Efficiency in bank regulation – Analyzing contagion in the Hungarian interbank network

by

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Abstract

This thesis investigates the potential gains of introducing higher capital requirements for systemically important financial institutions (SIFIs). To assess the effect of this differentiation, the analysis compares the proposed SIFI-based policy to the conventional general capital requirement regulation by estimating the losses caused by contagious bank defaults spreading in the Hungarian interbank network. A pivotal part of the applied methodology is connected to the lack of available information about the bilateral exposures in this system. To handle this obstacle, the reconstruction of the unobservable adjacency matrix was conducted by using three different methods - Maximum Entropy approach, Minimum Density approach and a copula-based approach – to provide a range for the estimations. The identification of SIFIs was done primarily by implementing a Shapley-value-based technique, but the study also contains a simple form of core-periphery decomposition and a more qualitative indicator-based measure as robustness checks. The results underpin the intuition that the SIFI-based regulation is potentially more efficient than the conventional policies; however, some possible pitfalls also emerge due to the imperfection of SIFI identification. As a complementary result, the thesis also offers an illustration of the advantages and the deficiencies of the implemented network reconstruction techniques.

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List of Abbreviations

SIFI: Systemically Important Financial Institution

CRR: Capital Requiremnt Regulation

ME: Maximum Entropy

MD: Minimum Density

CA: Copula Approach

LGD: Loss Given Default

CCP: Central Counterparty

FSB: Financial Stability Board

BCBS: Basel Committee on Banking Supervision

G-SIBs: Global Systemically Important Banks

D-SIBs: Systemically Important Banks on Domestic Level

Introduction

"Will the failure of a financial institution trigger the subsequent failure of others?" (Upper, 2011, p. 1) This question might be the most unsettling concern of economic regulators after the recent crisis. The chain of unexpected events have given economists a lesson about the threats coming from financial contagions and it became one of the most important challenges for policy makers, how to manage or even more importantly, how to prevent spillovers in the global economy. This claim came hand in hand with a new paradigm: the recognition of the importance of contagious effects made network science an emerging methodological framework in economics. It turned out, that there are mechanisms now - first of all in the financial intermediary sector – which were though not completely unknown in the previous regulatory mindset, but their magnitude was severely underestimated. After the crises during the '90s in Mexico and in Asia there were attempts to draw attention to contagious effects¹, but it gained momentum truly only after 2008. However, nowadays all the policies aiming at the enhancement of systemic stability are receiving great emphasis. I would like to contribute with my thesis to this aspiration by analyzing the efficiency of the currently proposed regulation for capital requirements, which is one of the most essential parts of the ongoing reform in the financial sector.

i.) Background of bank regulation

In order to be able to understand the necessity of recent network-based innovations, one should be familiar with the tendencies of bank regulation in the recent economic history. First and foremost, regulation in any sector can only be accepted in the capitalist mindset, if there is a market failure to fix, and the costs of doing so are less than the gains. These conditions

¹ E.g. Bae et al. (2000), Forbes and Rigobon (2002) and Rigobon (2003).

are the cause of many economic debates, and neither is bank regulation an exception. There was a minority, especially prior to the crisis, which represented the "free banking" standpoint (Selgin, 1988). They claimed that either there is no failure to compensate, or more often the competition on the market controls the situation more effectively than the state does. (Feingold, 2012)

After the crisis, it became widely accepted that due to their connectedness towards the real economy, banks have a special role and without regulation there is no mechanism to prevent the emergence of excessive risk-taking behavior. In addition, banks operate in a highly leveraged way compared to other sectors and information asymmetries are present on multiple levels. These characteristics combined with the interconnected nature result in massive systematic risk.

However, it is still not clear, which direction should we choose now: Do we need more restrictive policies, or the price of avoiding collapses is even higher than the damage caused by the crises themselves? Basel III proposals and capital requirement regulations and directives in the EU (CRR/CRD IV) are indicating clearly the former direction despite the unavoidable downsides of it. Meeting the increased capital and liquidity requirements is possible by adjusting either the equity or the asset side. In both cases, there will be pressure on the cost of capital, which leads to higher lending interest rates. The reduced credit supply accompanied by restrictive fiscal policy usually induces setback in the output growth and in employment. (Slovik and Courn`ede, 2011) Furthermore, it can be even more harmful, if the tightening is happening after a crisis period, since it can postpone the recovery and also strengthen undesired disintermediation in the financial sector. (Homolya, 2011) According to the model of the Bank for International Settlements, one percentage point increase in the capital requirements can lead to 0.19% point decrease in the GDP. However, their analysis is still in favor of the stricter regulation, which reduces the probability of the crises to such an

extent that causes long-term output being higher by 2% points. (BCBS, 2012b) Yet it is clear, that we should pursue the most efficient way of regulation to minimize the "price of stability".

The most promising suggestion so far to reach this goal is to identify those institutions which are so important due to their size, connectedness, or any other indicator of importance, that their failure would cause greater damage for the economy than their bail-out. For example, the decision to save AIG in September 2008 was motivated by the worries that its "failure under the conditions prevailing would have posed unacceptable risks for the global financial system and for our economy". (Bernanke, 2009) In order to avoid defaults which potentially jeopardize the stability of the system, regulation for these SIFIs (systemically important financial institutions) is planned to be stricter compared to smaller players. This also means, that the aggregated capital requirement level – and hence the output loss – could be lower than in a general, uniform regulatory scheme. In my analysis I perform the assessment of this efficiency effect on Hungarian data by simulating the impact of the different capital requirement regulations. Unfortunately, conducting this kind of analyses is not possible without making some compromises, which leads to potential departure from the ideal framework in several aspects.

ii.) Limitations and justification of the analysis

If the theoretical objective of the authorities was to create a regulation which delivers perfect stability in the economy, it would be – surprisingly – a relatively easy task. They should set the capital requirement up to a 100% level, and we would not be concerned with global bank crises any more. Of course it is not a realistic setup in our financial system due to several practical difficulties, but the even greater trouble with this fictitious world is that our objective function is not so simple. We care not only about stability, but also about market efficiency and output. I showed that there are calculations about the GDP effects of the

proposed regulatory measures, but we do not have a utility function representing all these factors. Economic agents might be willing to sacrifice some output in exchange for a balanced and sound economy, but there is no solid information neither about the exact "price" nor the functional form of it. However, a comparison between the two above mentioned policies is still valid, but we should keep in mind that it is possible to figure out only the relation between them, and an approximation of the difference.

In addition to this shortcoming, there is another simplification, which should be noticed. I restricted my work only to contagions induced by interbank lending which is related to the mechanism that if one institution goes bankrupt, its creditors from the financial sector will suffer a loss and if their equity is smaller than the loss, they can default too. Nevertheless, the vulnerabilities coming from the special characteristics of the financial sector are manifested in several other ways as well. Upper (2011) offers an exhaustive summary about the potential channels, and he also categorizes them in a way depicted in Table 1.

Channel	References	
Liability side		
Multiple equilibria/fear of other withdrawals	Diamond and Dybvig (1983), Temzelides (1997), Goldstein and Pauzner (2004)	
Common pool of liquidity	Aghion et al. (2000), Acharya and Yorulmazer (2008b), Diamond and Rajan (2005), Brunnermeier and Pedersen (2009)	
Information about asset quality	Chen (1999), Acharya and Yorulmazer (2008a)	
Portfolio rebalancing	Kodres and Pritsker (2002)	
Fear of direct effects	Dasgupta (2004), Iyer and	

Table 1 – Contagion channels in the banking system

	Peydró-Alcalde (2005), Lagunoff and	
	Shreft (2001), Freixas et al. (2000)	
Strategic behavior by potential lenders	Acharya et al. (2008)	
Asset side		
Direct effects		
Interheult len din e	Studies reviewed in the subsequent	
	chapters	
Povment system	Humphrey (1986), Angelini et al.	
i ayment system	(1996), Bech and Garratt (2006)	
Security settlement	Northcott (2002)	
FX settlement	Blavarg and Nimander (2002)	
Derivative exposures	Blavarg and Nimander (2002)	
Equity cross-holdings		
Indirect effects		
Asset prices	Cifuentes et al. (2005), Fecht (2004)	

If the focus was on the assessment of the overall contagious impact of a failure, one should include each identified mechanism in the analysis, which would be an overwhelmingly complex task to do. However, my intention is rather to contribute to the process of developing preventive policies, and for this propose, it is more useful to separate the channels one by one in order to test the effect of regulatory measures on them. In turn, it is questionable at this point, which channel should we concentrate on. Interbank lending did not cause so far too many bank defaults to my knowledge, but the lack of precedents is not due to its insignificance or irrelevance. Bank collapses triggered by this mechanism were prevented several times during the recent crises by bailouts provided by governments. Since these actions are very costly and they also entail moral hazard motives, elimination of this kind of contagion would likely enhance social utility. Another reason why interbank lending should be considered notable is that it belongs to direct contagions, and it can ignite indirect

contagions, for instance bank runs, gridlock or liquidity hoarding. (Dasgupta, 2004; Iyer and Peydró-Alcalde, 2005; Freixas et al., 2000) Of course, these dangers are present only if banks have a lot of interbank exposures. In the Hungarian banking system the ratio of interbank assets to total assets is more than 53%, which is certainly high enough to consider it necessary to be aware of the potential risks².

There is also a well-known practical obstacle for this kind of analyses, namely that for national bank systems only public balance sheet information is available due to privacy concerns. Although Hungary is one of the few countries where the central bank has data on bilateral interbank lending exposures, they cannot share it with any third party. Translating this into a more network-specific point of view, the barrier is that the whole structure of a given system is not available. What we can use in this situation is the aggregated data from the balance sheets, which are public for all the financial institutions operating as LTD (Private Company Limited by Shares) or PLC (Public Company Limited by Shares). There is a row for each bank about its assets and liabilities toward other financial institutions. This means that we know the strength of each vertex, but we do not know the links and neither the weights of the links. However, there are techniques which can be applied to reconstruct the missing matrix in order to conduct further analysis. In my thesis I performed three methods to overcome this obstacle.

Therefore, the objective of my thesis is twofold: primarily to find out which type of the capital requirement regulations (CRR) is more efficient, the network-based approach or the general CRR scheme; and secondly to compare various techniques for handling limited information availability problem, which is a common obstacle in these analyses. Furthermore, since network approach is barely present yet in the Hungarian economic literature, my study

² Own calculation based on Aranykönyv 2013 ("Golden Book"), which is an annual data reporting publication of the Hungarian Central Bank.

contributes to the field also by providing the first implementation of some methods on Hungarian data.

The scope of the thesis includes four main topics, which are also the basis of the structure of the paper. After reviewing the relevant literature, Section 2 deals with the problem of data availability. Section 3 describes a simple model of idiosyncratic stress events in the case of general CRR. Section 4 introduces ways of measuring systemic importance of the particular agents in order to identify SIFIs, while the comparison of the two types of regulations and the resulting policy implications are derived in section 5. Finally, the last section concludes the findings and makes suggestions for further research.

1) Literature review

Very few papers can be found that are dealing with either SIFI regulation or contagion due to interbank lending in Hungary. The most closely related study is Lublóy (2005), in which the author modeled the chain of circular lending contracts among banks, but did not consider regulatory interventions. She traced the impact of idiosyncratic failures by measuring the number of first-, and second-round defaults, the overall capital losses in the banking system and the proportion of the assets of the banks affected by the cascade mechanism. Since handling SIFIs is an utterly recent challenge, there is no extended research about the empirical experiences even in the international publications. (We will see empirical results only after the implementation of the policies, but we are only in the phase of preliminary analysis.) Some early investigations of the interbank market were done with tools and concepts of network theory by Boss et al. (2004), Iori (2005) and Boss et al. (2006), which however, did not include SIFI-based regulation in the analyses. According to this state of the related research, I found rather methodological papers concentrating on technical problems within network framework.

1.1) Network reconstruction

Considering the first fundamental part of the process of the analysis, one should overview the various network generating techniques. A not too sophisticated, but still a pioneering way to reconstruct a network is the Maximum Entropy (ME) approach, which was used many times, e.g. by Upper and Worms (2004) or by Elsinger et al. (2013). The standard ME procedure consists of two steps: dividing the total exposures as evenly as possible then using the RAS³ algorithm (Schneider and Zenios, 1990) to rebalance the adjacency matrix.

³ The acronym "RAS" has notational origins: $\hat{r}A\hat{s}$.

(Rebalancing is necessary to ensure that the sum of the individual quantities is equal to the original marginal distribution, i.e. the balance sheet data). Distributing each bank's total interbank lending as evenly as possible also means that ME results in an almost complete network, which can give us a uniformly distributed limit of credit relationships in any further impact assessment. However, the assumption of this level of diversification is not realistic, as Upper and Worms (2004) and Craig and Von Peter (2014) showed that the real network is rather sparse, and smaller banks use more central intermediaries, which trait creates a tier structure. In addition, ME suggests that the *degree*, which is one of the most important network properties has no meaning in the banking network topology.

These simplifications imply that ME is feasible only if no other information is present about the system, and these shortcomings called for further research. Drehmann and Tarashev (2013) improved ME by generating random perturbations around the ME matrix, then they chose the one with the highest concentration to get closer result to the sparse structure. Another, more complex enhancement is the Minimum Density (MD) method developed by Anand et al. (2014). MD tries to allocate the lending quantities using the fewest possible interbank links by imposing cost on establishing a new connection. Hence, it captures two characteristics of the real world banking systems: sparsity and disassortativity. In its pure form, minimum density gives the opposite extreme outcome: this can be used as the highly sparse limit of credit relationships for the estimations. However, if our goal is to recreate the most likely version of the true system, or provide a null-model in order to identify abnormal clustering or other network phenomena, other estimates might give more precise results. E.g. Mastrandrea et.al (2014) developed an enhanced version of maximum entropy method, which takes into account the degrees of the nodes as well, which makes it possible to improve significantly the effectiveness of the process. (Despite its promising features I could not implement their algorithm, because the central bank in Hungary is not allowed to share even the degree data.)

There are a few alternative approaches beyond ME to tackle network reconstruction. One of the most novel techniques was proposed by Baral and Fique (2012), who constructed a copula-based method. Since a copula is a cumulative distribution function (with uniform marginals), after some adjustment the balance sheet information can be input to generate probabilities of the bilateral exposures, which can be used to produce stochastic adjacency matrices. The main advantage of copulas over maximum entropy is the flexibility, which makes it possible to accommodate different dependence structures and find better fit than ME. Baral and Fique (2012) also conducted comparisons to ME concerning the precision of the estimations, and find that copula approach outperforms ME especially in cases where coreperiphery effect is more prevalent. Since this is a well-known characteristic of interbank lending networks, this feature has key importance in this application. (Berlinger et al., 2015)

Based on the qualities and the feasibility of the listed methods I decided to implement Maximum Entropy and Minimum Density algorithms to provide a range for the results of the simulations; furthermore, I also carried out the copula solution to compare the entropy based methods to a different approach.

1.2) Identification of SIFIs

The currently mainstream method for SIFI identification is the calculation of the weighted sum of various indicators. After the vulnerabilities of the banking sector came to light during the crises of 2007-08, the Basel Committee on Banking Supervision (BCBS) issued a methodology to identify systemically important banks (G-SIB). (The Financial Stability Board took over this framework and they publish their list of G-SIBs each November.) Their methodology was published in 2013 and an updated version in 2014.

(BCBS, 2013, 2015) They included five categories with equal weights (but each category consists of indicators with different weights). The indicators are chosen in a way to reflect the most possible aspects of externalities and also to reduce the risk of moral hazard. I have no knowledge about more complex version of the indicator-based method.

Another way to approach the identification is to develop models which are capable to estimate the contribution of individual banks to systemic risk. These models are at a relatively early stage of development, and there are concerns about their robustness and the ability to capture all the important aspects of systemic risk. (These are the main reasons why indicatorbased technique is used by the regulators for the time being.) However, there are very promising attempts which should be mentioned here. One group of the studies defines systemic importance of a given bank as the expected loss it causes due to a set of systemic shocks. It means that importance is the expected participation of banks in systemic events. Tasche (2008), Huang et al. (2010), Acharya et al. (2009), Brownlees and Engle (2010) and Battiston et al. (2012) serve as examples for this direction. An alternative measure was suggested by Tarashev et al. (2010). Their method tries to capture the contribution to the systemic cascades. The key concept to understand this is the idea of Shapley value (Shapley, 1953), which is an algorithm to allocate the value created in cooperative games across agents in game theory. Using this concept they found non-linear relationship between common risk factors and the probabilities of individual defaults. A similar technique was used by Staum (2012) to design deposit insurance system in the event of fire-sales based contagions.

1.3) Modeling contagion across banks

Most of the papers I covered use an algorithm developed by Furfine (2003) to model the effect of a cascade triggered by any shock. This mechanism is quite simple; it consists of the following three steps: (i) A bank defaults due to a idiosyncratic shock. (ii) Any bank defaults

as well, if its exposure towards the first bank (multiplied by the Loss Given Default parameter) exceeds its equity. (iii) If there is at least one other bank which suffers defaults due to the failures of the previous two based on the rule in step 2, the contagion continues. If there is no further default, the cascade stops. This algorithm is imperfect as it does not handle simultaneity; that is higher order defaults cause losses to banks that had collapsed in an earlier round. Eisenberg and Noe (2001) offer a solution to this concern as they showed that this problem has a unique solution; i.e. it is possible to determine the exact number of defaults due to the contagion. However, due to its simpler applicability and the potentially small extent of distortion (which will be present probably on both sides in the comparison) I decided to use Furfine's method.

2.) Network reconstruction methodologies

It is a widely known barrier in network analysis that the whole structure of a given system is not available; e.g. because of missing nodes/edges/weights etc. One faces with the same difficulty during analyzing interbank lending exposures because of the lack (or due to the not public nature) of this confidential data. Luckily, we are not completely blind on this system, as the balance sheets contain information about assets and liabilities toward other financial institutions. This information is available for all the financial institutions operating as LTD (Private Company Limited by Shares) or PLC (Public Company Limited by Shares) in a publication called "Golden Book" ("Aranykönyv") which is published by the Central Bank of Hungary. This source offers an opportunity to reconstruct the missing adjacency matrix using only the sums of the rows and columns, which are also known as marginals. Still, these balance sheet lines need to be slightly corrected, since the asset and the liability sides do not correspond perfectly to each other. On the liabilities side the only attainable variable is "The deposits from financial institutions" (accounting code: 1B2) which is highly distorted due to the presence of deposits coming from money funds and other financial enterprises. On the asset side we have "Interbank and central bank deposits" (accounting code: 1AB4), which contains exposure also toward the central bank, which does not contribute to the risks we are interested in. However, the amount of central bank deposits is much smaller and less distorting, so I decided to use this source. Adjusting the liability side to make it equal to this asset category I obtained a relatively clear representation of the sums of interbank lending. (This methodology would not be appropriate after 2013, since in 2014H2 the central bank changed the target variable from two weeks maturity bond, to two weeks *maturity deposits*. This action increased the stock of deposits materially.)

After altering the data I carried out three network generating algorithms in order to get a range for the estimations to reconstruct the adjacency matrix in the most reliable way. Firstly I will present the implementation of Maximum Entropy (ME) method, which is the historically most often used and quite simple solution. It results in a maximum density estimation offering a uniformly distributed limit of credit relationships for the further analysis. Density has an important role, because the number of edges influences the contagion materially through two contradictory effects: On the one hand, having more links increases the potential channels of contagion. On the other hand, the exposures are distributed across more bilateral connections, which enhance the resilience when a shock occurs. The final result depends on the level of connectivity and the amount of capital in the banking system. (Upper, 2011, p. 4) According to Allen and Gale (2000), if the network is almost complete, the probability of contagion is seriously underestimated. An enhanced version of ME is called Minimum Density (MD) method, which gives the opposite extreme outcome: this can be used as the highly sparse limit of credit relationships for our estimation. I also performed a third approach based on copulas (CA), which produces the same dense structure as ME, but allocates the quantities (weights of the edges) in a more realistic way.

2.1) Maximum Entropy method (ME)

The fundamental intuition behind using maximum entropy method is the following: Since we can observe only each bank's interbank assets and liabilities, there is no further restriction we could impose. In the absence of any additional information, the most rational solution is to choose a distribution which maximizes the uncertainty (also known as entropy in information theory) of the interbank exposures. Entropy maximization can be explained through the example of the probability distribution for the outcome of rolling a six-sided dice. Without any prior information that the dice is loaded in some way, the most sensible distribution to choose is one that assigns an equal probability to each of the six possible outcomes. So entropy maximization allows us to select a unique distribution making full use of available information without making any assumption about information that is not available. It means that we generate an adjacency matrix (rescaled between 0 and 1 and denoted as x_{ij}) as randomly as possible. The widespread mathematical formulization of this problem (coming from thermodynamics) is the following:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij} \ln(x_{ij})$$

subject to:

$$\sum_{j=1}^{N} x_{ij} = a_i$$
$$\sum_{i=1}^{N} x_{ij} = l_j$$
$$x_{ij} \ge 0$$

where l and a represent the assets and liabilities of each bank toward financial institutions. The Langrangian for this problem is:

$$\min L(x,\lambda,\mu) \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij} \ln(x_{ij}) - \sum_{i=1}^{N} \lambda_i \sum_{j=1}^{N} (x_{ij} - a_i) - \sum_{j=1}^{N} \mu_j \sum_{i=1}^{N} (x_{ij} - l_j)$$

Solving it we get simply:

 $x_{ij} = a_i l_j$

This solution is not suitable yet as it also implies that a bank may have an exposure to itself, so we should restrict the element of the main diagonal to be zero. Furthermore, this

matrix might violate the adding-up constraints. To solve this, we can use RAS algorithm (iterative proportional fitting) to balance the matrix. It consists of the following steps:

1) Calculating the sum of the rows:

$$\sum_{i} F_{ij} = a_i^*$$

2) The marginals divided by the sums:

$$r_i = a_i^*/a_i$$

3) Adjustment of the rows:

$$F_{ij} = r_i F_{ij}$$

4) Sum of the columns:

$$\sum_{j}F_{ij}=l_{j}^{\ast}$$

5) The marginals divided by the sums:

$$c_j = l_j^* / l_j$$

6) Adjustment of the columns:

 $F_{ij} = c_j F_{ij}$

This algorithm should be repeated until the sum of the squared errors will be small enough. I implemented this procedure using R to get the simulated network. (The code can be found in Appendix 1.)

2.2) Minimum Density approach (MD)

The fundamental assumption behind maximum entropy case was the absence of any further information beyond the aggregated balance sheet data. In the minimum density method the developers (Anand et al., 2014) of the approach overcome this belief, as actually, we do have at least two pieces of additional information about the network of interbank

exposures: (1) Establishing and maintaining linkages among banks is a costly action due to the expenses of risk management, information processing and creditworthiness checks. Hence, banks do not spread their interbank exposures across the whole network. (2) The active bilateral connections are not distributed completely randomly; it tends to be rather disassortative. It means that less-connected institutions are more likely to trade with moreconnected banks than other less connected banks. (Boss et al., 2004; Boss et al., 2006; Iori et al., 2005; Iori et al., 2008) This impact is underpinned by the observation of the existence of intermediary banks serving as money-centers. The MD procedure finds the most probable links based on these two additional aspects, and weights them with the largest possible amounts. The formulated way of the heuristic process that executes this method is the following (Anand et al., 2014. p. 2-5.):

Firstly, we create initial probabilities of having a link between two banks:

$$Q_{ij} = max \left\{ \frac{LD_j}{AD_i}, \frac{AD_i}{LD_j} \right\}$$

At each iteration, a link (i, j) is selected with probability Q(i,j), where AD(i) is a bank's current surplus and LD(i) is the current deficit to be met in the interbank market. The initial probabilities in Q represent the characteristics of the interbank network that small banks typically have links with large banks. The exposure Z(i,j) is loaded with the maximum value that this pair of banks can transact:

$$Z_{ij} = min\{AD_i, LD_j\}$$

If adding this link increases the value function below, V(Z), the allocation is retained.

$$V(Z) = -c\sum_{i=1}^{N} \sum_{j=1}^{N} \mathbf{1}_{[z_{ij}>0]} - \sum_{j=1}^{N} [\alpha_i A D_i^2 + \delta_i L D_i^2]$$

In this function c means the cost of having a link between two banks, while the second term handles the deviation from the marginals. According to this function, networks with a lower density have higher values. However, if the addition of Z(i,j) diminishes the value function, we also retain the link as long as the network including Z(i,j) is more likely than without the link.

In order to decide on this probability the authors proposed the following procedure: Since we want to generate networks that are both sparse and disassortative, we should derive a distribution by maximizing the sum of two terms representing these objectives. Let P(Z) be the probability distribution over all possible network configurations. The first part is then the expected value of networks based on the value function (networks with few links and thus with high value should be more likely). At the same time, to ensure disassortativity, P should be close to the prior Q. This can be obtained by maximizing the relative entropy between the probability distribution P and the initial Q. P can be derived by the solution of the problem consisting of the combination of the two parts:

$$\max_{p} \sum_{Z} P(Z)V(Z) + \theta R(P||Q)$$

where θ is the scaling parameter emphasizing the weight placed on finding solutions with similar characteristics to Q. The solution of this expression is attainable from the first-order conditions. If the probability of the network is lower after adding a new link, the connection will be removed. This procedure should proceed until the total interbank market volume has been allocated. To conduct this heuristic algorithm I asked the developers of the model to assist me with the Matlab code they used. I made slight modification to transform it in an appropriate form for the analysis on my data set.

2.3) Copula Approach (CA)

Baral et al. (2012) developed a novel network reconstructing algorithm, which uses copulas as the core of the method instead of maximizing entropy. Their proposal also applies RAS algorithm, but unlike the ME solution of Upper and Worms (2004) it does not treat all the connections equally, rather uses values assigned by a copula to generate a stochastic matrix. This matrix can be multiplied by the marginal exposures to create the adjacency matrix, which can produce a better match than the one estimated by ME. In any case, before I go into the details of CA, it might be useful to provide an example as a quick overview of copulas using Schmidt (2006) p. 2-3.

2.3.1) Copulas⁴

Consider throwing two dices which represent two random variables: X1 and X2. The outcome in both cases can vary between one and six. If the value of X1 is given, it means no information about the value of X2, i.e. they are independent. In turn, if we know that the two numbers are equal, assuming X1 as given we have full information on X2. To describe more precisely these two random variables we can use their cumulative distribution functions (marginals). However, they give us no information about the joint behavior. In the independent case the joint distribution function is simply the product of the marginals. Hence, we can notice that we use two ingredients to attain complete description of X1 and X2: the cumulative distribution functions and the type of their relationship, which is independence here. The main idea of copulas is exactly this separation of the marginals and the dependence.

Suppose a third case where X1 is always the number of the smaller throw and X2 is the larger one. Here we have strict monotonic relationship between X1 and X2: $X1 \le X2$. If we

⁴ based on Schmidt (2006)

know that X1=5, we can have a guess on X2 to be equal either 5 or 6 with 50% probability each. The joint distribution function in this situation can be written as:

$$P(X_1 \le x_1, X_2 \le x_2) = 2F(\min\{x_2, x_2\})F(x_2) - F(\min\{x_2, x_2\})^2$$

As a first step to disentangle the dependence structure we should transform the random variables into uniformly distributed ones. This is useful because a random variable can be always represented using the uniformly transformed values and the generalized inverse of the cumulative distribution function; therefore, the joint distribution function can be expressed using two independent and standard uniformly distributed random variables. In this form we can obtain the dependence structure, which is also known as a copula:

$$C(u_1, u_2) = 2\min\{1 - \sqrt{1 - u_1}, \sqrt{u_2}\}\sqrt{u_2} - \min\{1 - \sqrt{1 - u_1}, \sqrt{u_2}\}^2$$

The marginals transformed into uniform distributions can be used as a point of reference. The copula function then obtains the dependence structure using this reference. It must be also noted, that due to Sklar's theorem the marginals should be continuous. If this criterion is not met the copula is not unique.

2.3.2) Estimating bilateral exposures using CA

During the procedure of estimating the bilateral exposures by copula approach I followed steps outlined in Baral (2013). The first thing we must be aware of is to solve the problem that the marginals are discrete instead of being continuous. To estimate the probability density functions I used kernel density estimator, which is a non-parametric method with favorable characteristics for smoothing the data. It allows us to choose the type of the kernel function and also the bandwidth to avoid under- or oversmoothing. The general form of a kernel density estimator for the marginals of the adjacency matrix is defined as:

$$\widehat{f_h}(x_i) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - x_0}{h}\right)$$

where K is the kernel function (which integrates to one and has zero mean) and h is the bandwidth (The kernel density estimation method is this way similar to a histogram).

Firstly, I performed some preliminary analysis in order to get information about the nature of the densities of the marginals. Based on Baral (2013), I chose a normal kernel function to make plots of the variables. This function has the form:

$$\widehat{f_{h}}(x_{i}) = \frac{1}{\sqrt{2\pi}} e^{\left(\frac{x_{i}-x_{0}}{h}\right)^{2}}$$

I used the default Matlab kernel density bandwidth parameter which depends on the number of observations. It evaluates the function at 100 points covering the range of the given variable. By plotting both of the marginals we can learn about their distribution and the tail dependence, which relationship is necessary to explore since it will be the basis of the choice what kind of copula is the most suitable. For instance upper tail dependence means that with large values of the first variable also large values of the second variable are expected. This analysis is done by eyeballing whether the peaks in the densities of the two variables are correlated with each other. It is not obvious to pick the right copula, since there is no quantitative rule for this. Fortunately, in banking system structures – due to the connected nature – there is almost always some pattern, usually lower or upper tail dependence, which can be a hint to opt for an Archimedean copula, such as Clayton or Gumbel type copula. As the illustration of Figure 1 shows, Gumbel copula shows rather upper tail dependence, while Clayton has extremely high peak at the (0, 0) point, which means lower tail dependence.

Figure 1 – Illustration of Gumbel and Clayton copulas (respectively) Source: Schmidt (2006) p. 12



Figure 2 – Kernel density estimates for the balance sheet variables



Based on Figure 2 there is probably lower tail dependence between the sum of the rows and the sum of the columns of the adjacency matrix. Intuitively, there can be upper tail dependence as well, but it is more difficult to evaluate since there are lot less data points for

that region. Consequently, I opted for using Clayton copula, but it should be noted that choosing a functional form on 43 observations is challenging in any case and therefore there is high uncertainty about the right choice.

After deciding on the copula, one should transform the discrete values into uniformly distributed ones, which is required for any copula function. To do this, we can use kernel estimation again, but this time the uniform version of it:

$$\widehat{f_h}(x_i) = \frac{1}{2} \cdot \mathbb{1}_{\left\{\frac{x_i - x_0}{h}\right\} \le 1}$$

where .1 is the *indicator* function which indicates membership of an element in a subset.

The next step is the most crucial part of the procedure: the estimation of the dependence parameter; that is fitting the copula to the data. The easiest way to do this is using the built-in Matlab function *copulafit* which runs maximum likelihood estimation for the dependence parameter. Substituting this parameter in the copula function we can generate a matrix of cumulative probabilities, which represents the likelihood of links between agents. After rescaling this matrix to ensure that the probabilities add up to one, and applying the RAS algorithm for rebalancing, we will reach to the bilateral connections we were looking for. Since the RAS procedure uses the probabilities generated by the copula function, the bilateral connections – unlike in the ME case – are not obtained under the assumption of maximum uncertainty. Instead they are reflecting the dependence structure of the real system.

There is a further opportunity for enhancement in the CA approach. It can happen that fitting only one copula does not result in a good fit, because the dependence structure is more complex. (For instance there are lower tail dependence and upper tail dependence as well.) In this case it is also possible to use a mixture of copulas. Baral and Fique (2012) combined

Gumbel and Clayton copulas by dividing the data into two parts and applying the more appropriate copula for the subsets separately.

2.4) Comparison of the generated networks

For the sake of comparison among the approaches, I conducted a brief analysis using basic network measures about the Hungarian interbank system. I downloaded the balance sheet data of the 43 largest financial institutions. (There are 43 actors in the industry which are operating as LTD or PLC.)

I made illustrations in Gephi showing the generated networks for the three methods. Figure 3 and Figure 4 are showing the estimations for the network of the Hungarian interbank lending structure. The ME and the CA results differ only in the weights of the edges, but their basic structure is identical. In Figure 3 the weights, i.e. the size of the particular bilateral exposures are represented by the thickness of the edges. In Figure 4 (to make the differences more visible) the more important edges also have warmer colors. The size of the nodes indicates the number of degrees of each node, while the colors of vertices (transition from light pink to red) for the MD graph denote the eigenvector centrality of the banks. Eigenvector centrality is an indicator of the influence of a vertex in a graph. It assigns scores to the nodes based on the score of their connections (which is based on the score of the connections of the neighbors, etc.). It implies that connections toward nodes with high score contribute to the importance more than a connection toward nodes with low score.



Figure 3 – Illustration of the Minimum Density estimation of the Hungarian interbank lending

Figure 4 – Illustration of the Maximum Entropy (left) and the Copula approach (right) estimations of the Hungarian interbank lending network



If we look at the seemingly systemically important banks in the MD network, the method seems to be credible in this respect. The five major actors in the system are among the top eight banks in Hungary in basically all the indices or measures we can find. In the other two networks I highlighted only OTP bank (to keep the figure clear), but the other seemingly large banks on the illustrations are also in accordance with the reality. In order to compare the networks in a quantitative way as well, I used several measures, for which I provide some clarification in Table 2.

Measure	Explanation			
Average path length	The average number of steps of the shortest paths for all possible			
	pairs of network nodes.			
Density	The number of links as a percentage of the total number of			
	potential links (excluding self-loops).			
Network diameter	The longest of all the calculated shortest paths in a network.			
Modularity	Modularity is the fraction of the nodes falling within a given			
	group compared to the expected fraction if the links were			
	allocated randomly.			
Global clustering	An indicator of the extent to which banks in the system tend to			
coefficient ⁵	form clusters.			
Dependency	Dependency shows the ratio of the largest lending (borrowing)			
	amount and the sum of the lending (borrowing) of all the banks in			
	the system.			
Connected component	A connected component is a subgraph in which any two nodes			
	are connected to each other by at least one path.			

Table 2 – Simplified definitions of some network measures (based on Newman et al. (2006))

⁵ Both clustering and modularity measure the presence of cliques, but they have a different point of view. Networks with high modularity have a lot of connections among the nodes within modules but there are only few links between nodes in different cliques. Global clustering uses a different concept: it considers the density of closed triplets compared to all triplets. (A triplet consists of three nodes that are connected by either two (open triplet) or three (closed triplet) undirected ties.) It is easy to imagine graphs with high modularity, but low clustering coefficient, e.g. complete balanced bipartite graphs without any link between each other.

Table 3 shows these basic network parameters of the three methods calculated in Gephi (except from the dependencies; I used Matlab for those.)

	Minimum Density	Maximum Entropy	Copula Approach
Number of nodes	43	43	43
Number of edges	65	1025	1025
Avg. degree	1.512	23.84	23.84
Avg. path length	3.082	1	1
Density	0.036%	56.8%	56.8%
Network diameter	7	1	1
Modularity	0.408	0	0
Avg. clustering coeff.	0.068	0.736	0.736
Dependency (borrowing)	84.09	24.94	25.68
Dependency (lending)	92.79	12.54	14.47
Size of the largest connected components	42	42	42

Table 3 – Network measures for the three approaches

I have also tried to perform community detection using Gephi's built in modularity tool, but it was possible only in the case of the minimum density network due to the almost complete structure of the other two outputs. I found four communities, but Figure 5 shows only three of them since the forth one is a separated component which consists of only one node. The communities found this way are reflecting the assortative structure of the system, but the core-periphery nature is not present so explicitly.



Figure 5 – Communities in the network estimated by Minimum Density method

All the figures show clearly how large the imbalance is between the outcome of MD and the other two estimates. (The number of connected components is two in all cases due to one bank which has no interbank exposures according to the marginals.) Most of the numbers are identical for ME and CA, since the majority of the indicators in the table do not take into consideration the weights of the edges. The only categories where ME and CA are different are the dependency measures. Since they are calculated using the weights of the links their divergence is not surprising and also their relation is in line with the expectations: CA has the theoretical advantage to perform better in the case of strong core-periphery structure (which is the intuitive expectation for this network) where highest dependence is more likely.

The visualization and the calculated network measures confirm the other preliminary expectations as well. The ME and CA approaches deliver an unrealistic structure, which might underestimate the contagion in the case of a systemic stress event. They produce almost complete networks (Since sometimes the marginals have zero value, there are parts of the matrix which are zero even in these cases.) However, the minimum density estimates are also quite far from the real numbers, if we accept the estimation of 1% for the German interbank network density (Craig von Peter, 2014) as valid for Hungary as well.

Albeit all three methods produced outputs with deficiencies, further analysis of the system is possible and necessary. The most realistic result was given by Minimum Density method, but it might be still useful to run simulations on all the three versions at least for the sake of checking the robustness. In the next chapter I will continue the comparison of the matrices derived here, but with a more informative tool: I will perform stress simulation for analyzing shock events to explore the number of defaults and the expected loss due to an idiosyncratic shock.
3) Idiosyncratic shock simulation

This section introduces the simulation technique of the analysis, which will be the base also for SIFI identification and for the comparison across different regulatory policies. I divided this section into two subsections. In the first one I provide thorough description about the simulation setup and the assumptions I made during the calculations, while the second subchapter contains the results of the baseline scenario.

3.1) Simulation method

As the first step in the procedure of the simulation one has to decide what kind of distress should be used as a shock event. Since the focus of the analysis is the impact of contagions which are spreading through bank failures, I used exogenous idiosyncratic defaults of individual banks. This distress can drive banks to failure in two ways: (i) being the first randomly selected agent which defaults; and (ii) defaulting by contagion. The latter case occurs if an otherwise solvent agent is pushed into default by depressing the value of its interbank assets due to the default of other bank(s).

As a next step, in order to describe the exact mechanism of the contagion we should create the simplified balance sheets of the banks. Beside the interbank exposures there are two other essential ingredients which should be identified in the hypothesized balance sheets. The first one is the capital of banks which can be used as loss-absorbing buffer in a stress situation. Contagious cascades can be materially reduced by the adequately high level of this buffer, so it is important to think over carefully what can be recognized as capital buffer. The wide-spread consensus in practice is to consider only the capital that exceeds the regulatory minimum. (Berlinger et al., 2015) Since this grouping of the capital of banks is not available in public sources, I estimated the bank level excess capital from the aggregated data of the

Financial Stability Report of the National Bank of Hungary. I adjusted this data by proportioning it based on the balance sheet total of the individual banks.

The other pivotal item of the identification is the "size" of a given bank which represents the potential damage it can cause in the case of its default. This measure should proxy the effect of the bank failures on the real economy. I decided to use the stock of non-bank deposits for this purpose in my simulation. The rationale behind this choice is that even a defaulting bank causes losses to all of its creditors; we should handle interbank creditors with caution, because without distinction one might count the effect on them twice. Since in the case of interbank exposures the liabilities of one bank are assets of another, losses on these links are incurred by the equity holders (or other creditors) of other banks in the system. Consequently, if one includes interbank links as a measure of losses, they can be double counted at a system-wide level. (Drehmann and Tarashev, 2013)

Table 4 – Hypothesized balance sheets of the banking sector (Elements marked with grey are present in the simulation)

Assets	Liabilities
Interbank assets	Interbank liabilities
	Non-bank liabilities (deposits)
Non-bank assets	Excess equity
	Minimum equity

Now, we can formulate the contagion mechanism: We choose a bank randomly, and we assume that it defaults due to an idiosyncratic shock. Based on the generated adjacency matrices we know all the interbank links which will be affected by the fundamental default. We can apply an LGD (loss given default) parameter, which determines the loss proportional to the bilateral exposures. Contagion occurs, if this loss exceeds the excess capital of one of

the partner banks. Then, as a next round we apply the same algorithm for the newly collapsed agent(s) until the cascade stops and we reach equilibrium.

During this procedure I made several assumptions which should be mentioned:

There is no deposit insurance, or other guarantees: In reality there is in almost every country some kind of explicit guarantee for the liabilities of banks, and there is also a high probability of bailouts of some agents.

There is no adjustment from the banks: Since the contagion mechanism takes place abruptly, the banks do not alter their behavior as a response to the shock. It is not a realistic behavior, since banks probably adjust their strategies to the new situation. Furthermore, in systemically important situations also the state (the regulator) can intervene in order to ease the tension on the market.

Constant LGD: I assumed constant loss given default parameter for all the banks; however, in the reality LGD can vary in a large extent across different agents.

There is no cost/length of legal procedures: Due to the lack of information I did not take into account the costs of the legal procedure emerging after a default. (It can be considered as a part of the LGD.)

Only domestic exposures cause contagion: This assumption might lead to underestimation of the probability, or the severity of contagions, but there is no information available to overcome this bias.

Losses are shared equally across lenders.

The interest and the principal are counted together at repayment.

3.2) Results

I ran the above described algorithm for the default of every bank, and I obtained two types of outputs: The expected shortfall caused by the cascade (based on the stock of deposits), and the number of default as a proportion of all banks in the system. The code for this exercise (written in R) can be found in Appendix 1.

Figure 5 shows the expected loss calculated as the percentage of all deposits in the case of the Minimum Density network. We should keep in mind that this measure also contains the loss occurred by the default of the first bank, which may or may not cause a contagion. If we are curious about the expected shortfall in the system this is a well performing measure, but it results in a biased indicator concerning the contagious effects. I ran the simulation using three different LGD parameters (30%/60%/90%). These versions produced partly the expected ranking, i.e. we can see the highest shortfall in the 90%LGD case, but the other two scenarios do not show any difference. We can observe in Figure 6 that the seven largest banks have outstanding values, which is in accordance with the bias mentioned above.

Figure 6 – Expected shortfall (ES) as a percentage of the size (stock of deposits) of the whole banking sector (43 banks) with 30%/60%/90% LGD – Minimum density version



In order to filter out the distortion caused by the size of the banks and see only the contagious effects, I also ran a simulation for the number of defaults in the case of the failure of a given bank. Figure 7 presents the results of this measure. This figure is more informative concerning the contagious impact of the banks, and it is somewhat different from the previous outcome. There are also a few smaller agents (Commerzbank, two FHB entities and Gránit Bank) which seem to be important in this respect, while some of the large banks (Unicredit, Erste) are missing from the list of the most important institutions.

Figure 7 – Proportion of the defaulted banks after the failure of a particular bank with 30%/60%/90% LGD – Minimum density version



I conducted the same analysis for the Maximum Entropy and the Copula Approach based networks. Figure 8 shows the expected shortfalls in the ME case. There is no significant difference across the various LGD parameters, which can be surprising at first sight, but after examining Figure 9 (which shows the number of defaults) it becomes obvious that this strange result is due to the fact that there are only very few contagious events took place in this network.

Figure 8 – Expected shortfall as a percentage of the size (stock of deposits) of the whole banking sector (43 banks) with 30%/60%/90% LGD – Maximum entropy version



Figure 9 – Number of defaults as a percentage of the number of all banks (43) after the failure of a particular bank with 30%/60%/90% LGD – Maximum entropy version



Concerning the CA version, the outcomes can be seen in Figure 10 and Figure 11. These are almost identical with the ME results; the only remarkable difference is in the number of defaulted banks, which is zero even for the cases where Commerzbank and Raiffeisen Bank defaults initially. (Actually it is not zero, since the own defaults of banks are also counted in the measure, but there is no second round default.)

Figure 10 – Expected shortfall as a percentage of the size (stock of deposits) of the whole banking sector (43 banks) with 30%/60%/90% LGD – Copula Approach version



Figure 11 – Number of defaults as a percentage of the number of all banks (43) a after the defaults of different banks with 30%/60%/90% LGD – Copula Approach version



Although this simulation would be applicable to some extent also for the purpose of determining the systemic importance of the banks, I will introduce more sophisticated ways to do this in the next chapter. However, based on all the figures presented in this chapter, it is clearly visible that OTP Bank has the largest influence. (This finding is not surprising considering its really strong position in the market.) To gain a clearer picture about this outlier, I performed the separated simulation for the default of OTP Bank to see the spillovers. Moreover, this example offers an illustration how the contagion proceeds.

Figure 12 – Contagion triggered by the default of OTP Bank with 30%/60%/90% LGD in the Minimum Density network



Figure 12 shows the cascades in the case of 30% (left panel), 60% (middle panel) and 90% (right panel) LGD parameter. The red color denotes the initial default of OTP Bank; the orange refers to the defaults in the first round; while the banks marked with yellow are the second round defaults. There are no more rounds even in the 90% LGD case.

4) SIFI identification

In order to find systemically important institutions in the generated banking networks I performed three different approaches. The first one is constructing an indicator based index; the second is a simple version of core-periphery decomposition, while the third way is a simulation method based on the concept of Shapley value. I decided to use more than one method to explore the differences between the approaches and to get more solid results.

4.1) Indicator-based measurement of systemic importance

Indicator-based approach is the most prevalent way to identify SIFIs in practice. According to the overview of Weistroffer (2011), despite the obvious difficulty of choosing the appropriate measures and thresholds, indicators have several advantages which explain their widespread popularity: (i) They can be applied relatively easily even at a global scale; (ii) they are more robust than market-based measures (e.g. compared to asset price correlations or VaR calculations); (iii) they are easy to implement and (iv) indicators are transparent, i.e. they can provide guidance for the banks in which aspects they should reduce risk-taking. However, this last argument entails also the possibility of manipulation through mitigating exposures which are important for the rating, while taking more risk in other areas. (In order to prevent this behavior regulators have some discretion in the rating procedure.) Another important drawback of indicator-based measures is that they are not able to differentiate between a banks' contribution to systemic risk and its participation in systemic events. For instance, in the case of a central counterparty (CCP) the objective of the regulator should be to ensure the survival of the institution by building up sufficient buffers. It is not the intention to disincentive the CCP not being so interconnected since its primary function is to enhance stability by reducing the complexity of the OTC market. In other cases however, incentivizing agents to limit their contribution to systemic risk is more important than ensuring their viability. (Weistroffer, 2011) Consequently, differentiation in the evaluation of the indicators (by assigning peer groups and setting various benchmarks) should be a pivotal part of SIFI identification. (However, this argument is valid also for the other approaches which will be introduced in the next subchapters.)

Based on the suggestions of the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS, 2013, 2015) proposed a methodology, which aims at capturing the impact of the failure of an agent. It incorporates five categories with equal weights: size, interconnectedness, substitutability, complexity and cross-jurisdictional activities. However, these categories and the indicators within them were recommended for G-SIBs (Global Systemically Important Banks), while in Hungary there are only Systemically Important Banks on domestic level (D-SIBs). For these institutions BCBS (2012) recommends only to ignore the last category (cross-jurisdictional activities).

Another possible framework for grouping indicators can be the measurement of importance along the functions of the banking system. The conventional splitting of banking activities consists of three main categories: Financial intermediation; participation in financial markets; and maintaining financial infrastructure. The intuition behind this approach is that importance of an agent can be indicated by the extent of its participation in the banking functions. The variables which could be used as proxies for these categories are listed in Table 5.

Category	Variables		
Financial intermediation	 Stock of bank level lending (subdivided into household and corporate categories) Stock of bank level deposits (subdivided into household and corporate categories) 		
Participation in financial markets	 Turnover of uncovered money market for individual banks /aggregated turnover Turnover of FX swaps for individual banks /aggregated turnover Turnover of government bonds for individual banks /aggregated turnover Turnover of spot currency market for individual banks /aggregated turnover Interbank lending exposures Interbank FX swap exposures 		
Maintaining financial infrastructure	 Number of bank accounts Number of branches Extent of custody services 		

Table 5 – Variables for measuring importance by banking functions (Bold denotes the indicators I have access to)

Unfortunately, the range of publicly available data either for variables in Table 5 or for the BCBS recommendation is very limited, so I can present only a version of indicator based measures, which is rather degraded into a basic description of the Hungarian banking system.

	Financial intermediation	Participation in financial markets	
Banks	Ranking based on Lending+Deposits	Ranking based on interbank exposures	SIFI ranking
OTP Bank Nyrt	1	1	1
Kereskedelmi és Hitelbank Zrt.	2	3	2
ERSTE BANK HUNGARY Zrt	4	2	3
UniCredit Bank Hungary Zrt.	7	4	4
MKB Bank Zrt.	5	6	5
Raiffeisen Bank Zrt.	6	7	6
CIB Bank Zrt.	3	14	7
FHB Commercial Bank Zrt.	13	8	8
Hungarian Savings Cooperative Zrt	18	5	9
FHB Jelzálogbank Nyrt.	14	9	10

Table 6 – Top ten most important Hungarian banks according to the indicator-based measurement

The results of Table 6 consist of two elements: the ranking based on the banks' stocks of deposits and lending which represents their role in financial intermediation; and the ranking based on interbank lending exposures, which is also a proxy for contagious potential. The last column shows the ranking based on the equally weighted average of the previous two aspects. All the data are from the public data base of Aranykönyv ("Golden Book"). Since these results are based on only very few variables, it might be necessary to implement other approaches for identifying the systemically important banks. Still, the outcome of this simple examination will be useful for the purpose of robustness check to the further methods.

4.2) Core-periphery decomposition

It is a well-known feature of the banking system, that there are a few money-centers which are connected to many other less central banks. (Berlinger et al., 2015) This hierarchical, tiered structure was found for instance in the German interbank network by Craig and von Peter (2010). They had also found that banks' characteristics (various measures of size) help to explain their position in the interbank market. Consequently, tiering is not random, rather behavioral, as there are economic reasons (e.g. fixed costs) which explain this structure of the banking system. This means that the position in the core-periphery partition

can be used also to measure the systemic importance. However, we should note that this method can be applied reasonably only in the case of the MD network, since the other two reconstruction techniques resulted in almost complete graphs, so they do not have a core-periphery structure.

However, even in the real banking networks (and also in the MD network) there is no pure core-periphery formation, so one has to find a method to decompose the system in a way that approximates the core-periphery setup. There are several ways how to perform this decomposition, but – due to its simple applicability – I have chosen the following method proposed by Berlinger et al (2015): First, I used the Bron-Kerbosch algorithm (Bron-Kerbosch, 1973) to solve the maximum clique problem in R. This procedure results in a list containing the largest complete subgraphs of the network. As a second step I picked from this list the result which produced the lowest degree in average in the periphery-periphery subgraph. It suggests that the banks in the periphery have only a few links with each other and a stress event can seriously limit their access to the market. (Berlinger et al., 2015) The output of this approach can be seen in Figure 13. The core consists of only three banks: OTP, Erste and FHB. They are considered to be indeed among the largest banks in Hungary, but the (highly simplistic) assumption of the method, that only completely connected subgraphs can constitute a core clique excludes a lot of other large players.

Figure 13 – Core-Periphery decomposition of the Hungarian banking system simulated by Minimum Density method (red denotes the banks in the core)



4.3) Identification based on Shapley value

Since the results of this type of core-periphery decomposition are very limited due to the "completely connected clique" assumption, I implemented also a simulation to identify SIFIs in the Hungarian banking system. The core of the code for this procedure is the same as in the stress test simulation, but it is embedded in a formula based on the concept of Shapley value. Shapley value is a measure of importance which has its origins in game theory. The heart of the method is calculating the difference between the losses occurred after a shock event with and without the presence of a given bank in the banking system. If one wants to implement the Shapley value in its authentic form, it is required to compute this difference for all the possible subsystems of the network: $f(N^{SUB}) - f(N^{SUB} - i)$. Then the Shapley value will be the weighted average of the increments of risk that a bank generates when it participates in any subsystem of the network:

Shapley value_i (i, N, f) =
$$\frac{1}{n} \sum_{n_s=1}^{n} \frac{1}{c(n_s)} \sum_{\substack{N^{\text{SUB}} \supset i \\ |N^{\text{SUB}}|=n_s}} (f(N^{\text{SUB}}) - f(N^{\text{SUB}} - i))$$
 for all $i \in N$

where $N^{SUB} \supset i$ denotes all the subsystems that contains bank i, $|N^{SUB}|$ means the number of banks in a given subsystem and $c(n_s) = (n-1)!/(n-n_s)!(n_s-1)!$ is the number of subsystems containing bank I and are comprised of n_s banks. (Drehmann and Tarashev, 2013, p. 6.)

Unfortunately, this method requires extremely large computational capacity, so I had to make a simplification: I did not calculate the differences for all the subsystems, only for the whole network. This way, my SIFI identification measure for bank i contains the average difference between the losses in the whole system (caused by the defaults of all the banks occurring one by one) with and without the participation of bank i. I wrote the code for this procedure in R and it can be found in Appendix 1.

When applying this method, we should mind the following consequences: When a bank is removed from the network, not only the given bank, but all the links of it will be removed as well. For these cases I made two assumptions. I assumed that (i) the removed assets of this bank are reallocated into other risk-free assets, and (ii) the banks which borrowed from the removed entity can substitute their interbank financing with other sources.

After completing the procedure there are a large number of results due to the many combinations of LGD parameters, network reconstruction techniques and loss measures. I do not present all of them in the context of the SIFI identification, I show only two outcomes: the Minimum Density - 90% LGD realization of two measures which seem to be the most relevant.⁶ Figure 14 shows the average difference for all banks between the losses with and without their participation in the network during stress events. The figure shows two types of this measure: one which includes losses that occurred due to the own default of the given bank, and another, which excludes this effect and takes into account only the contagion induced losses. The latter version should be considered if we are interested in creating a framework in which we can motivate banks to avoid becoming systemically important. However, if we want to take into consideration all the losses caused by the default of a bank, the former measure is more appropriate. In my analysis, there is no significant difference between the two, since both versions produced the same outcomes; that is the intuitively largest banks turned out to be the most important.

⁶ I picked MD because it produced the most realistic network; and there were the most defaults in the 90% LGD case, so I think it provides the most information.





There is an even better way to explore the importance of banks from a point of view of contagion. Similarly to the evaluation of the stress test, we can use the ratio of defaulted banks in the system as well. In this case there is no distortion due to the "size" of the banks, since this approach gives us the pure contagion related impact. The result of it shown by Figure 15 is rather surprising. We can see that the agents which seem to be important here are totally different (except from OTP) compared to the previous figure. They are smaller, seemingly less important banks, but they are crucial in the case of contagion. Of course it is only the result of a simulation, but it can draw attention to the potentially hidden risk factors in the system. It can happen also in the real banking system, that some banks are unexpectedly significant (regarding their role in contagions). However, I think the objective of the policy makers is rather minimizing social costs, and for this purpose the previous measures are more suitable.

Figure 15 – Shapley value based measure of systemic importance based on the proportion of defaulted banks using 90% LGD parameter and Minimum density estimates



5) Comparison of SIFI based and general regulation

In this chapter I conducted the final part of the analysis, which is the comparison of the SIFI based approach and the general capital policies. To do this, I built the following framework: I increased exogenously the size of the capital buffer in two ways according to the two types of regulations. In the SIFI based approach I used the information about the identity of SIFIs obtained in the previous chapter. I chose the version where I considered the expected shortfall of the stock of non-bank deposits without the losses caused by the initial defaults. (In my opinion this method reflects the most reliably the objective of the regulation since the main purpose is to minimize the cost for the society.) For these selected banks (CIB, Erste, K&H, MKB, OTP, Raiffeisen, Unicredit) I increased the size of their capital buffer by 10% and I ran the same stress test I described in Section 3 with an LGD parameter of 90%. After I saved the resulted losses in a vector, I moved to the second part of the simulation, which was the implementation of the general regulatory framework. In order to get comparable results, I distributed the amount of additional capital buffer (used for the SIFIs in the previous step) across all the banks in proportion to their baseline buffers. I ran the simulations with same shocks, and I saved the losses similarly to the previous case. Finally, the difference between the vectors of losses can be interpreted as a measure of efficiency of the two policies. Since building up additional capital buffer has adverse effect on the output, I wanted to compare two situations where the same amount of extra buffer is applied. This way we can see that at a given level of welfare loss, which method performs better. I made the assumption here that the adverse economic effect is linear regardless of the initial level of the buffer of a bank, i.e. the reaction of banks depends linearly on the change in their capital buffer, but does not depend on the level of it.

The result of the comparison can be seen on Figure 16 not only for the 10% increase but also for nine further cases where the extra buffer is higher and higher until doubling the original size of the capital of the SIFIs.

Figure 16 – Difference between the SIFI based approach and the general capital buffer policy based on the losses caused by stress events (using 90% LGD in the stress tests)



According to Figure 16 in the cases of ME and CA the SIFI based excess capital policy works more efficiently at all capital levels by a range of 30-80 billion HUF gain compared to the conventional approach. However, in the MD version, there are huge negative results at 50% and 60%. This might be odd at first sight, but this result is actually drawing attention to a very important trait of this kind of policies: the sensitivity against the imperfect identification of SIFIs. These results are due to the fact, that some smaller banks are not considered systemically important, but they still can trigger damaging cascades if their capital level is relatively low. In this example, when the mortgage bank of the FHB group defaults, it ignites the default of the commercial bank of the FHB group in the case of the SIFI regulation, but if the capital buffer of the commercial bank is increased by at least 50%, it survives. In the SIFI based policy, this capital injection is not present, so this is the reason behind the setback on the figure. Starting from the 70% capital increase, this impact is offset by other gains of the

SIFI regulation, but this phenomenon is still a very instructive result. The SIFIs found by the selected method were in accordance with our expectations, but it turned out that in some cases this methodology performed rather poor. This result might be attributable to the unrealistic network structure which differs greatly from the real-world interbank system, but this potential drawback of the applied procedure is still valid. Despite this problem, MD produces also the highest average advantage of the SIFI approach, so we can conclude that its superiority is mostly underpinned.

We can compare the policies also along the number of defaulted banks (similarly to the previous chapters). This result is depicted on Figure 16:

Figure 17 – Difference between the SIFI based approach and the general capital buffer policy based on the proportions of defaulted banks (using 90% LGD in the stress tests)



Figure 17 shows unquestionable dominance of the SIFI based regulation over the general policy. The decline for MD in the 50-60% area can be found also in this case, but the series remains positive even in this region. Likewise to Figure 16, the highest average overperformance of the SIFI approach is produced by the MD case. This pattern can be explained by the sparse structure of the MD, where the probability of contagion is higher; consequently it highlights more the virtues of the SIFI based policy.

Conclusion

In my thesis I performed an analysis about the efficiency of a new regulatory instrument: the special treatment of the systemically important financial institutions (SIFIs). This line of policies gained momentum after the lessons of the current crises, where financial contagions took place through several channels causing damages even in the real economy. There are numerous uncharted territories in this area, so I had the opportunity to examine only a narrow subject, which was testing the intuition whether identifying SIFIs can help us create better capital requirement regulation than the nowadays still widespread general requirements. In this analysis I considered only interbank lending as the source of contagion. Since it is a well-defined and direct way of spillovers, and it can lead to other types of contagious mechanisms, this channel can serve as an appropriate framework to measure the efficiency of the regulatory approaches. Given the fact that all types of capital requirements lead to an adverse adjustment process in the financial intermediary sector, I defined the efficiency as the level of stability attained by a given amount of additional capital buffer, where stability was represented by the estimation of losses and the number of defaults caused by the failure of individual banks. In order to make it possible to conduct the analysis, I had to overcome a serious information availability barrier. There is no public data in Hungary about the bilateral exposures in the interbank network, so I implemented three different network reconstruction techniques, "Maximum Entropy", "Minimum Density" and "Copula Approach". Despite the fact that all of these methods produce networks with some deficiencies, it became feasible to run the simulation and identify SIFIs in the network.

The outcomes of the comparison partially confirmed the intuition that the network based regulation outperforms the conventional policy. In most of the cases SIFI-based approach resulted in lower expected shortfall (in the stock of non-bank deposits) by 30-80 billion HUF

and in fewer defaults by 2-7 percentage points in average in the three generated networks. Given that contagion occurred relatively rarely even using 90% LGD parameter in the MD case which is the sparsest network (which also means the highest probability of contagion), this differences can be considered quite large. However, there were a few realizations where the outcome was the contrary. The explanation for these negative results is rooted in the imperfection of the SIFI identification methods. In some cases, seemingly less important banks are not considered systemically relevant, but they still can trigger damaging cascades if their capital level is relatively low. A small, but general increase in the capital buffer of all banks can prevent this kind of cascades, but a regulation focusing rather only on large agents cannot. In reality, this situation might occur rarely, and its appearance in the simulation might be due to the unrealistically generated networks. Either way, it indicates further directions of research. Since the same data availability problem is present in many countries, we should develop better ways to reconstruct bilateral exposures. As a complementary result of the analysis, it turned out that MD approach produces the most realistic output due to the incorporation of characteristics observed in the reality, so it would be promising to build in even more real-life information in the reconstruction procedures. In addition to this, we also have to find SIFI identification techniques, which are capable to capture more reliably the contagious nature of the system for instance by involving further contagion channels in the models or taking into account also the behavior of the banks and governments. (They probably anticipate distress and react to the shocks on the market.) Another - maybe even more fundamental - course of research is finding out more about the utility function of the society considering the trade-off between stability and market efficiency. Without this information, our evaluation about a policy cannot be perfectly reliable.

Despite all the missing pieces, I think regulators moved in the right direction with the concept of SIFI regulation. Albeit this analysis suffers from several limitations, the results

suggest that the intuitive foundation of network based prevention of contagions is valid. However, for the sake of the effective implementation of this approach further research is necessary in the future.

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Appendix 1: Codes

RAS algorithm (R)

```
set.seed(189);
library(igraph);
***
***
adj <- read.table("rasinput.csv", header=T, sep=";");</pre>
adj <- as.matrix(adj);</pre>
m <- read.table("marginals.csv", header=T, sep=";");</pre>
m <- as.matrix(m);</pre>
l<-c(m[,1]);</pre>
a<-c(m[,2]);</pre>
error<-c()
for (i in 1:100) {
  for (j in 1:43) {
   if (sum(adj[j,])==0) {
     v<-0
   } else {
   v<-a[j]/sum(adj[j,])</pre>
   }
   adj[j,]<-adj[j,]*v</pre>
  }
  for (k in 1:43){
   if (sum(adj[,k])==0) {
     u<-0
   } else {
   u<-l[k]/sum(adj[,k])
   }
   adj[,k]<-adj[,k]*u
  }
e<-sum((colSums(adj, na.rm = TRUE, dims = 1)-1)^2)+sum((rowSums(adj,
na.rm = TRUE, dims = 1)-a)<sup>2</sup>)
error<-c(error,e)</pre>
}
```

Kernel density plots (Matlab)

[f,liabilitiesi,bw] = ksdensity(liabilities,'npoints',100,'bandwidth',10000);
figure
plot(liabilitiesi,f);

[f,assetsi] = ksdensity(assets,'npoints',100,'bandwidth',10000);
figure
plot(assetsi,f);

figure plot(liabilitiesi,f,assetsi,f);

Copula fitting (Matlab)

%% Matrix generating

%Transforming the data into continous form

x = ksdensity(a, a,'function','cdf'); y = ksdensity(l, l,'function','cdf'); [xx, yy] = meshgrid(x, y);

%% Fitting a clayton copula

[paramhat,paramci] = copulafit('clayton', [x y]); q = -1/(paramhat); $q1 = xx.^{(-paramhat)};$ $q2 = yy.^{(-paramhat)};$ $clayton = (q1 + q2 - 1).^{q};$ C = claytonfor i = 1:43 C(i, i) = 0;end

Dependency measures (Matlab)

% Dependency measures

boro = sum(minden(:,:),1); lend = sum(minden(:,:),2); boromax = max(minden(:,:),[],1); lendmax = max(minden(:,:),[],2); lratio = 100*lendmax./lend; bratio = (100*boromax./boro)'; l = find(~isnan(lratio)); b = find(~isnan(bratio)); % pick only active banks LendDep = mean(lratio(l)); BoroDep = mean(bratio(b));

Stress test (R)⁷

```
set.seed(3052343);
library(igraph);
LGD = 0.90
PD < -c()
ES <-c()
for (k in 1:43) {
## Creating the adjacency matrix
adj <- read.table("max ent output.csv", header=T, sep=";");</pre>
adj <- as.matrix(adj);</pre>
## Adding attributes to the vertices (being defaulted, capital buffer and
stock of depostits)
a <- read.table("attributes.csv", header=T, sep=";");</pre>
a <- as.matrix(a);</pre>
d<-c(a[,1]);</pre>
b<-c(a[,2]);
G <- graph.adjacency((adj), weighted = T);</pre>
V(G)$default <- 0;
V(G)$buffer <- as.numeric(as.character(c));</pre>
V(G)$deposit <- as.numeric(as.character(s));</pre>
## Plot the network
#plot(G, layout = layout.kamada.kawai(G), edge.arrow.size=0.3,
#vertex.size = 10, vertex.label.cex = .75)
## Contagion mechanism
stop <- FALSE
j <- 1
default <- list(k)</pre>
while(!stop ) {
  V(G)$default[default[[j]]] <- j</pre>
  j <- j + 1; stop_ <- TRUE
for( i in default[[j-1]]){V(G)$buffer <- V(G)$buffer - LGD*G[,i]}</pre>
  default[[j]] = setdiff((1:43)[V(G)$buffer < 0], unlist(default));</pre>
  if( length( default[[j]] ) > 0) stop <- FALSE</pre>
}
PD <- c(PD, sum(V(G)$default != 0)/43);</pre>
ES <- c(ES, sum(V(G)$deposit[unlist(default)])/sum(V(G)$deposit));</pre>
}
#ES(expected shortfall), PD (Probability of Deafault)
plot(ES);
plot(PD);
write.csv(PD, "PD.csv");
write.csv(ES, "ES.csv");
```

⁷ Based on Berlinger et al. (2015)

Core periphery decomposition (R)⁸

```
***
####### Core-Periphery decomposition #######
***
adj <- read.table("min den output.csv", header=T, sep=";");</pre>
adj <- as.matrix(adj);</pre>
adj[is.na(adj)] <- 0
adj[adj != 0] <- 1
G <- graph.adjacency(adj, mode = "undirected")</pre>
CORE <- largest.cliques(G)
for (i in 1:length(CORE)) {
 core <- CORE[[i]]</pre>
 periphery <- setdiff(1:43, core)</pre>
 V(G)$color[periphery] <- rgb(0,1,0)</pre>
 V(G)$color[core] <- rgb(1,0,0)
 print(i)
 print(core)
 print(periphery)
 H <- induced.subgraph(G, periphery)</pre>
 d <- mean (degree (H))</pre>
 print(d)
 windows()
 plot(G, vertex.color = V(G)$color, main = paste("Core-Periphery
decomposition"))
}
```

⁸ Based on Berlinger et al. (2015)

SIFI identification simulation (R)

```
library(igraph);
***
PDsifi <-c()</pre>
ESsifi <-c()
ownES < -c()
for (l in 1:43) {
###### Contagion in the whole system #####
***
LGD= 0.90
PD \leq -c()
ES <-c()
for (k in 1:43) {
## Creating the adjacency matrix
adj <- read.table("min den output.csv", header=T, sep=";");</pre>
adj <- as.matrix(adj);</pre>
adj[is.na(adj)] <- 0</pre>
## Adding attributes to the vertices (being defaulted, capital buffer and
stock of depostits)
a <- read.table("attributes.csv", header=T, sep=";");</pre>
a <- as.matrix(a);</pre>
s<-c(a[,1]);</pre>
<-c(a[,2]);
G \leq \operatorname{graph.adjacency}((\operatorname{adj}), \operatorname{weighted} = T)
V(G)$default <- 0
V(G)$capital <- as.numeric(as.character(c))</pre>
V(G)$size <- as.numeric(as.character(s))</pre>
## Contagion mechanism
stop_ <- FALSE
j <- 1
default <- list(k)
while(!stop ) {
 V(G)$default[default[[j]]] <- j</pre>
 j <- j + 1; stop <- TRUE
 for( i in default[[j-1]]) {V(G)$capital <- V(G)$capital - LGD*G[,i]}</pre>
 default[[j]] = setdiff((1:43)[V(G)$capital < 0], unlist(default));</pre>
 if( length( default[[j]] ) > 0) stop <- FALSE</pre>
}
PD <- c(PD, sum(V(G)$default != 0)/43)
ES <- c(ES, sum(V(G)$size[unlist(default)]))</pre>
}
ownES <- c(ownES,V(G)$size[1])</pre>
```

```
#### Contagion without the given bank #####
***
LGD= 0.90
PDs <-c()
ESs <-c()
for (k in 1:42) {
  ## Creating the adjacency matrix
 adj <- read.table("min den output.csv", header=T, sep=";");</pre>
 adj <- as.matrix(adj);</pre>
 adj[is.na(adj)] <- 0</pre>
 adj<-adj[,-1]
 adj<-adj[-1,]
  ## Adding attributes to the vertices (being defaulted, capital buffer
and stock of depostits)
  a <- read.table("attributes.csv", header=T, sep=";");</pre>
  a <- as.matrix(a);</pre>
 a<-a[-1,]
  s<-c(a[,1]);</pre>
 c<-c(a[,2]);
 G <- graph.adjacency((adj), weighted = T)
 V(G)$default <- 0
 V(G)$capital <- as.numeric(as.character(c))</pre>
 V(G)$size <- as.numeric(as.character(s))</pre>
  ## Contagion mechanism
 stop_ <- FALSE
  j <- 1
 default <- list(k)</pre>
  while(!stop ) {
    V(G)$default[default[[j]]] <- j</pre>
    j <- j + 1; stop_ <- TRUE
    for( i in default[[j-1]]) {V(G)$capital <- V(G)$capital - LGD*G[,i]}</pre>
    default[[j]] = setdiff((1:42) [V(G)$capital < 0], unlist(default));</pre>
    if( length( default[[j]] ) > 0) stop <- FALSE
  }
 PDs <- c(PDs, sum(V(G) \ default != 0)/43)
 ESs <- c(ESs,sum(V(G)$size[unlist(default)]))</pre>
}
#PDD<-PD[-1]
#ESS<-ES[-1]
## difference between impacts with(out) the bank
PDsifi <- c(PDsifi, sum(PD)-sum(PDs))</pre>
ESsifi <- c(ESsifi, sum(ES)-sum(ESs))</pre>
}
```

difference between impacts with(out) the bank
difference between impacts with(out) the bank
PDsifi <- c(PDsifi, sum(PD)-sum(PDs))
ESsifi <- c(ESsifi, sum(ES)-sum(ESs))
}
plot(PDsifi, ylab="PD difference", xlab="Banks")
plot(ESsifi, ylab="ES difference (due contagion)", xlab="Banks")
ESplot<-ESsifi+ownES*LGD
plot(ESplot, ylab="ES difference (contagion+size)", xlab="Banks")</pre>

Comparison between SIFI and general approach regulation (R)

```
library(igraph);
***
PDdiff < -c()
ESdiff<-c()
***
LGD= 0.90
for (1 in 1:10) {
 PDsifi <-c()
 ESsifi <-c()
for (k in 1:43) {
## Creating the adjacency matrix
adj <- read.table("copula output.csv", header=T, sep=";");</pre>
adj <- as.matrix(adj);</pre>
adj[is.na(adj)] <- 0</pre>
## Adding attributes to the vertices (being defaulted, capital buffer
and stock of depostits)
a <- read.table("attributes.csv", header=T, sep=";");</pre>
a <- as.matrix(a);</pre>
s<-c(a[,1]);</pre>
c<-c(a[,2]);</pre>
t<-c
c[c(6,11,20,29,32,38,42)] <- c[c(6,11,20,29,32,38,42)] * (1+1/10)
G <- graph.adjacency((adj), weighted = T)</pre>
V(G)$default <- 0
V(G)$capital <- as.numeric(as.character(c))</pre>
V(G)$size <- as.numeric(as.character(s))</pre>
## Contagion mechanism
stop_ <- FALSE
j <- 1
default <- list(k)</pre>
while(!stop ) {
 V(G)$default[default[[j]]] <- j
 j <- j + 1; stop <- TRUE
 for( i in default[[j-1]]) {V(G)$capital <- V(G)$capital - LGD*G[,i]}</pre>
 default[[j]] = setdiff((1:43)[V(G)$capital < 0], unlist(default));</pre>
 if( length( default[[j]] ) > 0) stop <- FALSE</pre>
}
PDsifi <- c(PDsifi,sum(V(G)$default != 0)/43)</pre>
ESsifi <- c(ESsifi,sum(V(G)$size[unlist(default)]))</pre>
```
```
***
LGD = 0.90
PDgeneral <-c()</pre>
ESgeneral <-c()
for (k in 1:43) {
  ## Creating the adjacency matrix
 adj <- read.table("copula output.csv", header=T, sep=";");</pre>
  adj <- as.matrix(adj);</pre>
 adj[is.na(adj)] <- 0</pre>
  ## Adding attributes to the vertices (being defaulted, capital buffer
and stock of depostits)
 a <- read.table("attributes.csv", header=T, sep=";");</pre>
  a <- as.matrix(a);</pre>
  s<-c(a[,1]);</pre>
 g<-c(a[,2]);</pre>
  gencap<-g+g/sum(g) *sum(c-t)</pre>
 G <- graph.adjacency((adj), weighted = T)
 V(G)$default <- 0
  V(G)$capital <- as.numeric(as.character(gencap))</pre>
  V(G)$size <- as.numeric(as.character(s))</pre>
  ## Contagion mechanism
  stop_ <- FALSE</pre>
  j <- 1
  default <- list(k)</pre>
  while(!stop ) {
    V(G)$default[default[[j]]] <- j</pre>
    j <- j + 1; stop_ <- TRUE
    for( i in default[[j-1]]) {V(G)$capital <- V(G)$capital - LGD*G[,i]}</pre>
    default[[j]] = setdiff((1:43) [V(G)$capital < 0], unlist(default));</pre>
    if( length( default[[j]] ) > 0) stop <- FALSE</pre>
  }
  PDgeneral <- c(PDgeneral, sum(V(G)$default != 0)/43)</pre>
 ESgeneral <- c(ESgeneral,sum(V(G)$size[unlist(default)]))</pre>
}
PDdiff<-c(PDdiff, sum(PDsifi)-sum(PDgeneral))</pre>
ESdiff<-c(ESdiff, sum(ESsifi)-sum(ESgeneral))</pre>
}
plot(PDdiff)
plot(ESdiff)
```

Appendix 2: List of banks

1	AEGON Magyarország Lakástakarékpénztár Zrt.
2	Agrár-Vállalkozási Hitelgarancia Alapítvány*
3	Banif Plus Bank Zrt.
4	Bank of China (Hungária) Hitelintézet Zrt.
5	BUDAPEST Hitel- és Fejlesztési Bank Zrt.
6	CIB Bank Zrt.
7	Commerzbank Zrt.
8	Credigen Bank Zrt.
9	DRB Dél-Dunántúli Regionális Bank Zrt.
10	DUNA TAKARÉK BANK Zrt.
11	ERSTE BANK HUNGARY Zrt.
12	ERSTE Lakás-takarékpénztár Zrt.
13	evoBank Zrt.
14	FHB Jelzálogbank Nyrt.
15	FHB Kereskedelmi Bank Zrt.
16	Fundamenta-Lakáskassza Lakás-takarékpénztár Zrt.
17	Garantiqa Hitelgarancia Zrt.*
18	GRÁNIT Bank Zrt.
19	KDB Bank Európa Zrt.
20	Kereskedelmi és Hitelbank Zrt.
21	Kinizsi Bank Zrt.
22	Központi Elszámolóház és Értéktár (Budapest) Zrt.
23	MagNet Magyar Közösségi Bank Zrt.
24	Magyar Cetelem Bank Zrt.
25	Magyar Export-Import Bank Zrt.
26	Magyar Takarékszövetkezeti Bank Zrt.
27	Merkantil Váltó és Vagyonbefektető Bank Zrt.
28	MFB Magyar Fejlesztési Bank Zrt.
29	MKB Bank Zrt.
30	Mohácsi Takarék Bank Zrt.
31	MV-Magyar Vállalkozásfinanszírozási Zrt.*
32	OTP Bank Nyrt.
33	OTP Jelzálogbank Zrt.
34	OTP Lakástakarékpénztár Zrt.
35	Pannon Takarék Bank Zrt.
36	Polgári Bank Zrt.
37	Porsche Bank Hungaria Zrt.
38	Raiffeisen Bank Zrt.
39	Sberbank Magyarország Zrt.
40	SOPRON BANK BURGENLAND Zrt.
41	Széchenyi Kereskedelmi Bank Zrt.
42	UniCredit Bank Hungary Zrt.
43	UniCredit Jelzálogbank Zrt.