the period of 2007-2011, impacts of responses to the crisis on interbank markets in six developing Central and Eastern European countries[84] (including Hungary) through changes in interbank interest rates. Hryckiewicz concluded that standard measures introduced for providing liquidity in response to the crisis of 2008 have not proved to be effective in stabilising the interbank market. Hryckiewicz suggests that regulators should introduce tools that reduce uncertainty in the interbank market in a crisis situation.

As a fifth suggestion, I would also like to draw attention to the importance of reducing uncertainty in the interbank market. In order for reciprocity-based insurance schemes of interbank markets to work efficiently and for intermediaries, who are core players, to be willing to stand between two peripheral participants in addition to managing their own liquidity needs, in the absence of physical collateral, trust is crucially important. Therefore, any action that strengthens confidence also helps the risk sharing system to function properly.

[84] Poland, Hungary, Czech Republic, Latvia, Estonia and Lithuania

# 8. Summary

In my dissertation, a descriptive research was first conducted, in which the network of the unsecured interbank HUF deposit market was examined. In Chapter 2, I presented that players in an economy tend to manage their liquidity at several levels at the same time; and, based on academic literature, I sorted out the different liquidity concepts related to each level.

I described the most important characteristics of unsecured interbank credit transactions, of which the lack of financial collateral together with the significant volume (up to tens of billions of HUF) may create significant risk. This is due to the strong information asymmetry on the interbank market, credit rationing and short squeezing. Taken together, these phenomena may explain that in the interbank deposit market, unlike in many other markets, the most important factor is quantity adjustment rather than price adjustment (raising interest rates due to higher risk). Quantity adjustment is mostly achieved through partner limits.

As partner limits applied to each other are among the most secretly guarded data of banks, therefore, even though price adjustment is less significant, only the interest rates evolved in the interbank market can be analysed. These interest rates are also crucial because monetary policy may exert an impact primarily on them. The operation of the main monetary policy instrument, the interest rate corridor (which plays a key role in monetary policy transmission) was covered in detail, together with the required reserves. The impacts of the Self-financing Programme of the MNB announced in 2014, and the effects of the system of quantitative restrictions on the interbank deposit market were studied separately.

In order to gain a deeper understanding of the modes of action of interbank markets and to shed light on some new aspects thereof, the effects of three different types of shocks on the behaviour of participants and on the structure of the market as a whole were presented in detail. These shocks were the 2008 global financial crisis, the liquidity effects generated by the Treasury Single Account in 2009 and 2010, and the deterioration of the sovereign credit rating of the Hungarian state at the end of 2011.

Subsequently, the evolution of interbank loans and deposits were reviewed based on MNB's regularly published statistics on credit institutions. It is established, in general, that, over the past decade and a half, the credit portfolios of credit institutions have increased significantly, both for HUF and foreign currency transactions, their maturity is typically within 30 days, and the size of the non-performing portfolio has been negligible.

In Chapter 3, I turned from publicly available data to a research database containing all unsecured interbank HUF loans for the period of 2012-2015. Regarding the maturity of transactions, it was found that overnight interbank loans accounted for 91% of transactions in the market in the period examined. As foreign authors examining other domestic or regional interbank markets have come to very similar proportions in literature; therefore, it seems that the predominance of O/N transactions can be considered general in this market.

After that, I split the sample into two parts to compare the distribution of overnight interbank transactions with the distribution of credit transactions with a maturity of over one day. These distributions were compared through histograms, box diagrams, a Q-Q graph, as well as a homogeneity analysis. I found that the null hypothesis of the test for homogeneity can be rejected at any standard significance level; the distribution of amounts of O/N transactions is different from the distribution of amounts of transactions with a maturity of over one day; and this difference was stable over time in the period of 2012-2015. Thereby, I empirically confirmed hypothesis *H1*. As my aim was to examine interbank transactions specifically serving liquidity purposes, I excluded from the analysis any longer-term transactions with other characteristics and not serving exclusively this purpose.

Almost throughout the period of 2012-2015, the interbank interest rate fluctuated in the lower half of the interest rate corridor, close to the interest rate on overnight central bank deposits, from which we can conclude that the interbank market was basically characterised by abundant liquidity. Interbank interest rates sometimes stepped out of the interest rate corridor, suggesting temporary market disruptions. These smaller shocks were mostly due to a change in the sovereign credit rating of the Hungarian state and the transformation of the monetary policy toolbox.

These events can also be tracked in the evolution of figures for the monthly aggregated transaction amounts. As a result, the aggregate volume of transactions increased more than the number of transactions. One possible explanation for this phenomenon is that, as a result of these shocks, participants decided to reduce partner limits considered less reliable and to obtain the necessary funds from the few, most reliable players on the market.

For a deeper explanation of the quantity adjustment, I examined the concentration of lending and borrowing. Both the Gini and Herfindahl-Hirschman indices showed that borrowing was more concentrated than lending in terms of both volume and number of transactions. Loans were provided by an average of 10-15 active banks typically to only 5-8 borrowers in the period examined. I tested this observation by using a two-sample z-test for comparing expected values and confirmed a significant difference in concentration between the borrowing and lending sides of the interbank market, as expressed in hypothesis *H2*.

Then I described the basic concepts and metrics related to networks, such as the average degree, the degree distribution, the shortest path, the average path length, and several indicators to measure connectivity. The average path length fluctuated steadily around 2 during the period examined, i.e. each participant could, on average, come into contact with any other bank operating in the interbank market through the insertion of a single participant (intermediary).

The average clustering coefficient was significantly higher than the density throughout the period studied, i.e. despite the relatively few relationships, the domestic unsecured interbank deposit market was characterised by a high degree of interconnectedness. This phenomenon may indicate that the interbank market network consists of interconnected parts with a modular structure, similar motivation and functions, where (intermediary) participants connecting the otherwise isolated parts of the network have a special role to play.

Network metrics used in foreign academic literature for examining several countries in the region and also global, cross-border interbank networks show a high degree of similarity with the network metrics I measured. From the fact that markets – though operating in different currencies, with different participants, and in many respects separated from each other – are so similar when examined along several dimensions, we can conclude that the unique set of features of unsecured interbank deposit markets (no physical collateral and the primary purpose of transactions is liquidity management) and the underlying factors related to market failures (asymmetric information, transaction costs, economies of scale and scope, liquidity provision and risk sharing) will form a special network structure.

In Chapter 4, after presenting the basic network models, I focused on the core-periphery structure observed in interbank market networks, which is essentially a special version of the hierarchical network model. I described the discrete core-periphery model, from which I switched to the continuous symmetric model and the so-called coreness measure that can be calculated from it.

As one of the main scientific added values of my thesis, I presented a special version of the widely used coreness measure developed by *Boyd et al. [2010]* by modifying it with a concave weight function, which is the result of our joint work with my supervisors. Using the definition of the core-periphery model as a starting point, I defined four properties that a properly functioning coreness measure must fulfil. These criteria are (1) the proper handling of purely core and purely periphery cases; (2) Lip-monotony; (3) invariance to addition/removal; and (4) robustness. I described cases where the original, non-weighted coreness measure violates one of these criteria, but the new, modified measure properly handles and eliminates the anomalies of the original indicator. Finally, I demonstrated by a simulation method that the new, weighted coreness measure provides a more robust separation of core and peripheral participants, not only in stylised, simple networks but also in a real interbank market network; thereby, I accepted hypothesis *H3*.

Regarding the robustness test implemented, it should be noted that, although statistically the new weighted measure was more robust in the analysed real network compared to Boyd's original coreness measure, the extent of improvement was much lower than in the case of pure (or nearly pure), stylised core-periphery networks.

After the descriptive part, starting from Chapter 5, I focused on causal relationships underlying in the background. The evolution of the core-periphery structure presented in detail is attributable to intermediary activities within the network. In an unsecured interbank market, core players ensure the smooth operation of the entire market by not only managing their own liquidity but by taking extra risks as stepping in as intermediaries between two peripheral players.

Over the past decade and a half, rapid technological advances, digitalisation, and declining transaction costs have led to a wealth of financial innovations that have questioned the viability of traditional financial intermediaries. Contrary to the examples presented, intermediaries in unsecured interbank deposit markets seem unavoidable and their importance has not diminished in recent decades.

By processing the relevant academic literature, I analysed the question of why banks, as financial intermediaries, also need intermediaries in interbank markets. The five main reasons are (1) to ensure continuous liquidity in the market and thus to address shocks, (2) to resolve asymmetric information situations, (3) to reduce various transaction costs, (4) to exploit the potential benefits of economies of scale and scope, and ( 5) risk sharing. The presence of intermediaries facilitates the proper functioning of interbank markets along these five functions and reduces the negative effects arising – in the absence of intermediaries – in connection with the factors listed above.

In the remainder of Chapter 5, I demonstrated that very significant and ever-increasing intermediary activities can be observed in the interbank market. Thereby, hypothesis *H4* (in relation to the volume of intermediation activities) is confirmed. After that, I turned to estimate the amount of profits a player may generate from intermediation: first, by calculating with the weighted average interest rate; and, secondly, I gave an absolute upper estimate of profits realised from intermediation. The two estimation methods resulted in hardly any change in the order of individual banks, i.e. the order can be considered robust in terms of the estimation method chosen. Each of the estimates showed that, although banks carry out significant intermediation activities, profits from intermediation are far below the magnitude expected based on academic literature, i.e. intermediaries act in the hope of something other than profits. Thereby, I rejected hypothesis *H5*. There was a player in the market that carried out intermediation activities at a loss. As a for-profit institution was concerned, this phenomenon was difficult to interpret under the traditional assumption of "rationality".

According to the academic literature, three main motivations for intermediation are possible: (1) making profits; (2) selfless, philanthropic assistance; or (3) risk-sharing.

On the basis of logic, I concluded that the main motivation for intermediaries in the unsecured interbank deposit market is probably risk sharing. In the interbank deposit market, participants reciprocally help each other to smooth out their liquidity imbalances. Thus, core intermediaries are not motivated by profit when they take on risk to step in between two peripheral participants, but they act for a kind of "insurance" so that, should they encounter some liquidity shortage later, they can expect reciprocity from their previously assisted partners.

In Chapter 6, building on the results of a joint research with my co-authors, I compared the network of informal interpersonal loans of an underdeveloped small village in North-

Hungary inhabited mainly by the Roma with the interbank market. In both markets, transactions are unsecured and their primary purpose is liquidity management, i.e. the essential function of the examined networks is the same, only the circumstances are different.

I have shown that, when examining the markets as a whole, we can, apart from differences in the characteristics of players and transactions, find only similarities almost exclusively. For example, there is a strong presence of information asymmetry in both markets, so that participants, either informally or through their formal systems, continuously rate and monitor each other and apply partner limits. The risks managed are asymmetric in the sense that satisfying the lack of liquidity is the more pressing problem, and the placement of surplus funds is a less important aspect. The main driver of transactions in both markets is liquidity management, the efficient operation of which is something to which intermediaries make a significant contribution.

A concentration analysis made for each of the two markets showed that, while few lenders lend funds to many borrowers in the interpersonal network, the opposite is true for the interbank market. A possible explanation for this phenomenon is that structural liquidity shortage is typical for the interpersonal lending market, while systemic excess liquidity is typical for the Hungarian unsecured interbank deposit market.

Both networks have a hierarchical structure, but interestingly, a higher degree of hierarchy can be observed in the interpersonal network. The interpersonal network consists of several interconnected sub-networks (cousins, grandparents, wider kinship), which usually communicate with each other through their central participants. In other words, central players (bridges) in the interpersonal network connect otherwise separated network parts, which phenomenon may explain the high level of hierarchy in the interpersonal lending market. Thus, I demonstrated the similarity of the examined unsecured credit markets along several dimensions, and thereby, I rejected hypothesis *H6*.

After that, I examined the motivation of intermediaries in the interpersonal lending market. Based on academic literature, I formulated the statement in hypothesis *H7* that the main motivation for transactions in the interpersonal lending market is selfless, philanthropic assistance from the rich to the poor.

Based on the diverse database of households that make up the interpersonal network, it can be stated that the lending activity of richer households is low, but those living below the relative poverty threshold have developed a dense system of lending relations, with most of the loans provided by the poor to each other. Therefore, the main motivation for transactions is not selfless, philanthropic assistance, but risk sharing, as described for the interbank market. Disadvantaged people operate an insurance scheme based on reciprocal assistance, where they are willing to lend funds in excess of their own liquidity management needs, knowing that if they subsequently encounter difficulties with liquidity, they can count on financial support from the community. Thereby, I came to results that contradict the relevant literature, and I rejected hypothesis *H7*.

*Table 27:*

Summary results of the examined hypotheses

| Examined hypotheses | Decision |
|---|---|
| *H1: The distribution of overnight and longer-term unsecured interbank transactions significantly differ.* | Accept |
| *H2: The concentration of borrowing is significantly higher than the concentration of lending, both in terms of volume and the number of transactions.* | Accept |
| *H3: A coreness measure adjusted by a concave weight function allows for a better and more robust classification than before.* | Accept |
| *H4: Intermediation activities in the Hungarian unsecured interbank deposit market are of significant volume.* | Accept |
| *H5: In the Hungarian unsecured interbank deposit market, the main motivation of intermediation activity is to make profits.* | Reject |
| *H6: The network of the examined interpersonal loan market differs significantly from the Hungarian unsecured interbank deposit market network.* | Reject |
| *H7: The main motivation for transactions in the interpersonal loan market is selfless, philanthropic assistance provided by the rich to the poor.* | Reject |

*Source: own edition.*

Examining the ethnic composition, I found that interpersonal loans are particularly common among the Roma, i.e. Roma households play a key role in the operation of the informal credit market in the village and in managing liquidity shocks as part of the community.

To close the chapter, I listed a number of other possible research directions that could be used to learn about new aspects of unsecured credit markets. Of these, I find the network of short-term debts between businesses particularly promising. The information needed for this could be obtained, for example, from regular VAT returns, which are non-public data held by the National Tax and Customs Administration. Employees of the MNB received this database for research purposes and published two working papers in 2020. In my opinion, this database still has much untapped potential.

Finally, in the last chapter, after presenting causal relationships, I listed possibilities for utilising my research results. I made policy recommendations on interpersonal loans first and then on the interbank deposit market.

In addition to the results listed above, when summarising the lessons learned from the large-scale programme launched for disadvantaged Roma with support from the European Commission in 2011, it can be established that the collective “safety net” provided by the informal loan market in the village is more important to those living in deep poverty than an investment product offered to each individual separately with an annual risk-free return of 100%. Therefore, programmes encouraging the poorest to make individual savings are ineffective.

It is a common belief about those living in underdeveloped areas that the way to their rise takes through the development of their financial knowledge and awareness. In contrast, the poor as “the jugglers of money” *(Gosztonyi [2018])* can manage extreme liquidity shocks extremely consciously and even masterfully, by operating their own informal risk management systems. In other words, the prime reason for their disadvantage is not related to their lack of financial awareness; a fact I recommend for policy makers to consider when designating directions for development.

Turning to my proposals related to the interbank market, I would first like to draw the attention of experts and regulators to the weighted coreness measure presented as a methodological innovation in Chapter 4, which allows for a better and more robust classification of core and peripheral banks than before.

After introducing the new Basel III liquidity requirements, banks are faced with a very strict set of rules. Credit institutions thus turn inwards and focus on flawlessly maintaining their own liquidity positions, a situation less allowing them to participate in maintaining the insurance scheme implemented based on reciprocity in the interbank market. In this case, the predominance of individual-level regulations may cause detriments to systemic stability; so regulators may find it worthwhile to make even greater efforts to balance micro- and macro-prudential interests.

Another novelty of the Basel III regulation is the introduction of macro-prudential considerations, which apply extra prudential rules and supervisory rigour to the most important banks in terms of systemic risk, the so-called G-SIBs, on the basis of a predefined scoring system. This scoring system explicitly penalises loans taken and granted by large banks in the interbank market. Due to sanctions involving significant capital requirements, the world's leading banks are constantly encouraged to reduce their interbank activities and invest their excess liquidity in government securities. These Global Systemically Important Banks are the largest intermediaries in the world's interbank markets, the partial elimination of which significantly reduces the efficiency and shock absorption capacity of the interbank market. This was the most significant cause of a severe collapse of the market on 16 September 2019, referred to as a "repocalypse", which led to an entire freezing-up of the U.S. interbank repo market. Managing systemic risks is of key importance, in my view, but tying the hands of the largest intermediaries may pose a serious threat to the liquidity of the interbank market. In addition, the unified G-SIB scoring system triggers the same reactions to external shocks from the largest market participants, which amplifies the impact of shocks and may lead to the collapse of the market.

Turning from international regulations to the domestic interbank market and monetary policy, the last decade of Hungarian monetary policy has been characterised by the fact that, in the event of major market shocks, the MNB almost immediately "switched the interbank market to manual control" by introducing a favourable-interest rate central bank instrument, which was beneficial in terms of the efficiency of monetary transmission, but it was detrimental to the smooth functioning of the interbank market. In my opinion, monetary policy-makers should definitely consider this when redesigning the toolbox and should use these tools only on a temporary basis for a short period of time.

In conclusion, I would like to draw attention once again to the key role of intermediation in the interbank market. In the absence of physical collateral, the key to an active and well-functioning market is trust, the strengthening of which should be the primary task of regulators in this market. Any regulation that increases confidence will facilitate the smooth operation of the risk sharing system established in the interbank market.

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