Systemic Risk and Contagion in the Hungarian Interbank Market

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Submitted to

Central European University

Department of Economics

In partial fulfillment of the requirements for the degree of

Master of Arts

Supervisor: Peter Kondor

Budapest, Hungary

2015

Abstract

Assessing systemic risk in interbank markets became increasingly important after 2008 for banks and regulators alike, as domino effects are one of the main forces propagating illiquidity crises in banking systems. Research on contagion shows that network structure is an important factor in determining systemic risk. This paper analyzes systemic risk in the Hungarian banking system between 2003 and 2011, and contagion effects in modified versions of the Hungarian interbank network. I use a complete dataset of uncollateralized interbank transactions provided by the Hungarian National Bank to construct interbank networks for each year. Simulating domino effects in the created networks, I find that the Hungarian interbank market is highly resilient, with no contagious scenarios and no substantial capital losses throughout the 9 years. Trial simulations are provided as an exercise to evaluate contagion in different network structures. Results show that there is no systematic difference between the importance of a major lender and a major borrower in propagating contagion. Another lesson from the exercises is that increasing interconnectedness changes the amount of contagion in the network. These changes, however are not systematic, and capital losses do not change significantly compared to the less interconnected network.

Acknowledgements

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Contents

1. Introduction

The financial crisis brought about fundamental changes in financial regulation, as the banking system experienced liquidity problems of major proportions. Increased regulating measures were necessary, since the liquidity problems of individual banks influenced major parts of the network on several occasions, due to high systemic risk. Resulting changes in banks' lending schemes, capital requirement and leverages led to a risk averse environment in financial markets. Therefore, economists and policymakers are increasingly interested in finding optimal policies and market structures that minimize systemic risk, while maintaining activity in financial markets. A key source of systemic risk is interbank loan transactions between commercial banks, as the default of a single bank can cause multiple banks to fail by defaulting on interbank loans. The spread of defaults is defined by precise relationships and transactional amounts between counterparties, or in other words by the structure of the interbank network. Allen and Gale (2000) and Acemoglu et al. (2013) find that network structure plays an essential role in determining systemic risk in the interbank market. Therefore it is a relevant problem to find a network structure that minimizes systemic risk, while putting minimal constraints on banks' interbank trading activity.

This paper analyzes systemic risk in the Hungarian banking system between 2003 and 2011, and contagion effects in modified versions of the Hungarian interbank network. Systemic risk in Hungary is examined by simulating domino effects in the uncollateralized interbank network. Simulation results show that the Hungarian interbank network is highly robust to idiosyncratic shocks, as capital losses in worst case scenarios and average capital losses are not substantial throughout the 9 years of interest. I use modified versions of the original network to examine how changes in network structure affect contagion. One of the main findings is that the presence of major lenders and major borrowers have an equally important role in terms of

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systemic risk. Comparing capital losses and contagion in the original Hungarian interbank network structure to a more densely connected network shows that although the number of contagious scenarios changes, this change is not systematic and effects on average capital losses are negligible.

A complete database of uncollateralized interbank transactions between 2003 and 2011, provided by the Hungarian National Bank is used for simulating domino effects. Average daily interbank exposures were calculated for each year to serve as the edges of the 9 interbank networks analyzed in this paper. I collected data related to Hungarian banks' regulatory capital from publicly available financial stability reports[1], and used it to define buffer capital[2] values for each bank. I simulated the effect of an idiosyncratic shock in the 9 obtained interbank networks by assessing contagion and capital losses in all possible scenarios.

In the simulation, banks are assumed to default if their total losses (originating from the external shock, or from a defaulted loan) reach the amount of buffer capital available to them. Each scenario begins with an unexpected shock hitting one of the banks in the network, this means that in a network with N nodes, N scenarios were simulated. If the bank hit by the external shock defaults, it is unable to meet his lenders' claims, and lenders suffer a decrease in their buffer capital. If any of the lenders run out of buffer capital, they also default and their lenders also suffer capital losses. The simulation stops when there are no additional lenders defaulting due to contagion. The described method is similar to that used by Degryse and Nguyen (2007) , Lublóy (2005) and Upper and Worms (2004). Details of the simulation methodology are included in Chapter 5.

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[1] Average system wide regulatory capital was collected from Financial Stability Reports (2003-2011), available on the website of Hungarian National Bank.
[2] Buffer capital can be interpreted in a similar way to tier 1 capital, it is the most liquid asset class available to banks to defend against negative liquidity shocks

Simulation results show that the Hungarian interbank network is highly resilient to contagion, with no contagious scenarios throughout the 9 years of interest. Worst case scenario capital losses were between 1-6% and average capital losses ranged from 0.1% to 0.6%. Losses were lowest in 2009 due to a large decrease in interbank market activity and an increase in banks' regulatory capital as a reaction to the crisis. Although interbank market activity reached pre-crisis levels in 2011, average capital losses remained smaller than before 2008, due to the increase in regulatory capital.

I ran several rounds of simulations excluding the largest banks in the network. These scenarios were used to assess the importance of major banks regarding systemic risk. Excluding major banks moderately decreased average capital losses, but the amount of decrease in losses did not vary much throughout the 9 years. When excluding major lenders and major borrowers from the network, I found that there is no systematic difference between the capital losses related to a major lender and a major borrower in the interbank network. Average capital losses related to large banks rather stem from the amount of interbank activity (be it lending or borrowing), and position in the network.

In the last set of simulations, I disallowed daily average exposures larger than 2 billion forints, and rewired the network to increase interconnectedness. Rewiring was done in a way that interbank liabilities of individual banks did not change, only banks' interbank assets changed during the procedure. Increasing interconnectedness resulted in a substantial change in the number of contagious scenarios. However, differences between contagion in the original network, and the rewired one were not systematic. Although the rewiring procedure led to major changes in network structure, differences in capital losses were not significant. The driving force of differences in contagious scenarios and the reason behind negligible differences in capital losses requires further research.

The rest of this paper is organized as follows: Chapter 2 provides an introduction to the contagion literature, with an emphasis on previous studies simulating domino effects on interbank markets. Chapter 3 describes the dataset received from the Hungarian National Bank, the interbank network that is mapped out for the 2003-2011 period, and the underlying assumptions. Chapter 4 contains a general analysis of the Hungarian interbank network, including trading volumes, centrality, and term structure. Chapter 5 introduces the simulation methodology used to assess contagion, while main results are presented in Chapter 6. Chapter 7 concludes.

2. Literature review

Systemic risk and financial contagion can originate from several different sources in a banking system. These sources of contagion can be seen from two angles, (1) shocks can have a negative effect on banks' liquidity through their liabilities or assets and (2) systemic risk can arise in the network due to indirect or direct relationships between banks. Three distinct sources of systemic risk are most commonly examined in the literature: bank runs, asset price decreases (i.e. fire-sales) and interbank exposures. Bank runs are the major source of systemic risk that have an effect through banks' liabilities, as banks with an overlapping group of debtors may experience a bank run simultaneously. This can create liquidity needs of large portions, and can subsequently lead to fire-sales, as mentioned in Fecht (2004). Fire-sales and interbank exposures affect banks via the asset side of their books, as their outstanding loans or asset portfolios decrease in value. Fire-sales represent an indirect channel of systemic risk, whereas interbank exposures lead to direct contagion, as counterparties are at risk of a knock-on default. This chapter summarizes major findings on systemic risk in the literature, categorized by the three distinct sources of contagion.

Research on bank runs started earlier than on the other two sources of systemic risk, with Diamond and Dybvig's (1983) discussion of the damage of bank runs to the banking system. This paper has little implication for systemic risk, however, as it analyzes the damage to a single bank, representative of the whole financial system. Nonetheless, Diamond and Dybvig's (1983) study paved the way for numerous papers, assessing systemic risk due to bank runs. First, Temzelides (1997) used a repeated version of Diamond and Dybvig's (1983) game-theoretic model with multiple banks, thus being able to examine contagion in the banking system. The author finds that assuming a local structure of depositors and banks (depositors and banks are grouped in geographic locations, this way banks in the same location are more

likely to have similar groups of depositors) generates contagion. Contagion effects become stronger with decreasing the size of the banks in the system.

Freixas et al. (2000) analyzes depositor behavior in a setting with uncertainty, taking into consideration interbank exposures in the system. In this paper liquidity problems arise initially from depositor behavior, and so called 'speculative gridlocks' can occur in the banking system. In this setting, depositors liquidate their deposits prematurely at local banks for fear of a lack of liquidity in the banking system. Dasgupta (2004) examines the relation between depositors' behavior and interbank loans. The paper concludes that the existence of interbank exposures facilitates contagion via speculation by depositors, moreover, the effect of speculative bank runs are found to be increasing in the amount of exposure between banks.

In the literature about fire-sales, a main approach can be distinguished regarding the reason for potential buyers not being able to stop downward spirals in asset prices. In one of the earlier models, Shleifer and Vishny (1992) develop the approach that asset prices can plummet drastically due to distress, because potential buyers are also in distress and therefore assets continue to be sold at a price below the intrinsic value. Caballero and Simsek (2013) recently contributed to this literature by adding uncertainty and interbank lending to fire-sales models. In this paper, the authors argue that uncertainty is a key element to amplify small initial shocks to the network, and can create contagion and significant damage to a network even when shocks are not substantial compared to the total amount of liquid assets in the banking system.

Also regarding fire-sales, Fecht (2004) analyzes the spread of contagion through fire-sales in 3 different settings: market-oriented, bank-oriented and the mixture of the 2 settings. In the market oriented setting, the number of households seeking investment opportunities is small relative to the number of banks, whereas the opposite is true for the bank-oriented system.

The author concludes, that contagion through fire-sales cannot occur in either of the extreme settings. Only in the intermediate case - where the number and bargaining position of banks is similar to that of households – can fire-sales lead to contagion in the banking system.

The central question of theoretical papers on contagion in the interbank market is whether a more equal distribution of exposures, i.e. an increase in density within the network decreases risk. Allen and Gale (2000) and Freixas et al. (2000) – among others – argued, that the resilience of a banking system to an unexpected shock increases with interconnectedness. Vivier-Lirimont (2006) and Blume et al. (2011) find, however, that higher interconnectedness may have a negative effect on systemic risk in the network.

In light of the differing theoretical findings about the resilience of a dense network, Acemoglu et al. (2013) systematically analyze the reaction of different network structures to large and small shocks alike. The authors find dense networks to have a "robust yet fragile" nature, when it comes to the size of the shock. Dense networks are the most robust in cases where the number and the size of the shocks is small. In turn, for large shocks - be it multiple medium sized shocks or one big shock – the complete network is the most fragile, while the ring network (the most sparse network, where all banks have 1 lending and 1 borrowing counterparty) is found to be more resilient than the complete network. The authors also show, that the resilience of complete networks as a function of shock size resembles a phase transition, meaning that below a certain threshold complete networks are the most resilient, and above that threshold they become the most fragile network structure.

Regarding empirical simulations on knock-on defaults and contagion in the interbank market, the literature can be divided into two groups. In one group, authors are restricted to analyzing contagion on an estimated network of bilateral exposures, as only aggregate interbank liabilities and assets of individual banks are available in most countries. These

datasets do not specify banks' counterparties and transactional amounts, therefore authors have to estimate bilateral exposures. Degryse and Nguyen (2007) and Upper and Worms (2004) estimated exposures in the Belgian and German interbank market respectively, in order to assess domino effects.

The methodology used in this paper is based on the simulation model used in the above mentioned two papers, but substantial differences regarding data make results difficult to compare[3]. Degryse and Nguyen (2007) find the median scenario to result in the loss of 3.33% of the total tier 1 capital in the network and only 3.79% of total capital is lost in the worst case scenario for Loss Given Default (LGD)=100%. Upper and Worms (2004) estimate average capital losses due to contagion to be around 0.85% at LGD=75%, while worst case scenario losses amount to a staggering 76.3% in their simulation. Our results regarding mean values are closer to those obtained for the German banking system, while we find worst case scenario capital losses similar to Degryse and Nguyen (2007). As earlier stated, results are not fully comparable due to differences in the underlying network of bilateral exposures.

The other group of empirical papers on interbank market contagion simulates domino effects on a complete dataset of bilateral transactions. Simulating knock-on defaults on the US uncollateralized interbank market at LGD=40%, Furfine (2003) finds the US interbank market to be highly resilient to contagion. Worst case scenario capital losses account for 0.8% of total banking assets and average capital losses are negligible due to only 7 banks failing as a result of contagion in a 60 day period.

Lublóy (2005) uses a Hungarian dataset on uncollateralized interbank loans in 2003, which is similar to the dataset analyzed in this paper. The network analyzed by Lublóy (2005),

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[3] One difference stems from the fact that Degryse and Nguyen (2007) and Upper and Worms (2004) use estimated exposures. Another, possibly more important, difference is that Belgian and German data contains both collateralized and uncollateralized loans, whereas only uncollateralized interbank exposures are analyzed in this paper.

however, differs from exposures examined in this paper, since Lublóy assesses the effect of contagion on 50 selected days in 2003, whereas this study examines domino effects on average daily exposures for each year. Despite this difference, simulated capital losses in this paper are close to results obtained by Lublóy (2005), as seen in section 6.1. Worst case scenario losses at LGD=100% throughout the selected 50 days amounted to 3.53%, while the author found average capital losses to be 0.53% of total tier 1 capital in the banking system.

The work of Mistrulli (2005) is also closely related to this paper, with the slight difference that both collateralized and uncollateralized loans are included in the Italian database, analyzed by Mistrulli. The author finds worst case scenario losses between 0.5-8.5% of total tier 1 capital for the 1990-2003 period, whereas average capital losses cause only negligible damages ranging from 0-0.05% for LGD=100%. While worst case scenario losses are found to be similar in this paper, average capital losses are significantly higher, as discussed in more detail in section 6.1.

3. Data on Hungarian interbank transactions

Data on uncollateralized interbank transactions was provided by the Hungarian National Bank, including both short- and long-term loans between commercial banks in Hungary. The database contains domestic exposures between January 2003 and January 2012. As Hungarian banks are obliged to report all their domestic interbank transactions, the database used in the analysis can be considered complete. Entities within the same banking group are analyzed separately, as aggregating interbank activity within a banking group was not possible due to anonymity. Within group transactions, however, are not considered throughout the analysis, as they are not included in the database. Moreover, within group transactions would not necessarily represent the state of the interbank market, since the risk of counterparty default is not taken into account when lending to an entity within the banking group. Within group transactions would rather bias the analysis by including loans that are provided for liquidity management purposes within a banking group.

Based on the detailed data on interbank loan transactions, an aggregate interbank network was mapped out for each year between 2003 and 2011, providing 9 networks altogether. Commercial banks constitute the nodes of the network (including banks within banking groups separately), while the edges represent average daily exposures between two banks[4]. An edge in the network can also be interpreted as the sum of transactional amounts between two banks throughout the year weighted by the probability that the transaction would be open when an unexpected external shock hits. An implicit assumption behind this interpretation is, that the timing of the external shock is independent of both interbank market

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[4] To calculate the average daily exposures for a given year (e.g.: 2003) between 2 banks i and j, the following formula was used:

$$L_{ij}^{2003} = \frac{\sum_k transactional\ amount_k * term_k}{total\ \#\ of\ workdays\ in\ 2003}$$

Note that if a loan's term spanned over 2 years (e.g.: beginning in November 2003, ending in February 2004), it was treated as two separate loans, one ending on the last workday of the year, and the other beginning on the first workday of the next year.

activity and calendar day, so in principle the shock can hit on any day with equal probability. Altogether, the aggregated network of a given year can be seen simply as the average of daily exposure networks throughout the year, or in other words, they represent the mean exposures from the empirical distribution of interbank exposures.

This approach has not been widely used in the contagion literature – one example is the work of Mistrulli (2005) - for several reasons. First, complete interbank loan data spanning over multiple years is not available in most countries, therefore most of the studies so far are restricted to a period of less than a year. In these studies, daily interbank exposures are taken into consideration, and simulations are run on randomly selected days throughout the period of analysis. Examples of such studies are Lublóy (2005) and Furfine (2003). Second, in certain countries there is no complete data on interbank exposures, thus the network has to be estimated from aggregate exposures, which contain information only about the total interbank assets and liabilities of each bank, the counterparty and the transactional amounts are not known.

Another, more commonly used (Lublóy, 2005; Furfine, 2003) method of assessing systemic risk in the interbank network, as mentioned previously, is to randomly select several days within a certain time period, and run a stress test using daily exposures. The main upside of this approach is that the worst case scenario represents a more vulnerable state of the banking system, compared to the state that the yearly average represents. This means that the worst case is not only the worst in terms of the initially defaulted bank, from which the contagion started, but also in terms of the current exposures on the interbank market.

The downside of the method used by Lublóy and Furfine is that for a larger timespan, approximately 50*N (where N is the number of banks in the network) scenarios have to be simulated per year, which totals around 9*50*25=11 250 scenarios for the 9 years in our case, compared to 9*25=225 using the average yearly network. The main hardship in following the

first method, however, is not computing, but data cleaning. In the first case 9*50=450 networks have to be created to analyze 50 randomly selected days per year, whereas in our case 9 networks were created.

In the contagion literature it is common to evaluate the effect of contagion on the tier 1 capital of the banks (Lublóy, 2005; Degryse & Nguyen, 2007; Furfine, 2003; Mistrulli, 2005). As the database provided by the Hungarian national bank does not include tier 1 capital, and there is no publicly accessible source containing information about tier 1 capital, the equity capital of the Hungarian commercial banks is used instead. Throughout the analysis it is assumed that the banks' equity capital[5] is equal to their regulatory capital.

According to the Basel II. Accord, the required Capital Adequacy Ratio[6] (CAR) is 8%, and if any bank's regulatory capital falls short of the 8% CAR, a monitoring procedure is started, and in more severe cases (if liquidity problems are expected to continue) it quickly becomes common information that the bank has liquidity problems. Therefore instead of having banks default when their tier 1 capital reaches 0, we assume that banks default, or get into an irreversible illiquidity spiral (banks in the network are assumed not to be willing to lend to a bank with severe illiquidity problems) if their regulatory capital falls short of the required 8%[7].

The amount of the regulatory capital above the required 8% is the buffer capital that banks are able to use in case of unexpected shocks, without drawing attention to their illiquidity

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[5] As the dataset received by the Hungarian National Bank is anonymized, it is assumed that the banks with higher interbank activity have higher amount of equity capital. In essence banks were sorted by their interbank activity and then matched to the sorted equity capital data (the bank with the highest interbank activity was assumed to have the highest equity capital in the system, the bank with the 2nd highest activity was assumed to have the 2nd highest equity capital, and so on).

[6] Note that CAR in this paper is not defined as $\frac{Tier\ 1\ capital + Tier\ 2\ capital}{Risk\ Weighted\ Assets}$, instead I use the minimum capital requirements specified by the national regulator, the Hungarian National Bank.

[7] In reality if a bank's regulatory capital falls below the required 8% CAR, it does not necessarily imply going bankrupt in the near future. Monitoring and supervising is done by the central bank upon reaching the 8% CAR as a first step, further measures are taken at 6%, while reaching 4% CAR practically means insolvency.

problems. In this sense buffer capital has a similar role to tier 1 capital in our analysis. Buffer capital was calculated for individual banks using publicly available data on equity capital[8], assuming that it is equal to regulatory capital. Average Capital Adequacy Ratios in the Hungarian banking system were collected from the financial stability reports of 2003-2011[9], all banks are assumed to have a CAR equal to the system-wide average, lacking data on individual banks' CARs. Thus, if the system-wide average in a given year was 10%, knowing that the required CAR is 8%, then $\frac{10-8}{10} = 20\%$ of the banks' regulatory capital is used as their buffer capital.

Using buffer capital throughout the analysis provides heterogeneity, since banks not only differ in their positions in the network (exposures), but they also have different buffer capital to interbank exposures ratios. So in principle it can happen that while one bank has average interbank loans equal to 10 billion forints throughout the year with 5 billion buffer capital, another bank would have interbank loans worth 10 billion forints with 50 billion in buffer capital. While the first bank can be highly vulnerable to contagion through its interbank position, the second bank has no risk of default through interbank market contagion.

Mistrulli (2005) argues that in order to analyze the effect of changes in the interbank network structure on contagion, one has to assume a constant tier 1 capital to total interbank assets ratio over time to exclude the effects of capital cyclical patterns. In sections 6.3 and 6.4 - after assessing contagion in the Hungarian market - I analyze effects of changes in interbank market structure, and keep the buffer capital to total interbank activity ratio unchanged in order to rule out changes in contagion due to capital cycles.

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[8] Data on Hungarian Commercial Banks' equity capital was collected from Hungarian National Bank reports (2003-2011)

[9] Source: Hungarian National Bank Financial Stability Reports (2003-2011)

4. Structure of the Hungarian interbank market

In this chapter, basic descriptive statistics are used to assess tendencies and structural changes in the Hungarian interbank market between 2003 and 2011. The analysis of the network is provided with special focus on changes after 2008, when effects of the financial crisis reached Europe[10]. As described in Chapter 3, this paper includes an analysis on uncollateralized interbank loans as provided by the Hungarian National Bank. There is an important distinction between examining the effect of the crisis on the overall interbank market (including collateralized and uncollateralized loans), as the increase in counterparty default risk is expected to have a larger effect on the uncollateralized market.
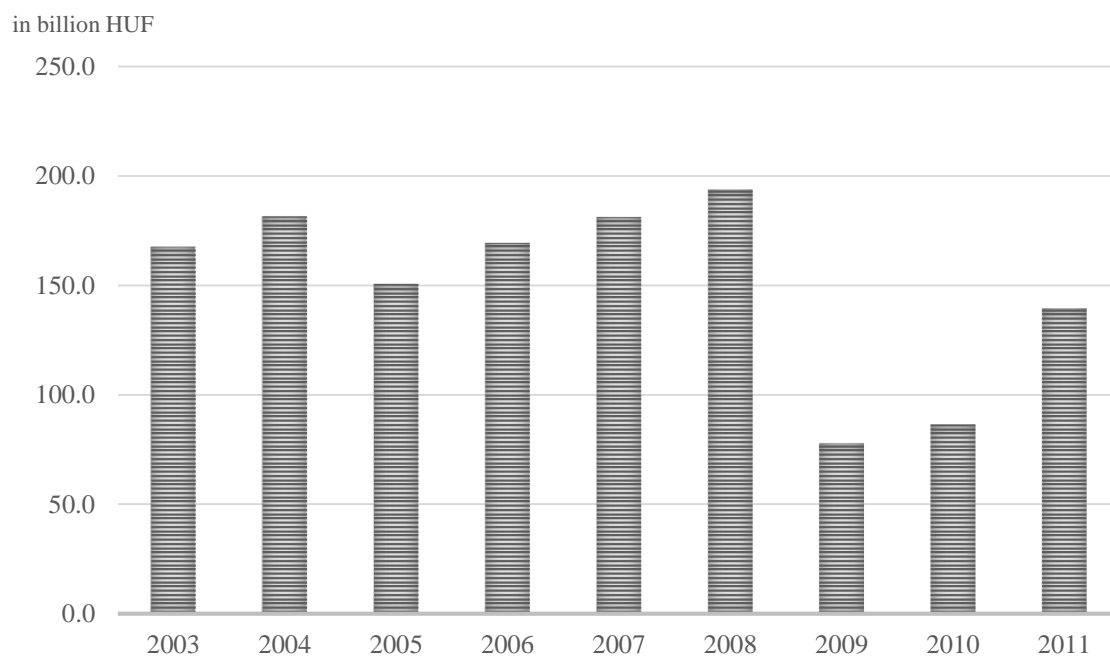
Figure 1: Total transactional amounts in the Hungarian network between 2003 and 2011

Activity on the uncollateralized interbank market dropped drastically after 2008, as shown in Figure 1, when the risk of entering uncollateralized transactions became higher. There is a small increase in activity in 2010, but 2011 is the first year after the crisis where activity

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[10] The crisis reached Europe in 2008 October, as documented by Mark Landler; The New York Times Online (Landler, 2008)

comes close to pre-crisis levels. Data from 2012 January support the increasing trend in market activity, as daily average trading volumes amount to 150 billion Forints. This suggests that banks' greatly decreased their activity for 2 years due to the crisis, but after 2011, the interbank market rapidly reached volumes of pre-crisis activity.

Due to limited activity on the market, the average number of counterparties decreased in a similar fashion to average liabilities, as captured by Figure 2. Banks were exposed to the highest number of counterparties in 2006 after a sharp increase from 2005. In 2009 and 2010 banks had around 2 counterparties in the interbank network on average, which means that network activity decreased both in terms of volume, and interconnectedness as banks became more selective in choosing their counterparties. Similarly to transactional amounts, the average number of counterparties increased to reach pre-crisis levels in 2011, which suggests that banks' withdrawal from the interbank market lasted only for 2 years after the crisis.
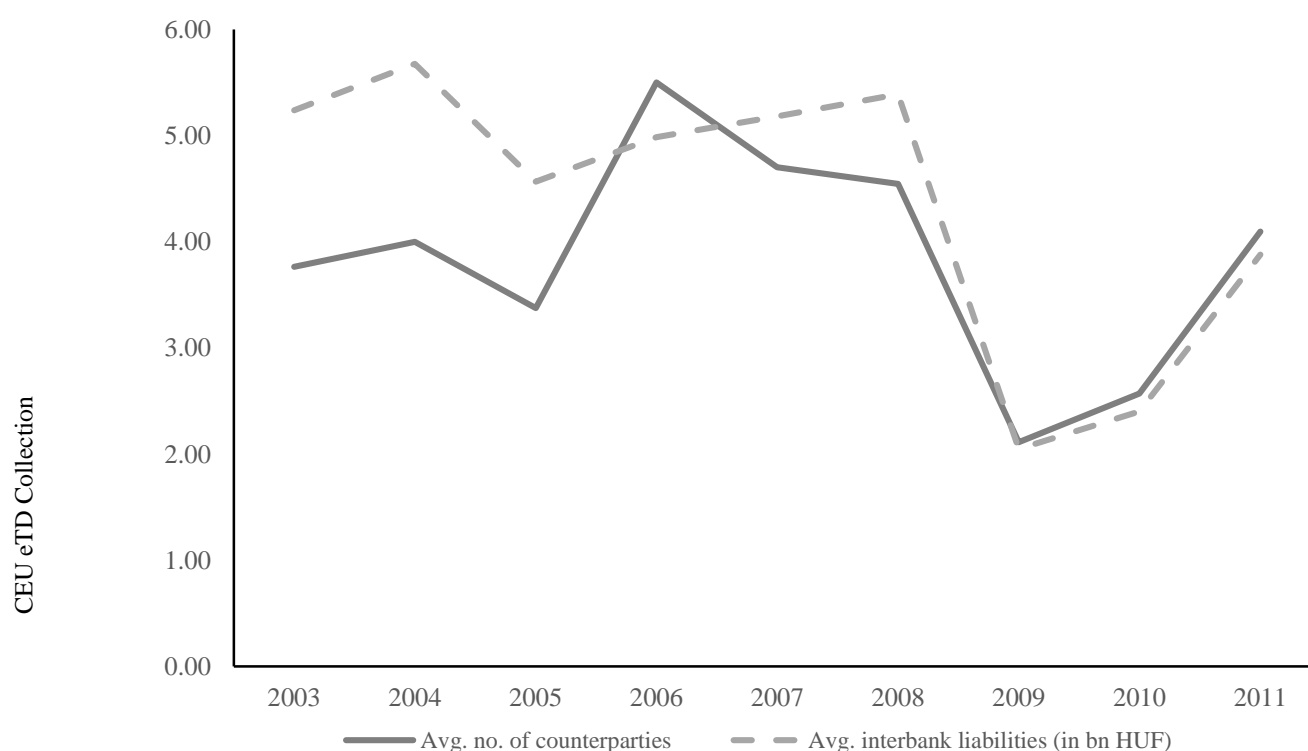

Figure 2: Average number of counterparties and interbank liabilities

Interbank networks in Hungary (between 2002 and 2003) and Belgium are found to be highly central, resembling a "multiple money center" structure by Lublóy (2005) and Degryse and Nguyen (2007) respectively. This remains true for the Hungarian interbank market after 2003 as well, as documented by Tables 1 and 2. Table 1 shows transactions in which the 4 most active banks (throughout the 9 years) were involved as a percentage of total interbank transactions. The Hungarian interbank market is highly central in this sense, as the 4 largest banks take part in more than two-thirds of total interbank transactions throughout the 9 years.

The centrality of the network decreases smoothly between 2003 and 2007, but starting from 2008 the network becomes more central with the 4 largest banks taking part in 4 out of 5 transactions in the market in 2008, 2010 and 2011. 2009 is an exception in this case as the largest banks only account for 66% of the transactions. It is important to note, that the significant increase in centrality after 2009 is mostly driven by the largest bank, which is responsible for 40% and 33% of interbank transactions in 2010 and 2011 respectively. Altogether, the Hungarian interbank network is highly central between 2003 and 2011, as the 4 most active banks take part in the majority of the transactions. There is a substantial increase in the percentage of transactions involving the largest banks starting from 2010, largely due to the increased role of the largest bank.

Top 4 banks by interbank activity	2003	2004	2005	2006	2007	**2008**	2009	**2010**	**2011**
1st	27.62%	29.40%	24.48%	22.35%	21.13%	**20.67%**	20.36%	**39.72%**	**32.77%**
2nd	20.78%	11.13%	12.56%	16.06%	14.00%	**24.38%**	24.97%	**12.33%**	**19.95%**
3rd	12.37%	16.91%	17.02%	17.99%	17.69%	**13.88%**	14.97%	**24.95%**	**17.42%**
4th	13.84%	15.37%	15.79%	11.77%	13.83%	**18.14%**	6.07%	**8.73%**	**10.36%**
Total	74.61%	72.81%	69.84%	68.17%	66.64%	**77.07%**	66.37%	**85.73%**	**80.49%**

Table 1: Interbank transaction volumes of the 4 most active banks
as a percentage of total transaction volumes

It is also worthy to examine how exposed banks are to a single counterparty. This is captured by Table 2, where the average exposure of an individual bank towards its most frequent counterparties are shown as a percentage of total transactions. Banks with low interbank activity were excluded from the analysis, as they are likely to have 1 or 2 counterparties in total, thus adding an upward bias to average exposures to most frequent counterparties. Therefore, banks with daily average interbank activities below 0.5 and 1 billion forints were excluded.

Most frequent counterparties		2003	2004	2005	2006	2007	2008	2009	2010	2011
Cutoff=0.5	1st	24.63%	27.38%	23.68%	24.49%	26.50%	**34.38%**	**45.63%**	**40.88%**	**47.04%**
	2nd	13.54%	14.33%	13.94%	16.27%	16.69%	15.67%	18.01%	17.87%	18.17%
	3rd	10.38%	10.78%	10.69%	11.00%	11.41%	11.39%	10.71%	10.33%	11.52%
	Sum	**48.56%**	**52.50%**	**48.31%**	**51.76%**	**54.59%**	**61.45%**	**74.35%**	**69.07%**	**76.74%**
Cutoff=1	1st	24.61%	26.71%	22.54%	21.27%	24.48%	**31.34%**	**42.95%**	**41.94%**	**47.01%**
	2nd	13.50%	13.94%	13.13%	14.92%	15.67%	14.41%	16.57%	17.77%	18.48%
	3rd	10.20%	10.62%	10.79%	11.07%	11.80%	11.54%	10.79%	9.70%	11.54%
	Sum	**48.31%**	**51.27%**	**46.47%**	**47.27%**	**51.95%**	**57.29%**	**70.31%**	**69.41%**	**77.02%**

Table 2: Average exposures towards most frequent counterparties

Results can be considered robust since excluding medium size banks did not change average exposures significantly. Average exposure to the 3 most frequent counterparties between 2003 and 2007 account for roughly half of an individual bank's interbank transactions. As in the case of centrality (measured by the ratio of transactions in which the most active banks are included), average exposures also increase after 2007. Starting from 2008, banks are more exposed to their largest counterparty, as there is roughly a 10 percentage point increase in the exposure to the most frequent counterparty in 2008, and another 10 percentage point

increase in 2009. This can make the network more prone to knock on defaults assuming that banks' tier 1 capital to interbank liabilities ratio does not increase[11].

Concluding this chapter, we look at the term structure of interbank transactions throughout the 9 years of interest. The term structure of the Hungarian interbank market is shown by Figure 3. Overnight loans make up the majority of interbank transaction volume, as more than 90% of the volume lent in the interbank market is through overnight loans. In general, the relative volume of overnight loans do not vary much throughout the years, with no big changes in longer term loans either.
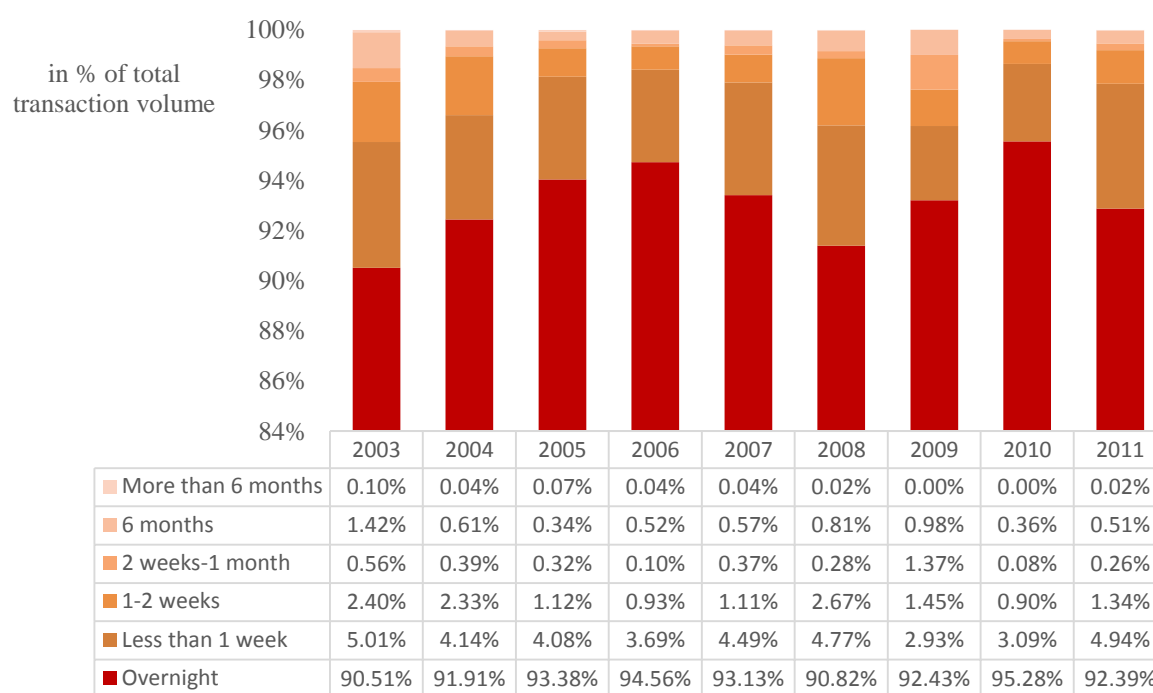

	2003	2004	2005	2006	2007	2008	2009	2010	2011
■ More than 6 months	0.10%	0.04%	0.07%	0.04%	0.04%	0.02%	0.00%	0.00%	0.02%
■ 6 months	1.42%	0.61%	0.34%	0.52%	0.57%	0.81%	0.98%	0.36%	0.51%
■ 2 weeks-1 month	0.56%	0.39%	0.32%	0.10%	0.37%	0.28%	1.37%	0.08%	0.26%
■ 1-2 weeks	2.40%	2.33%	1.12%	0.93%	1.11%	2.67%	1.45%	0.90%	1.34%
■ Less than 1 week	5.01%	4.14%	4.08%	3.69%	4.49%	4.77%	2.93%	3.09%	4.94%
■ Overnight	90.51%	91.91%	93.38%	94.56%	93.13%	90.82%	92.43%	95.28%	92.39%

Figure 3: Volume of overnight and long-term loans in the Hungarian interbank market

A slight shift towards longer term loans in 2009 is visible on Figure 3, however, as 2.35% of total transaction volume is lent through loans having terms longer than 2 weeks. Prior to 2009, loans with terms higher than 2 weeks comprise around 1% of total volume (except for

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[11] An increase in a bank's tier 1 capital relative to its interbank liabilities would mean that the same amount of direct exposure to a single counterparty means less risk in terms of knock on default, since the bank has more capital to defend against shocks.

2003, where this ratio is also 2%), so the increase in 2009 is not negligible. As we have seen in Figure 1, total transactional amounts in 2009 were about half of the volume in 2008, so essentially the absolute value of long term loans did not increase in the network, but banks mainly decreased their activity in loans spanning between 1-2 weeks. The increase in longer term loans in 2009, wore off in 2010 and 2011, as the relative volume of loans spanning more than 2 weeks decrease below 1%, and total interbank activity increased to pre-crisis levels.

To sum up, activity and structure in the interbank network shows that banks reacted to the crisis in 2008 in multiple ways. Total transactional volume decreased greatly in 2009 and practically stayed on the same level in 2010. In 2011, however banks increased their activity to pre-crisis levels. This level looked to stabilize in the beginning of 2012 as well, as supported by interbank data from January 2012. The interbank market also showed signs of increasing concentration towards already highly central banks after 2008, as banks supposedly turned to more trustworthy counterparties in the uncollateralized market.

Individual exposures to single banks, most probably due to the network becoming more central, increased substantially after the crisis hit Europe. This is a possible negative sign, as knock on defaults are more likely to occur when exposures to single banks are higher, ceteris paribus. The term structure of interbank lending did not vary greatly throughout the 9 years, with the only notable observation being that the relative volume of long term loans doubled in 2009, meaning that banks mainly decreased their activity in terms of short-term lending and borrowing. This structure, however was only present for one year, as banks increased their short-term lending to pre-crisis levels after 2009.

5. Simulation Methodology

To assess systemic risk and contagion in the Hungarian interbank market, a methodology based on Degryse and Nguyen (2007) is used, which is very similar to the simulation models in Lublóy (2005) and Upper and Worms (2004). Due to differences in the acquired data, several points of the methodology used in Degryse and Nguyen (2007) are either changed or omitted. As exposures towards foreign banks are not part of the database, our analysis is restricted to domestic contagion, in contrast to Degryse and Nguyen (2007), who study bilateral exposures towards foreign banks as well. Instead of using an $N * (N + M)$ matrix to summarize interbank exposures - where N is the number of domestic banks, and M is the number of foreign banks - our case simplifies to an $N * N$ matrix X, containing exposures to domestic banks only.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \reflectbox{$\ddots$} & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \reflectbox{$\ddots$} & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{bmatrix}$$

Source: Degryse and Nguyen (2007)

Having a complete matrix of bilateral exposures, and buffer capital for each bank, the 9 interbank networks spanning from 2003 to 2011 are defined. For each year, N scenarios were simulated, in each scenario contagion effects originating from an unexpected shock to one bank are measured. Following the notation in Degryse and Nguyen (2007), the failure of banks is evaluated according to the following inequality:

$$C_i < \sum_{j=1}^{N} \lambda_j \theta x_{ij} , \tag{1}$$

where C_i is the buffer capital of *bank i*; λ_j is a dummy, that is equal to 1 if *bank j* defaults at some point in the scenario, and 0 otherwise. θ stands for the Loss Given Default ratio that is

assumed to be equal for all exposures throughout the network. x_{ij} is the average daily amount

lent from *bank i* to *bank j* throughout the year. x_{ij} represents gross exposures between *banks i*

and *j*, due to the assumption that in case of default, bilateral netting between banks is not

possible[12]. (1) can be interpreted in the following way: *bank i* defaults whenever its total

exposure to defaulted banks multiplied by LGD exceeds its buffer capital, in other words the

sum of the average daily amount lent by *bank i* to defaulted banks multiplied by LGD exceeds

bank i's buffer capital.

The simulation evaluates whether (1) holds for each bank in multiple rounds. The

simulation starts with evaluating whether the bank initially hit by the unexpected shock has

enough buffer capital, to remain solvent. If the bank does not default, the simulation stops and

capital losses do not occur in the scenario. On the other hand, if the shock is large enough to

make the bank default, the simulation starts to evaluate the consequences of the initial bank's

default. Note that the values of λ and C are updated after each round, the lambdas of the banks

that defaulted in the most recent round is made equal to 1, and losses in buffer capital are stored.

In the first round, the immediate neighbors of the initially defaulted bank are evaluated. If any

of them defaults, there is a second round. In the second round all neighbors of the banks that

defaulted in the first round are assessed. If any of them defaults, the simulation continues for a

third round after the vector λ ($N * 1$ vector with λ_i as the 'i'th element) is updated. This

mechanism continues until no more banks default after the last update of the vector λ.

I use a simple network to provide an example of the simulation mechanism, shown on

Figure 4. The coloring of the nodes represent their total amount of interbank liabilities, with

dark red nodes having large amounts of liabilities and grey nodes having few, or no liabilities

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[12] This assumption is also used in the study of Degryse and Nguyen (2007) and Upper and Worms (2004).
Degryse and Nguyen find that relaxing this assumption substantially decreases contagion in the interbank
market.

at all. Banks are represented by nodes, edges represent interbank transactions between banks. The width of the edges indicate the value of the loan in billion Forints. The direction of the edges represent the possible flow of contagion, so arrows point from the borrower to the lender. An example for interpreting interbank relations is between bank 0 and bank 1, bank 0 borrowed 11 billion forints from bank 1, since the arrow points towards bank 1.
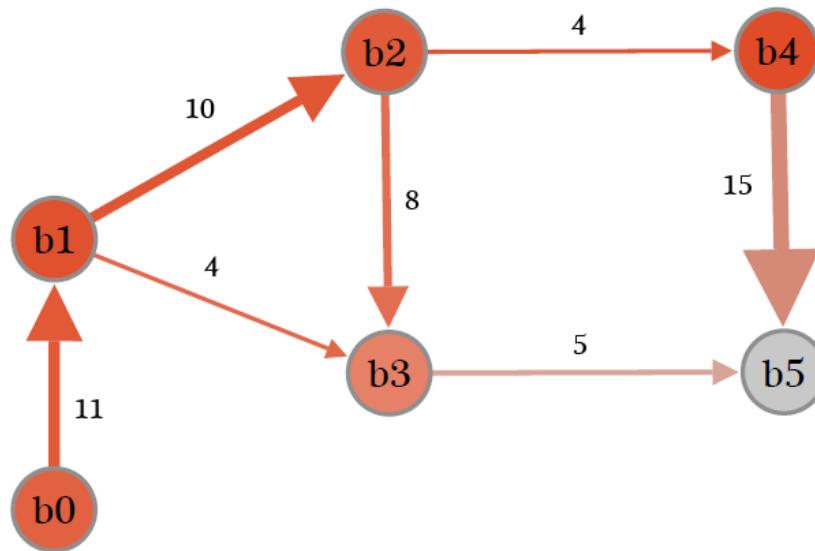

Figure 4: Sample interbank network showing interbank transaction volumes

For simplicity, let's assume that all banks have a buffer capital equal to 10 billion Forints, and LGD=100%. Assume that bank 0 (b0) gets hit by an unexpected shock in the sample scenario and incurs losses of 11 billion Forints. In this case the buffer capital of bank 0 dried up, so bank 0 defaults due to the initial shock hitting the network. Capital losses of bank 0 are not measured, as they occurred by assumption. The simulation model then starts the first round, assessing all banks that have direct exposures to bank 0. In our example, there is only one such bank, namely bank 1. Bank 1's buffer capital is less than the losses occurred, since bank 0 defaulted on a loan worth 11 billion Forints. Therefore bank 1 defaults in the first round, before the second round starts, λ and C values are updated, changing the value of λ_1 to 1. In the second round, immediate lenders of bank 1 are evaluated. While bank 3 does not fail, bank

2 defaults as a result of 10 billion Forints in loans outstanding towards bank 1. No other banks are evaluated in the second round, therefore λ and C values are updated, including a 4 billion Forints decrease in bank 3's buffer capital, and the default of bank 2.

As only bank 2 failed in the second round, bank 2's lenders are assessed in round 3. Bank 4 does not default, since it has 10 billion in buffer capital compared to a 4 billion loss due to the default of bank 2. Bank 3 however incurs losses of 8 billion Forints, which is higher than its remaining buffer capital of 6 billion. In the fourth round only bank 5 is evaluated according to (1), since it is the only lender of bank 3. Bank 5 has a higher amount of buffer capital than its losses at LGD=100%, thus bank 5 remains solvent. As no other bank suffer damage to their buffer capital, no banks defaulted in the fourth round, so the simulation stops. Note, that the default of bank 4 would have resulted in bank 5's bankruptcy, but as bank 4 did not fail, the simulation did not evaluate bank 5's position as a lender of bank 4.

Altogether, the methodology used in this paper is a simple, but widely used method in the literature, to assess contagion and capital losses in the interbank markets. This simulation method assesses domino effects due to an unexpected external shock, in an environment, where contagion can only spread via interbank exposures between banks. The simulation assesses the solvency of every bank that is directly or indirectly affected by the initial shock in multiple rounds. The extent of contagion in the simulation depends on banks' buffer capital, the specific interbank relations, the size of interbank exposures and the assumed Loss Given Default ratio in the network. A major limitation of this method is that it only concentrates on the direct exposures between banks, present in the interbank market. Expectations and reactions of banks, depositors, or any external agents are not taken into account as the effect of bank runs or asset prices is not evaluated in the model.

6. Results

Chapter 6 presents simulation results for 2003-2011, based on interbank exposures provided by the Hungarian National Bank, and equity capital data collected from publicly available financial stability reports. The simulation scenarios not only differ in terms of the year that is analyzed, but several assumptions are added or relaxed, in order to assess contagion in different settings. The simulations were run in the software Matlab, the code of the simulation is included in Appendix A.1.

This chapter begins with the assessment of contagion in the Hungarian interbank network using the average yearly exposures and buffer capital extracted from the database. In section 6.2, two sets of simulations are run with decreased capital, in order to increase contagion effects. This is necessary for assessing how different changes to the original Hungarian market structure affect contagion. Contagion effects are measured in section 6.3, assuming that a bank with high interbank activity exits the market. In section 6.4, the cutoff value is decreased, resulting in a more connected network, with additional nodes. A rewired version of the original network is also analyzed, creating a more connected version of the network, while keeping the number of nodes, the total amount of buffer capital, and the total amount of interbank exposures unchanged.

6.1 Contagion in the Hungarian interbank network

To assess contagion in a realistic setting, the first series of simulations were conducted without any changes to the data on Hungarian interbank exposures and equity capital (assumed to be equal to regulatory capital). The results of these simulations for LGD=100% are included in Table 3 spanning 9 years. Only results assuming 100% LGD are shown, since no contagion occurred in any of the years. With no contagion at LGD=100%, there can't be contagion at lower LGD levels, thus all results regarding capital losses at lower LGDs are linear functions

of the results shown in Table 3 below. This stems from the fact that without contagion, the only losses in each scenario originate from the outstanding loans of the initially defaulted bank. These losses are fully accounted in the LGD=100% case, but with LGD=X%, only X% is accounted for. In a scenario without contagion, both average losses and losses in the worst case scenario are linear functions of LGD, if contagion occurs, however, this linearity is lost.

We also limited the analysis to examining a large shock - large enough to make the bank with the highest buffer capital default – since decreasing the value of the external shock only means excluding scenarios where the bank initially hit by the shock is large enough to survive. Therefore decreasing shock size in this setting is equivalent to taking out the scenarios when the largest banks are hit by the shock. As we will see, the Hungarian network is highly robust in case of large shocks, therefore only the worst case (LGD=1 with a large unexpected shock) is presented in more detail.

The first 4 rows of Table 3 show the results of the worst case scenario (WCS) for each year, the lower part shows average capital losses and network descriptives. *Origin of contagion* shows the ID number of the bank that is assumed to initially default at the beginning of the worst case scenario. In each scenario, capital losses of the bank defaulting by assumption are not taken into account. *Weighted average out-degree* shows the average amount borrowed[13] by a bank in the system. *Number of defaults* and *number of contagious scenarios* show the defaulted banks in the worst case scenario and the number of scenarios where at least one bank defaulted due to contagion respectively. Years with notable changes in capital losses or capital cycles (captured by interbank assets to buffer capital ratio) are emphasized in bold.

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[13] Note that 'Total interbank liabilities' are equal to the total amount of loans borrowed in the network, but the term 'Total interbank assets' bears the same value in our case. The analyzed network is assumed to be closed, none of the banks can lend to outside institutions, and there are no external sources banks can borrow from. For this reason the sum of the amounts lent in the banking system has to equal the sum of the borrowed amounts, and weighted average out-degree is equal to weighted average in-degree.

	2003	2004	2005	2006	2007	2008	2009	2010	2011
Origin of contagion	24	12	5	24	7	13	24	13	13
# of defaults	0	0	0	0	0	0	0	0	0
Capital lost (in billion HUF)	21.85	18.64	10.24	22.00	10.33	19.53	8.74	22.53	29.05
% of total buffer capital lost	6.09%	4.24%	2.11%	4.60%	1.86%	3.10%	0.93%	2.29%	2.69%
# of contagious scenarios	0	0	0	0	0	0	0	0	0
Average capital lost (% of total buffer capital)	0.62%	0.63%	0.33%	0.49%	0.40%	0.51%	0.10%	0.11%	0.25%
Weighted average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
# of banks	32	32	33	34	35	36	38	36	36
Total interbank liabilities (in billion HUF)	167.6	181.6	150.7	169.5	181.3	193.9	77.9	86.4	139.6
Total buffer capital (in billion HUF)	359.1	439.3	484.9	478.4	556.3	629.9	940.7	986.0	1081.1
Interbank liabilities to buffer capital ratio	46.7%	41.3%	31.1%	35.4%	32.6%	30.8%	8.3%	8.8%	12.9%

Table 3: Simulation results for the Hungarian interbank network between 2003 and 2011

No contagion occurred at LGD=100% throughout the 9 years due to high buffer capital in the banking system. Even in 2003, the most vulnerable year in terms of interbank exposures to buffer capital ratio, the total amount of buffer capital is more than twice as much as total interbank liabilities in the network. Average capital losses and capital losses in worst case scenarios also reflect the stability of the Hungarian interbank network, with highest capital losses typically between 1-4% and average capital losses below 0.5%. Exceptions are 2003 and 2004, but even in these cases average capital losses were at a negligible 0.6%, and the highest capital loss was 6%, when a bank with high interbank exposure to several counterparties was the target of the external shock.

Worst case scenario capital losses are similar to that found by Degryse and Nguyen (2007), who measure WCS capital losses to be 3.79% of total tier 1 capital in the Belgian

interbank network at LGD=100%. Wells (2004) and Mistrulli (2005), however find WCS losses to be around 16% in the UK and Italy respectively. Note that our setting differs from those in the 3 mentioned papers, as those studies analyze contagion through both collateralized and uncollateralized exposures, while this paper examines contagion through uncollateralized loans.

A key factor regarding damage to the banking system through interbank exposures is the ratio of the sum of interbank exposures to the total buffer capital[14] available in the system. There is a general decreasing trend in the interbank assets to buffer capital ratio until 2009, where banks' reaction to the crisis is captured. One key feature of this reaction is that banks withdrew from uncollateralized loans after 2008. Total uncollateralized interbank assets (or in other words activity in the uncollateralized interbank market) dropped to 40% of the pre-crisis levels in 2009 and 2010, but bounced back to pre-crisis level in 2011.

Another element of banks' reaction to the crisis is that the total buffer capital in the system has drastically increased - by almost 50% - immediately after the crisis reached Hungary in October 2008. These two reactions led to a huge drop in the exposures to buffer capital ratio in the interbank network, as it dropped from 30.8% to only 8.3%. This means that while an average bank would have approximately 3.3 Forints of buffer capital for every Forint of interbank liability pre-crisis, the average bank post-crisis would have more than 12.5 Forints of buffer capital for every borrowed Forint. Altogether banks largely decreased their activity in the uncollateralized interbank market in 2009 and 2010 as a reaction to the crisis, but in 2011 interbank market activity was close to pre-crisis levels with better capitalization compared to the 2003-2008 period.

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[14] Tier 1 capital is a more direct measure of capital available to banks at the time of an unexpected shock. Due to the lack of data on commercial banks' tier 1 capital in Hungary, buffer capital was used instead, as discussed in more detail in Chapter 3.

Looking at both average capital losses and losses in the worst case scenario, values are mostly driven by changes in the weighted average out-degree and the interbank liabilities to buffer capital ratio. This is reasonable given that no contagion occurred, thus average capital losses in an absolute sense (not as the percentage of total buffer capital) are fully determined by the amount of loans that the initially defaulted bank was unable to pay back. Since average capital losses are calculated as a percentage of the total buffer capital, an increase in capitalization can decrease the relative amount of damage. The interbank liabilities to buffer capital ratio is more important in scenarios where contagion occurs, since the liabilities to capital ratio of a bank carries information about how prone that bank is to default through contagion.

In conclusion, the Hungarian interbank market was robust throughout 2003-2011, showing signs of precautiousness with interbank market activity decreasing drastically in 2009-2010. In 2011 interbank market activity got back to pre-crisis levels, all the while being more stable than before 2008 by having a high level of buffer capital compared to interbank exposures. As no contagion occurred throughout the 9 years, network structure did not have a significant effect on capital losses. The main drivers of capital losses in these simulations were the average amount borrowed by a bank and the ratio of interbank exposures to buffer capital.

6.2 Simulations with decreased capital

As mentioned in the previous section, no contagion occurred in any of the analyzed scenarios, therefore in sections 6.2-6.4, scenarios are analyzed with decreased capital to provide a setting for assessing the effects of network structure on capital losses and contagion. In this section we still allow system-wide capitalization to vary across years (as in section 6.1), but the total amount of buffer capital in the banking system is decreased in order to have contagion in the network. This is necessary since without contagion, capital losses to the

banking system are fully determined by the total amount of interbank exposures, whereas in a contagious setting, network structure also has an effect on capital losses.

In this chapter the results of two sets of simulations are presented, one with the assumption that all banks have their buffer capital decreased by 50%, and another with a 75% decrease in each bank's buffer capital. One possible explanation for such a setting is that when an unexpected shock hits a bank that is active in the interbank market, financial distress can stem from several sources apart from interbank exposures. Examples are distress from corporate and private loan defaults, plummeting asset prices (fire-sales in severe cases) and depositor bank runs. These circumstances can only be considered realistic in case of a large unexpected shock hitting the network, therefore in the rest of this paper we focus on examining the effects of such shocks.

Results of simulations at LGD=100% assuming different buffer capital levels are shown in Table 4. Results at original buffer capital levels are shown with dark grey, light grey indicates results assuming 50% buffer capital, and white stands for 25% buffer capital. At 50% buffer capital, the network is still quite robust, with contagion occurring only in 2003, 2007 and 2008. Out of these 3 cases, the interbank network was most prone to contagion in 2008, when contagion occurred in 3 different scenarios. The 1% average capital loss in 2008 is also the highest value after 2005, this shows that right before the crisis reached Hungary, the network was in a more fragile state, compared to the previous 3 years. Starting from 2009, capital losses show a sharp decline due to increased buffer capital relative to interbank exposures, as already seen in section 6.1.

	2003	2004	2005	2006	2007	2008	2009	2010	2011
Origin of contagion	24	12	5	24	7	13	24	13	13
	24	12	5	24	7	13	24	13	13
	24	12	5	15	7	13	24	13	13
# of defaults	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0
	2	1	0	2	1	0	0	0	2
% of total buffer capital lost	6.09%	4.24%	2.11%	4.60%	1.86%	3.10%	0.93%	2.29%	2.69%
	12.10%	8.49%	4.22%	9.19%	3.72%	6.20%	1.86%	4.57%	5.37%
	24.34%	16.48%	8.44%	18.52%	7.29%	12.40%	3.72%	9.14%	10.78%
# of contagious scenarios	0	0	0	0	0	0	0	0	0
	1	0	0	0	1	3	0	0	0
	2	4	1	2	5	4	2	1	4
Average capital lost (% of total buffer capital)	0.62%	0.63%	0.33%	0.49%	0.40%	0.51%	0.10%	0.11%	0.25%
	1.24%	1.26%	0.66%	0.98%	0.80%	1.01%	0.20%	0.22%	0.50%
	2.47%	2.54%	1.33%	2.03%	1.59%	1.96%	0.38%	0.44%	0.94%
Interbank liabilities to buffer capital ratio	46.7%	41.3%	31.1%	35.4%	32.6%	30.8%	8.3%	8.8%	12.9%
	93.3%	82.7%	62.2%	70.9%	65.2%	61.6%	16.6%	17.5%	25.8%
	186.7%	165.4%	124.3%	141.7%	130.3%	123.1%	33.1%	35.1%	51.7%
Average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
# of banks	32	32	33	34	35	36	38	36	36

Table 4: Simulation results with decreased capital levels

At 25% buffer capital, the number of contagious scenarios increases throughout all years. 2004, 2007, 2008 and 2011 can be considered the most prone to contagion, with having at least 4 contagious scenarios. Although capital losses are small in 2009, it is interesting to see that contagion occurs in 2 cases even with average out-degree dropping to 2.05. In these scenarios, two small banks lent large amounts to medium-sized banks, which led to their default when the idiosyncratic shock hit their borrowers. Altogether, there was at least one contagious scenario in all the years examined, while networks before the crisis and in 2011 were the most prone to contagion.

The effects of contagion on capital losses can be assessed by comparing capital losses in the three different simulations: when buffer capital is at its original level, at 50% and at 25% of the original level. The most notable effect of contagion on capital losses in this setting can

be seen in 2004. Without contagion, both the average and the worst case scenario capital losses would be multiples of the capital damage in the base case, as losses are linear in LGD and capitalization if no contagion occurs. In 2004, capital losses in the worst case scenario of the simulation at 25% of the original buffer capital should equal 17% with no contagion, instead losses account for 16.5% of the total amount of buffer capital in the network. This effect can be considered low in relative terms, but in absolute terms capital losses decreased by 550 million forints due to contagion. Other notable contagion effects include a 0.07 percentage point increase in average capital losses in 2006 (compared to a setting without contagion) and a 0.06 percentage point drop in average capital losses in 2008 and 2011, representing 77 and 66 million forints in absolute terms respectively.

A decrease in capital losses due to a higher level of contagion sounds counter-intuitive, since contagion increases the number of banks that are affected by the shock, and opens new channels (exposures of the defaulted bank) for capital losses. In this simplified, closed model, however, it can happen that for example a bank that defaulted through contagion has no interbank liabilities, therefore absolute capital losses do not increase. Thus relative capital losses are less than in a scenario with no contagion, since a defaulted bank can limit capital losses if it does not have any interbank liabilities.

We can think of this in a similar way to Acemoglu et al. (2013), who introduce outside financiers - or in other words senior creditors - in their model, that soak up capital losses in such settings. The authors in this paper assume that every bank needs an equal amount of borrowed capital to finance a project, which can be borrowed either from banks within the network, or from external sources. If a bank has less exposure within the network, it would imply that outside financiers bear more of the losses in case of default. Thus we can think of a bank with no, or negligible average daily interbank liabilities as a bank with low direct risk towards the banking system, bearing higher risk to a group of senior creditors or stakeholders.

In reality the capital losses borne by the group of external stakeholders might propel back to the banking system through various channels (corporate and private loan defaults, decreasing asset prices or bank runs), but the simplified setting used in our analysis does not account for such factors.

The presence of contagion can also increase capital losses if the shock can subsequently hit banks after one bank defaults due to contagion. 2006 is the only year where contagion increased WCS, and average capital losses. With no contagion, losses in the worst case scenario should equal 18.38%, and average capital losses should equal 1.96%, whereas with contagion, capital losses are 18.52% and 2.03% respectively. A difference of 0.14% in worst case scenario losses can be considered negligible, while a 0.07% increase in average losses means contagion increased capital losses throughout all scenarios in 2006 by 33.5 million Forints on average. Since this is the only year where such an effect arises, results suggest that contagion does not have a significant negative effect on capital losses in the Hungarian interbank network.

At all three buffer capital levels, damage to the network is still mostly driven by the total amount of liabilities, which means that "introducing" contagion did not have a large effect on capital losses in most cases. This is due to the fact that idiosyncratic shocks are unlikely to make large banks default through contagion, since average interbank exposures of large banks towards a single counterparty are negligible compared to their buffer capital. It might happen, however, that smaller banks lend relatively high amounts compared to their buffer capital regularly to one of the largest banks in the network. In this case, if the idiosyncratic shock hits one of the big banks, smaller banks, who are regular lending counterparties to this institution, are in danger of default. In a setting with multiple shocks hitting the network at the same time, it is possible that several medium or small banks default in a way that triggers the default of a top 5 bank - in terms of capital. Such a scenario is not included in our analysis, as the effect of multiple shocks are out of the scope of this paper.

6.3 Exit of a bank with high interbank market activity

In this section contagion and capital losses to the banking system are analyzed in a setting where a large bank is assumed to exit the interbank market, or close operations in the country altogether. 2 pairs of simulations are compared to the base case, in the first two simulations the 2 banks with the highest interbank activity throughout the 9 years are assumed to exit the market. In the second pair of simulations, the largest borrower and the largest lender of each year quit the market. As mentioned at the beginning of the chapter, capital cycles are accounted for in sections 6.3 and 6.4 by assuming that each bank has a constant total interbank liabilities to buffer capital ratio throughout the years. The main purpose of this assumption is to focus on the effect of network structure on capital losses and to be able to compare results not only across different settings, but across years in the same setting as well.

Differences in worst case scenario capital losses are relatively small between 2004 and 2009, as shown in Figure 5. In 2003 the worst case scenario excluding bank 13 results in higher relative capital losses than the baseline scenario. An explanation for this is that the decrease in the absolute damage to the network had a smaller effect than the decrease in the total amount of capital available to the network with the exit of bank 13. This way relative capital losses can increase if a bank does not play a key role in the worst case scenario, but decreases total buffer capital in the system by a substantial amount. This was also the case in 2010 and 2011, when bank 24 was assumed to exit the market. In sum, bank 13 and bank 24 did not play important roles in the worst case scenarios in 2003 and 2010-2011 respectively.

On the contrary, the large increase in baseline worst case scenario losses after 2009 is largely due to the presence of bank 13. This is captured by the difference in worst case capital losses between the base case and when bank 13 exits the market. Bank 13 became a large borrower in 2010 and 2011 with a daily average of 27.2 billion forints of interbank liabilities. In both years, contagion occurs when bank 13 defaults, with 1 bank defaulting in 2010 and 2

banks in 2011 due to contagion. Table 5 shows that there is a 10 percentage point decrease in capital losses in the scenario excluding bank 13, which means the interbank position and large exposures of bank 13 represents high risk in 2010 and 2011.

Scenario		2003	2004	2005	2006	2007	2008	2009	2010	2011
Base scenario	Origin of WCS	24	12	5	24	7	13	24	13	13
	WCS capital losses	11.78%	8.48%	6.70%	13.04%	6.19%	9.26%	9.66%	18.50%	15.78%
	Average capital losses	1.21%	1.27%	1.05%	1.37%	1.35%	1.48%	1.03%	0.90%	1.40%
	Average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
Exit of bank 13	Origin of WCS	24	12	18	24	7	5	24	7	24
	WCS capital losses	13.81%	7.70%	5.99%	13.92%	6.59%	10.07%	9.64%	8.49%	8.84%
	Average capital losses	0.87%	0.99%	0.76%	1.20%	1.12%	1.39%	0.97%	0.57%	1.23%
	Average out-degree	3.79	4.01	3.45	3.45	3.86	4.27	1.63	1.45	2.61
Exit of bank 24	Origin of WCS	5	12	5	15	7	13	43	13	13
	WCS capital losses	6.02%	9.31%	7.52%	13.33%	6.92%	7.72%	7.46%	20.08%	16.69%
	Average capital losses	1.02%	1.23%	1.01%	1.21%	1.31%	1.25%	0.82%	0.95%	1.24%
	Average out-degree	4.15	5.04	3.99	4.18	4.45	2.98	1.54	2.10	3.10

Table 5: Simulation results when large banks are excluded from the network

This is supported by Figure 6, showing that the exclusion of bank 13 results in significant decreases in average capital losses compared to the base case. Let us take the network in 2010 as an example, where the exclusion of bank 13 decreased average capital losses from 0.9% to 0.57%, meaning that on average bank 13 was responsible for 37% of the capital losses throughout different scenarios. An important thing to note is that the role of banks
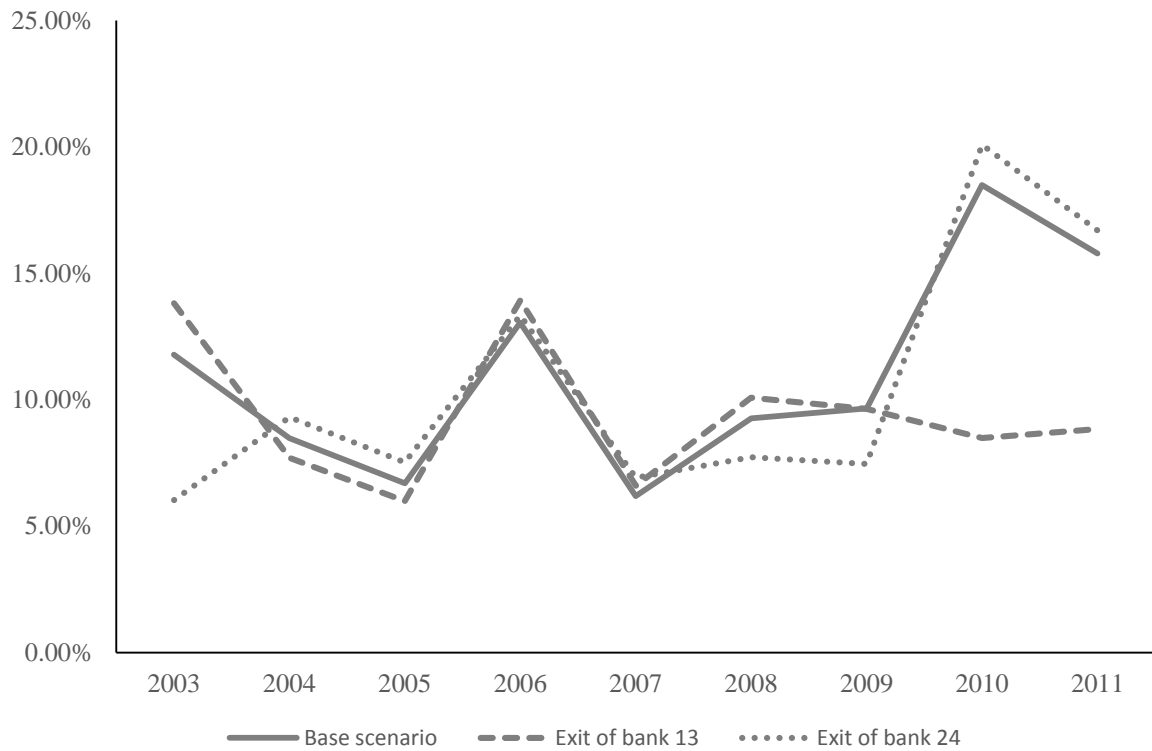
34

Figure 5: Worst case scenario capital losses when large banks are excluded from the network
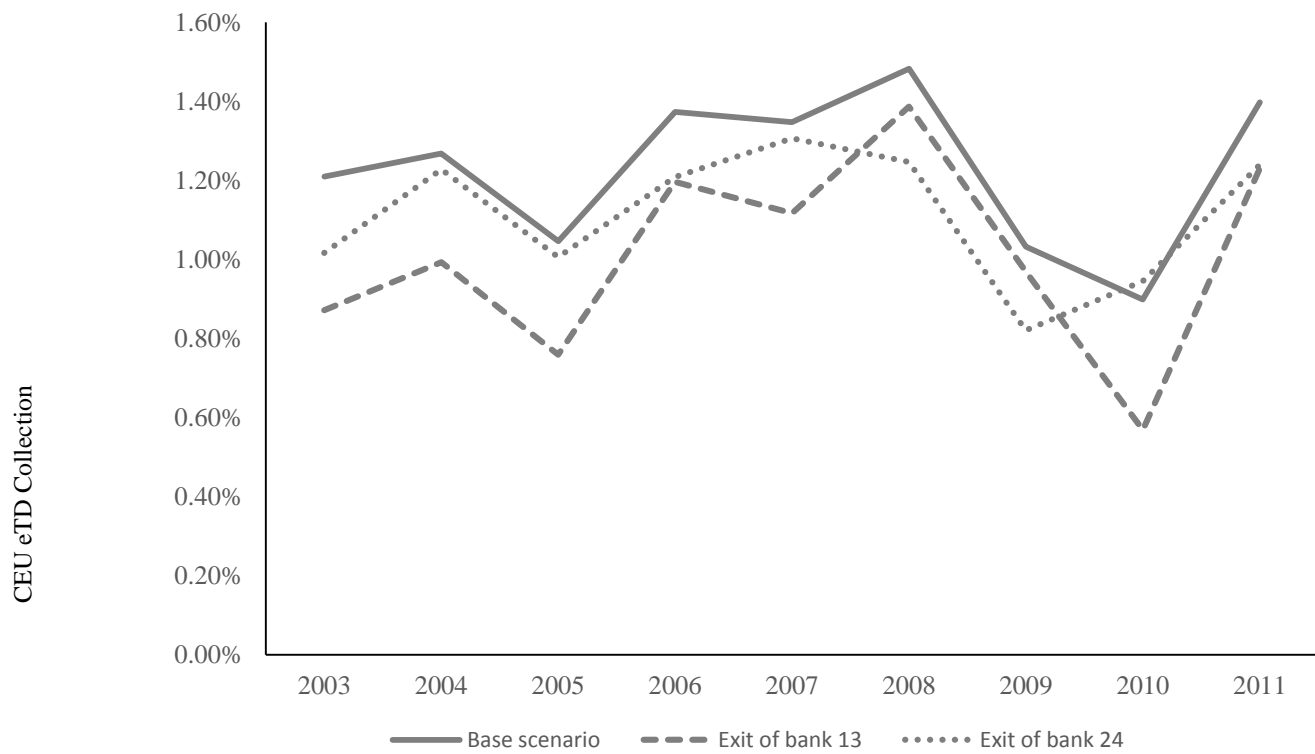
Figure 6: Average capital losses when large banks are excluded from the network

13 and 24 changed greatly in the network after 2007. Before 2007 bank 13 was a major lender and bank 24 was mostly active in borrowing. After 2007, however, bank 13 became a major borrower, while the overall interbank market activity of bank 24 decreased, and became more balanced between lending and borrowing. This suggests that the role of major borrowers and lenders regarding capital losses is quite balanced, as both bank 13 and bank 24 experienced major changes in their interbank activity, but this is not reflected in the average capital losses related to these banks. Another observation supporting the balanced role of lenders and borrowers is, that bank 24 was the biggest lender in 2008, and the biggest borrower in 2009, while bank 13 was the biggest borrower in 2008. This is also not reflected in average capital losses, as in both years bank 24 bore more capital losses on average throughout different scenarios.

In the remaining part of section 6.3, the role of major borrowers and lenders is discussed to provide a better picture on the observation that lenders and borrowers seem to have similar impact on average capital losses to the network. Table 6 presents numerical results of simulations excluding the biggest lenders and borrowers for each year, while Figures 7 and 8 show capital losses in the worst case scenario and average capital losses respectively.

Differences between capital losses in worst case scenarios are still relatively small until 2007. From 2008, however, the role of the major lender increased, and starting from 2009 the role of the major borrower also increased dramatically, especially in 2010, when bank 13 took over the role of major borrower in the network. In fact, the role of bank 13 is so important in 2010, that if we exclude bank 13, the network falls apart to several distinct subnetworks. The resulting network by excluding bank 13 is visualized on Figure 9.

Scenario		2003	2004	2005	2006	2007	2008	2009	2010	2011
Base scenario	Origin of WCS	24	12	5	24	7	13	24	13	13
	WCS capital losses	11.78%	8.48%	6.70%	13.04%	6.19%	9.26%	9.66%	18.50%	15.78%
	Average capital losses	1.21%	1.27%	1.05%	1.37%	1.35%	1.48%	1.03%	0.90%	1.40%
	Average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
Exit of borrower	Origin of WCS	5	21	24	15	21	5	43	7	24
	WCS capital losses	6.02%	7.46%	5.36%	13.33%	6.16%	10.07%	7.46%	8.49%	8.84%
	Average capital losses	1.02%	1.13%	0.85%	1.21%	1.30%	1.39%	0.80%	0.57%	1.23%
	Average out-degree	4.15	4.83	3.85	4.18	4.52	4.27	1.54	1.45	2.61
Exit of lender	Origin of WCS	24	12	18	24	7	13	43	13	13
	WCS capital losses	13.81%	7.70%	5.99%	13.92%	6.59%	7.72%	6.79%	14.79%	13.32%
	Average capital losses	0.87%	0.99%	0.76%	1.20%	1.12%	1.25%	0.96%	0.68%	1.26%
	Average out-degree	3.79	4.01	3.45	3.45	3.86	2.98	1.58	1.50	3.26

Table 6: Simulation results when major lenders and borrowers are excluded from the network

Average capital losses, shown in Figure 8, indicate that there are differences between simulations excluding major lenders and borrowers, but these differences are not systematically related to whether we exclude borrowers or lenders throughout the 9 years. Before 2009, major lenders have a higher importance in average capital damage to the network, but starting from 2009, average capital losses are less when excluding the major borrower from the analysis. This supports the observation that there is no systematic difference between the capital losses related to a major lender and a major borrower. Average capital losses related to large banks rather stem from the amount of interbank activity (be it lending or borrowing) and network position. This is supported by the observation that the importance of bank 24 decreased in 2010, when its interbank activity decreased.
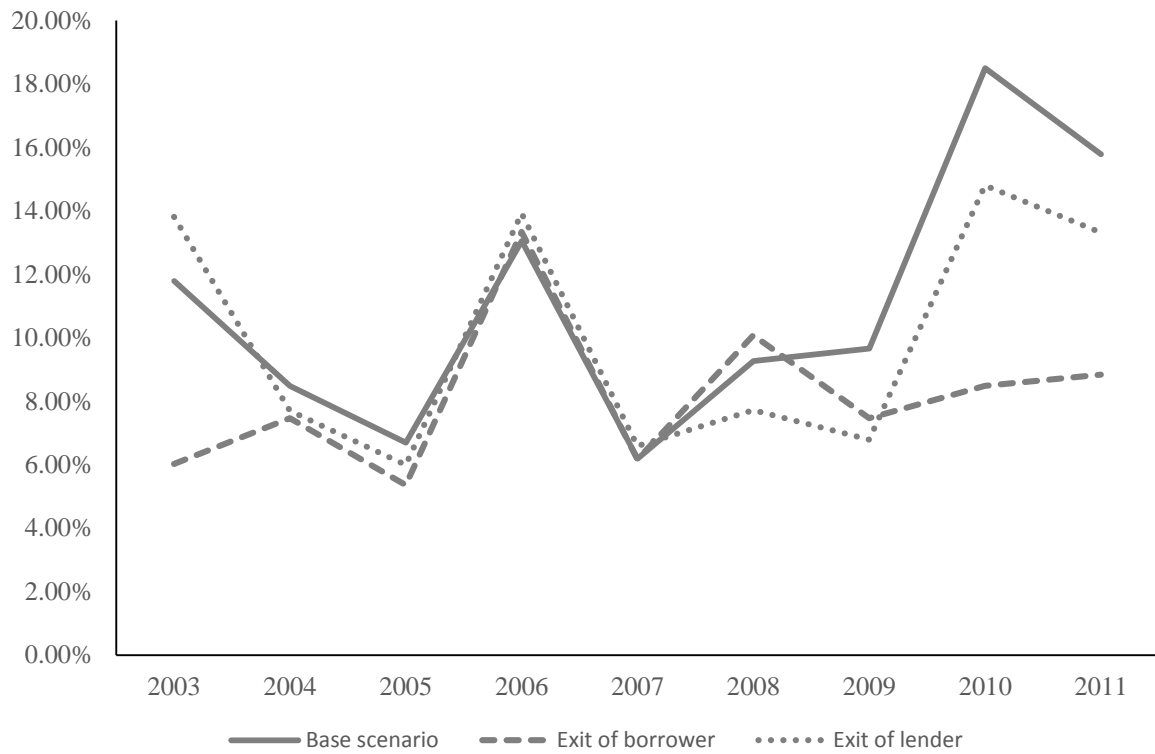
Figure 7: Worst case scenario capital losses when major lenders and borrowers are excluded from the network
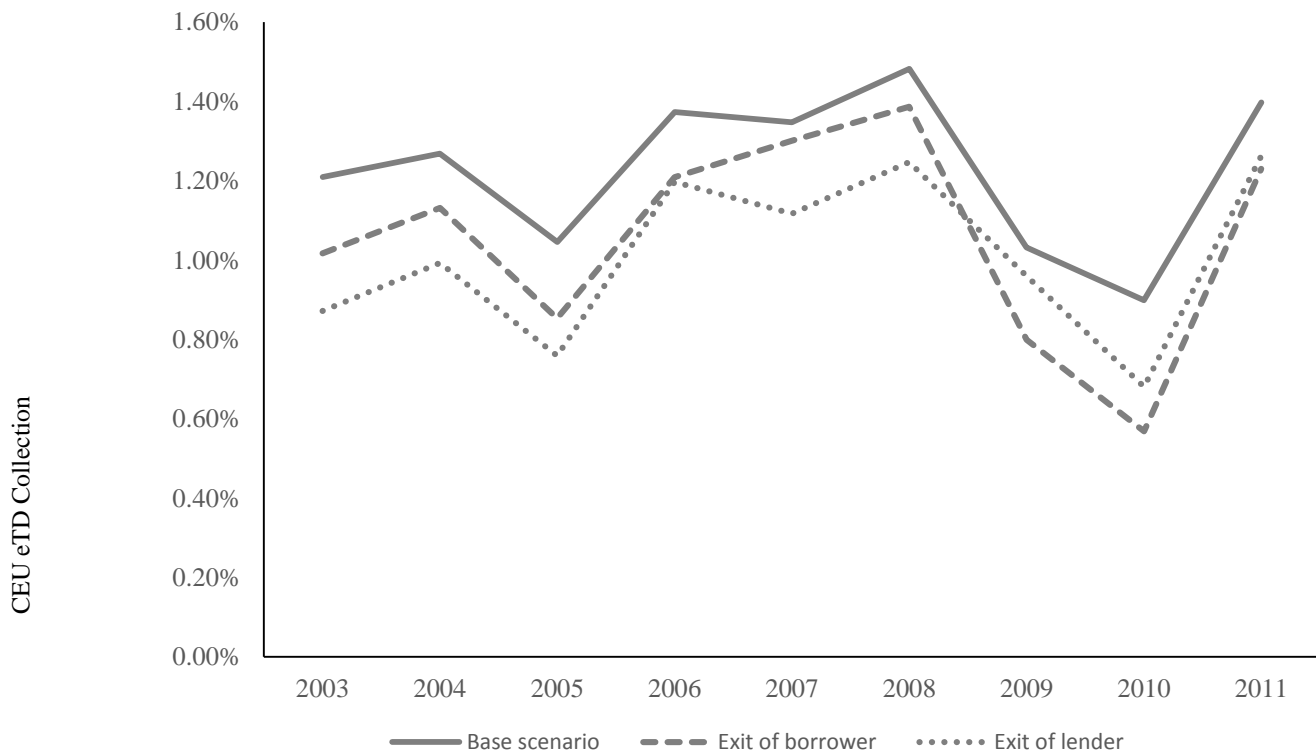
Figure 8: Average capital losses when major lenders and borrowers are excluded from the network

Simulation results in section 6.3 show that the role of major banks in average capital losses to the network increased after 2008. Large banks also pose a bigger threat in worst case scenarios after 2009, as seen on Figure 7. This can be explained by the fact that the interbank network became less connected after 2008, with the 2009 and 2010 network falling to several disconnected parts when excluding major banks as shown in Figure 9. Similarly to Figure 4 in Chapter 5, the coloring of the nodes represent banks' total amount of interbank liabilities, with dark red nodes having large amounts of liabilities and grey nodes having few, or no interbank liabilities at all.
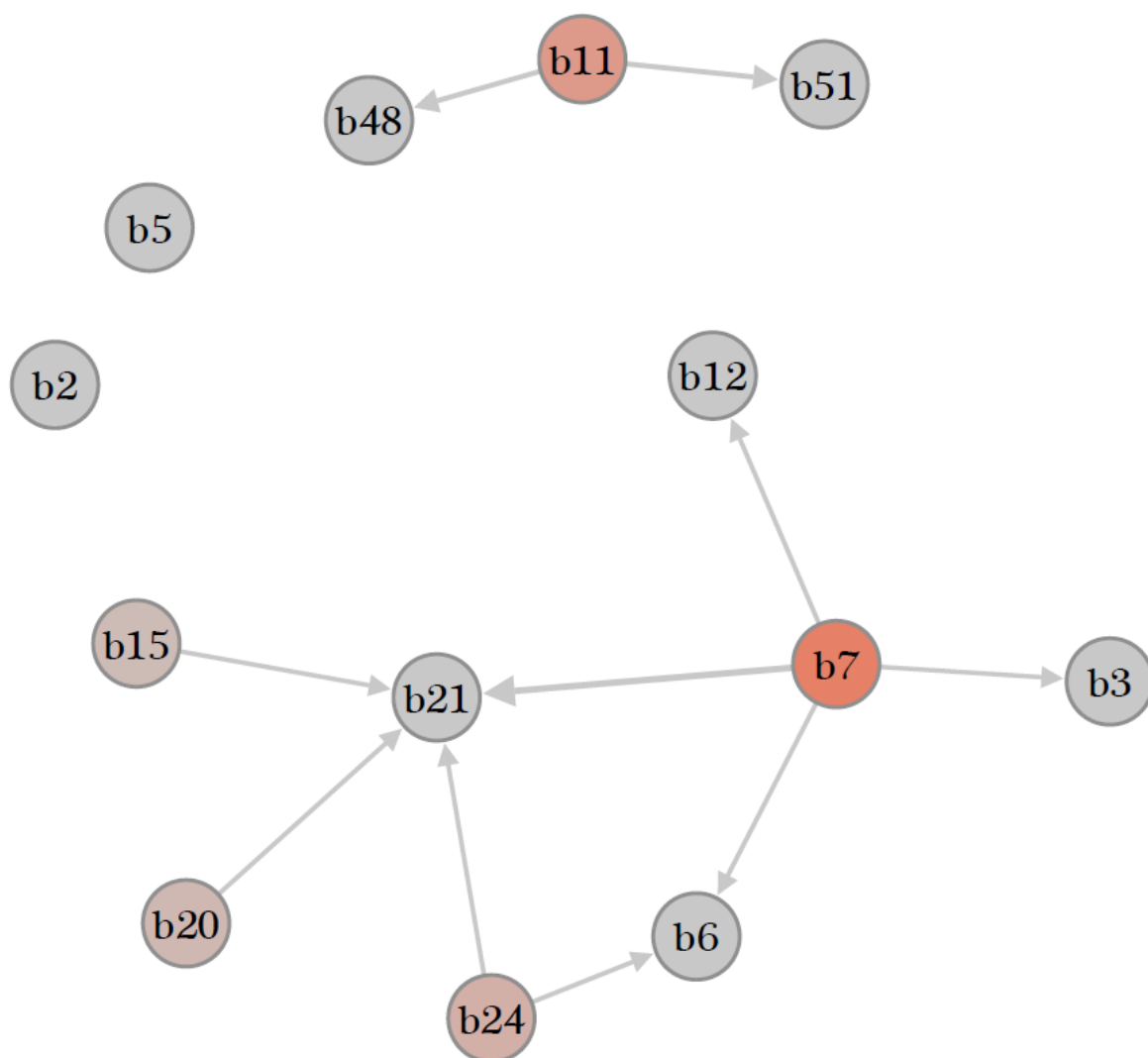
Figure 9: 2010 Hungarian interbank network when excluding bank 13

As for the higher importance of bank 13 in 2011 regarding average capital losses, this is partly due to bank 13 taking part in 32.8% of the interbank transactions in 2011 (weighted by the transactional amount and the term of the loan) compared to a pre-crisis average of 24.3%. Another observation based on simulation results is, that there is no substantial and systematic difference between excluding the major lender and the major borrower from the network. This is true for both capital losses in the WCS and average capital losses.

6.4 Effects of changing density, and disallowing large interbank loans

The effects of connectedness on contagion and capital damage to the interbank network have been discussed in several papers before 2007, and the number of studies related to systemic risk in financial networks has greatly increased after the crisis. Several papers, including Allen and Gale (2000) and Freixas et al. (2000), have argued that a more interconnected network is less prone to contagion. Acemoglu et al. (2013) find, however, that dense networks are "robust yet fragile" when it comes to large shocks, meaning that above a certain threshold connected networks lose their resilience. Although our simulation setting slightly differs from the models in the papers mentioned above, this chapter seeks to examine differences in contagion and capital losses as a result of changing the connectedness of the network. Similarly to section 6.3, two scenarios are compared to the base case in terms of contagion, capital losses in the worst case scenario and average capital losses.

Simulated results for three different scenarios are shown in Table 7. As in section 6.3, the first third of the table contains results of the base scenario. The second part of the table shows the results assuming a cutoff of 0.8 billion forints. This means that average daily exposures between 0.8 and 1 billion forints are added compared to the base case. The inclusion of these loans leads to several smaller banks appearing in the network, thus the resulting network has more nodes and is more connected than the base scenario, leading to higher total interbank exposures, but also higher total buffer capital in the network.

Scenario		2003	2004	2005	2006	2007	2008	2009	2010	2011
Base scenario	Origin of WCS	24	12	5	24	7	13	24	13	13
	WCS capital losses	11.78%	8.48%	6.70%	13.04%	6.19%	9.26%	9.66%	18.50%	15.78%
	Average capital losses	1.21%	1.27%	1.05%	1.37%	1.35%	1.48%	1.03%	0.90%	1.40%
	Average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
	# of contagious scenarios	1	1	0	1	3	2	3	2	4
	Most defaults in one scenario	1	1	0	1	1	1	1	1	2
	Total number of defaults	1	1	0	1	3	2	3	2	6
Cutoff=0.8	Origin of WCS	24	12	24	24	7	13	24	13	13
	WCS capital losses	14.32%	8.88%	7.51%	13.04%	6.68%	10.13%	10.59%	20.01%	16.79%
	Average capital losses	1.50%	1.39%	1.26%	1.50%	1.54%	1.60%	1.13%	1.05%	1.53%
	Average out-degree	5.53	5.62	4.70	5.12	5.46	5.42	2.41	2.58	4.03
	# of contagious scenarios	1	1	0	1	3	2	3	2	4
	Most defaults in one scenario	1	1	0	1	1	1	1	1	2
	Total number of defaults	1	1	0	1	3	2	3	2	6
Rewiring	Origin of WCS	24	12	5	24	7	13	24	13	13
	WCS capital losses	11.94%	8.48%	7.29%	13.04%	6.19%	9.26%	10.53%	18.13%	16.82%
	Average capital losses	1.21%	1.27%	1.16%	1.42%	1.38%	1.52%	1.06%	0.91%	1.50%
	Average out-degree	5.24	5.68	4.57	4.99	5.18	5.39	2.05	2.40	3.88
	# of contagious scenarios	0	2	4	0	2	2	3	1	4
	Most defaults in one scenario	0	1	1	0	1	1	1	3	3
	Total number of defaults	0	2	4	0	2	2	3	3	6

Table 7: Simulation results with decreased cutoff value and rewired network

The scenario at cutoff=0.8 still does not represent a setting where the effects of higher density can be analyzed, since increased total interbank exposures, buffer capital, and also changes in average exposures have an effect on capital losses. Therefore a new network is

created and analyzed in the third scenario by disallowing large transactions in a way that does not change interbank liabilities and buffer capital for any of the banks.

The procedure of rewiring in a simple network is shown in Figures 10 and 11. All interbank exposures above 2 billion forints are selected, and split into 'n' equal amounts, 'n' being the largest integer less than equal to the underlying exposure. Borrowers are fixed, and assumed to borrow from n-1 additional counterparties, towards which they were not borrowers in the base scenario. This way all edges in the rewired network have weights between 1-2 billion forints, and interbank liabilities of individual banks did not change, neither did the total interbank exposure of the network.
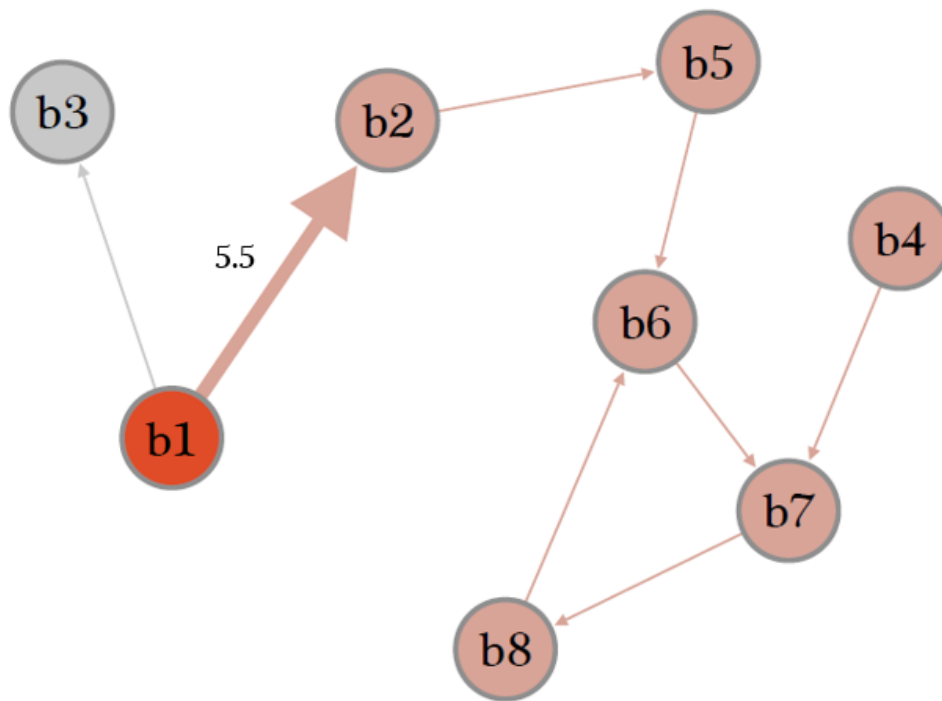
Figure 10: Sample network before rewiring

In the original sample network, shown in Figure 10, the only exposure larger than 1 billion Forints is between bank 1 and bank 2. Bank 1 borrows 5.5 billion Forints from bank 2 in the original network. Since borrowers' total exposures are fixed, bank 1 has to split his

borrowings into 5 equal exposures amounting to 1.1 billion Forints each. 1.1 billion exposure remains towards bank 2, so four banks are randomly selected that are not already lenders towards bank 1. In the sample network, 5 banks are not already lenders toward bank 1 (bank 2 and bank 3 are already lenders), four out of these are chosen randomly. Assume banks 5, 6, 7 and 8 are chosen. They are each assumed to lend 1.1 billion Forints to bank 1. The result of rewiring on the sample network is seen on Figure 11.
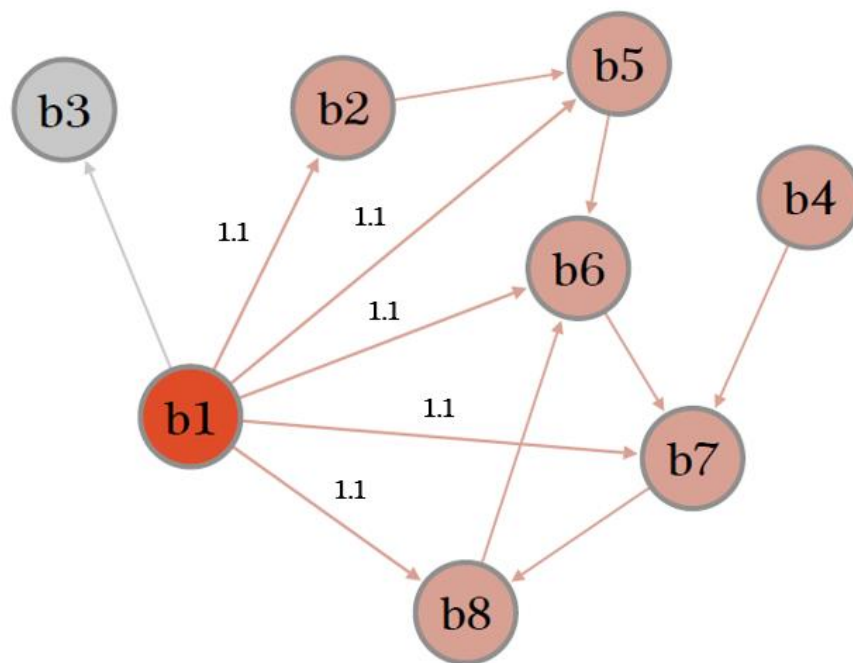
Figure 11: Sample network after rewiring

The rewired network became more connected, while interbank liabilities of individual banks did not change. The only characteristic that changes throughout the rewiring process is the interbank assets of individual banks. This rewiring procedure results in a more dense network compared to the base scenario. The results of simulations on the rewired network are shown in the lower third of Table 7.

As capitalization effects are accounted for in the base scenario, Table 7 shows that the network is most prone to contagion after 2006. The number of contagious scenarios and bank

defaults after the crisis are particularly interesting, given that after 2008 the average out-degree, and the overall connectedness of the network dropped drastically, but the number of contagious scenarios and defaults did not decrease. This suggests that the effects of a drop in average out-degree after 2008 was countered by the effects of the network becoming more central, as discussed in Chapter 4.

Capital losses in the scenario with decreased cutoff value were higher compared to the base scenario, as Figures 12 and 13 show. The network became more interconnected by adding edges and nodes, but the effect of adding new exposures, through which contagion can spread was higher than the effect of adding new nodes, thus increasing total buffer capital. In essence, the network became less capitalized but more connected, therefore negative effects are not surprising. Contagion results in the cutoff=0.8 simulation verify our choice of cutoff=1, since there is no change in the number of contagious scenarios, or the number of defaulted banks compared to the base case. Change in buffer capital and interbank liabilities is accounted for in the rewiring scenario, where only interbank assets of individual banks change. Individual interbank liabilities, total buffer capital and total interbank exposures remain at the same level.

Although the average number of counterparties has greatly increased with rewiring, as shown in Table 8, and the size of the exposures were restricted between 1-2 billion forints, this did not have a large effect on capital losses. Differences in worst case scenario losses are negligible, apart from a 1 percentage point increase in 2011 and a 0.9 percentage point increase in 2009. Moreover, in 2010 worst case scenario losses decreased compared to the base scenario. This can be explained by the structure of the network. In 2010, the interbank network was highly central, with 18 edges representing average daily exposures above 1 billion forints. Out of these 18 edges only 2 have weights over 3 billion forints, and these 2 edges are interbank liabilities of a major bank, bank 13. Redistributing these 2 loans resulted in a network structure similar to a star network, but slightly more connected as shown in Figures 14 and 15.
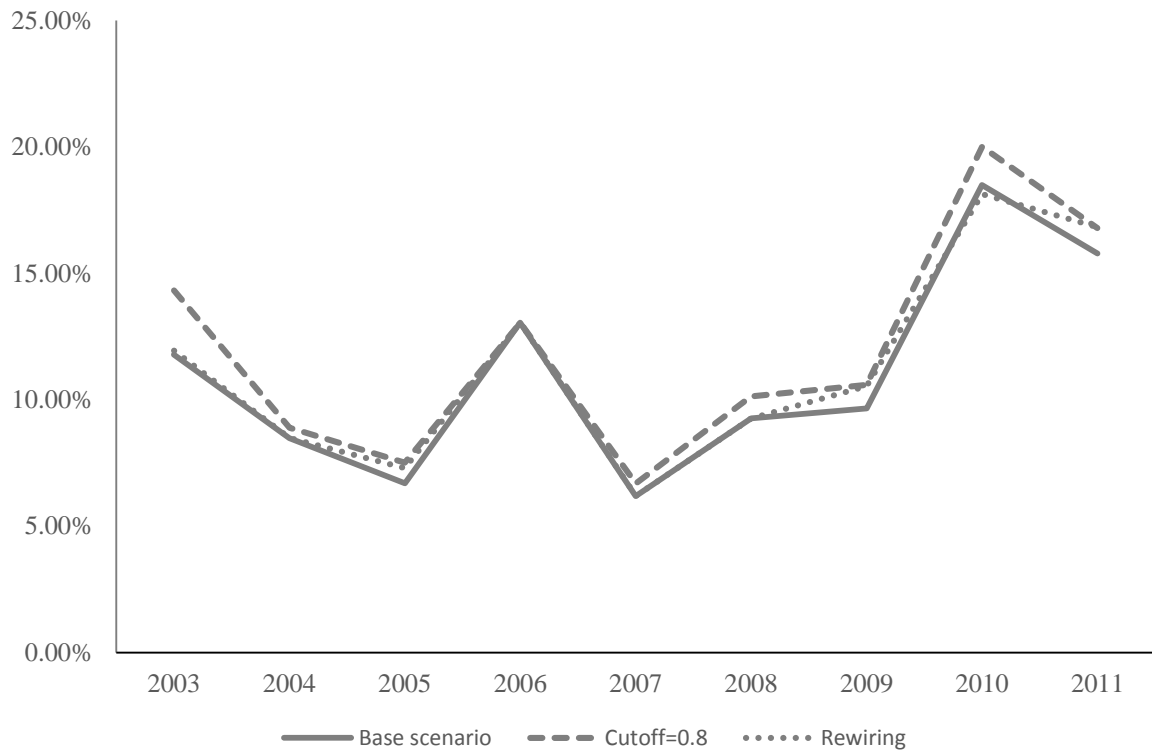
Figure 12: Worst case scenario capital losses with cutoff=0.8 and in the rewired network
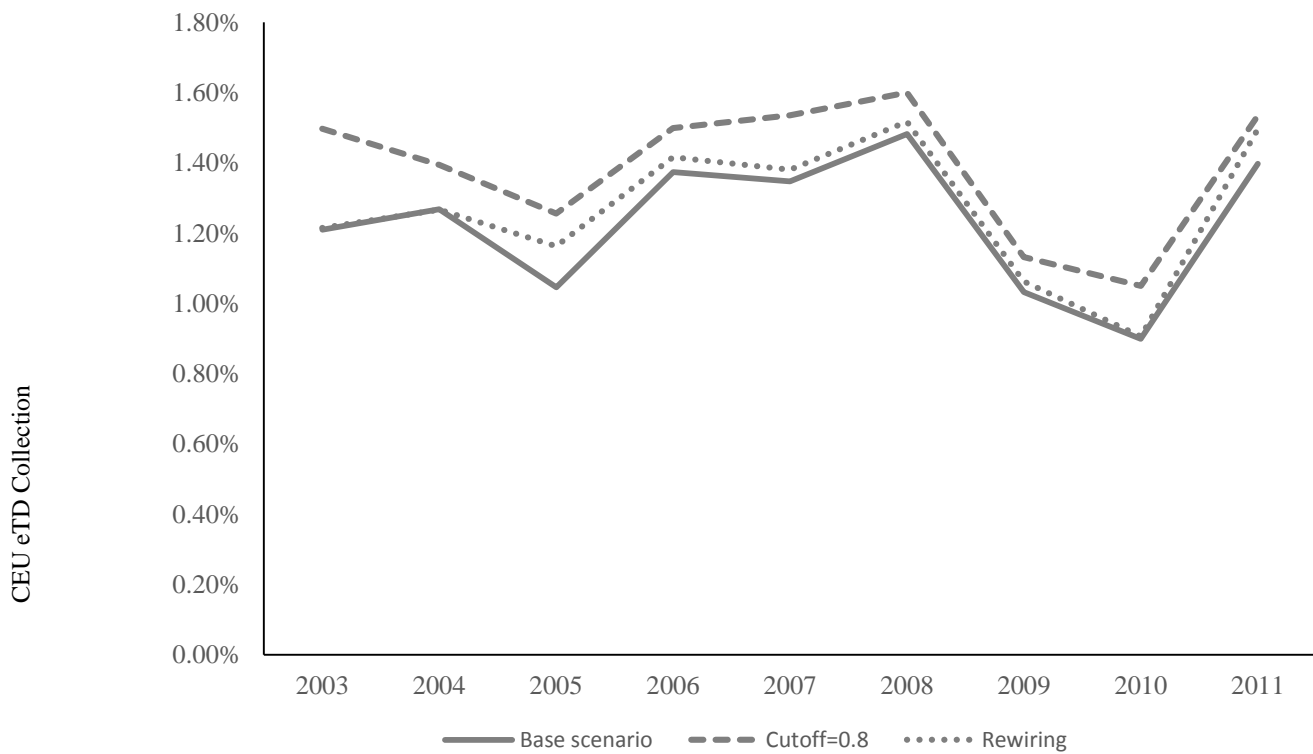

Figure 13: Average capital losses with cutoff=0.8 and in the rewired network

This redistribution of the network in 2010 allowed for 3 defaults in the rewiring scenario, compared to a single default, the default of bank 2 in the base scenario. If banks with low, or no borrowing activity default, capital losses can be limited compared to a case without contagion. This is the reason behind the decrease in damage in 2010 as a result of increased density, as the 2 additional defaulting banks have no borrowings through which damage could spread further in the network. The rewiring process did not have a large impact on average capital losses either, with notable increases occurring in 2005 and 2011, due to the increase in contagious scenarios and the number of defaulted banks in these scenarios. As there are few major institutions and several smaller banks in the Hungarian network, the rewiring resulted in banks with low buffer capital lending to large institutions. These smaller banks defaulted, leading to more contagion in 2005 and 2011.

Average number of counterparties	2003	2004	2005	2006	2007	2008	2009	2010	2011
Base scenario	3.76	4.00	3.38	5.50	4.70	4.55	2.11	2.57	4.10
Rewiring	6.71	7.58	5.38	7.75	6.30	8.36	3.22	3.86	6.95

Table 8: Average number of counterparties in the original and the rewired network

Results show that capital losses do not change significantly by increasing the connectedness of the network. Exceptions are the networks in 2005 and 2011, where the number of defaulted banks increased, thus average capital losses increased. This tendency was not confirmed in other networks, as differences in capital losses in other years were not substantial. Negligible changes due to increased interconnectedness suggest, that in small networks, with a relatively low number of contagious defaults, capital losses are mainly driven by the total amount of interbank exposures and buffer capital in the network. Another important implication is that limiting banks' average daily interbank exposures below 2 billion Forints

towards key counterparties does not affect capital losses, and therefore systemic risk in the network.
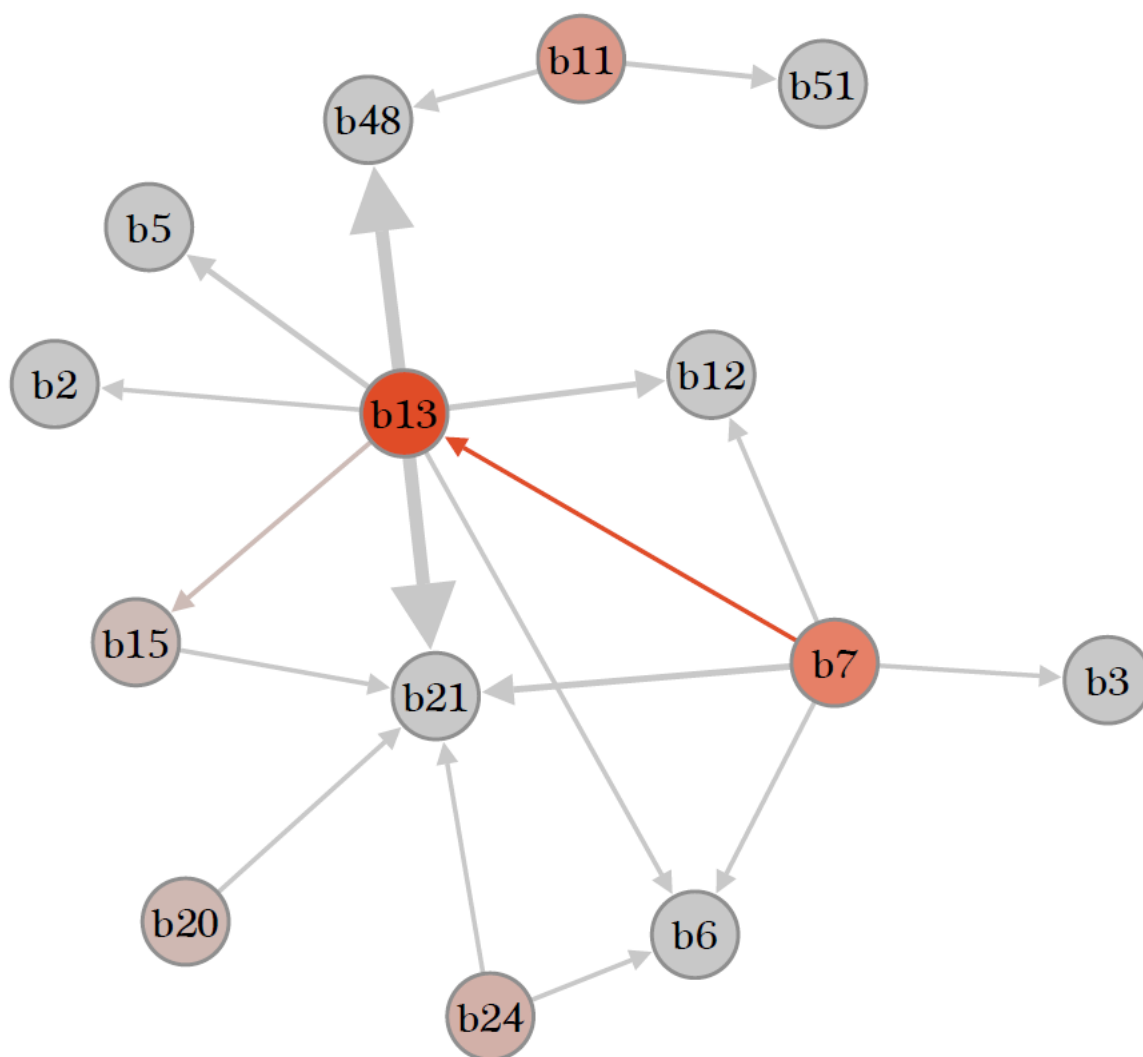

Figure 14: Hungarian interbank network in 2010

Differences in the number of contagious scenarios and the number of defaulting banks are not systematic, as the number of contagious scenarios decreased in 4 cases, while an increase was present in 2 cases. The total number of defaulted banks throughout the scenarios was higher in the base scenario also in 4 cases, while simulations on the rewired network had more defaults in 3 years. This shows that using a simplified setting in a small network, increasing connectedness can both increase and decrease contagion in the network. Changes in

contagion throughout the years are not systematically related to average interbank exposures in the network as the large drop in average out-degree did not have an effect on the number of defaulted banks after 2008, as shown in Table 7. Altogether, the driving force of differences in contagious scenarios is not clear from the simulation results, and requires further research.
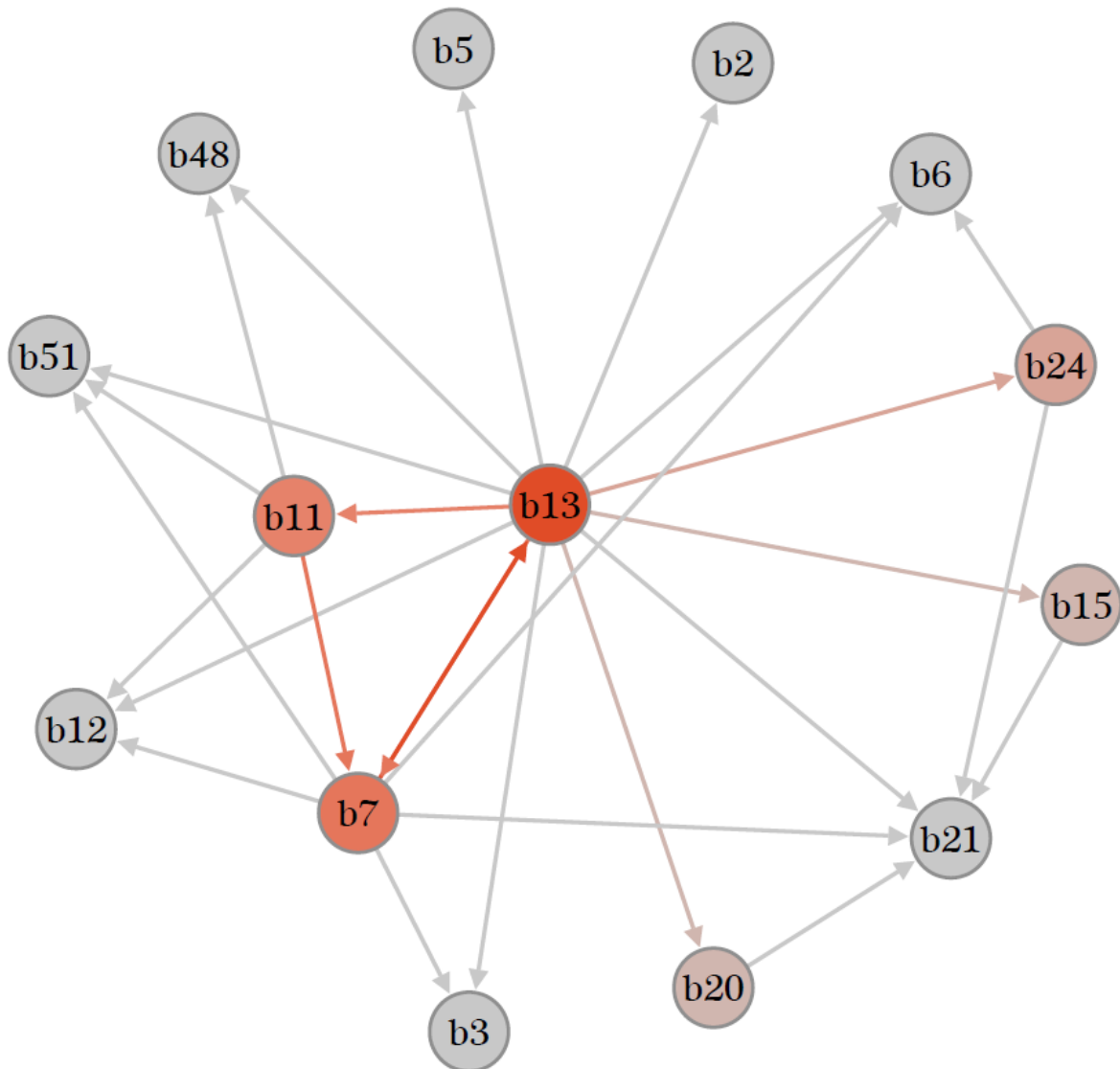

Figure 15: Rewired network in 2010

7. Conclusion

Assessing systemic risk in interbank markets became increasingly important after 2008 for banks and regulators alike, as contagion is one of the main forces propagating illiquidity crises in banking systems. Studies by Freixas et al. (2000), Allen and Gale (2000) and Acemoglu et al. (2013), among others, find that the structure of interbank networks has an effect on systemic risk in the banking system. This paper uses a complete dataset of uncollateralized interbank transactions between 2003 and 2011 in Hungary to examine general trends and simulate contagion effects in the interbank market.

This paper finds that Hungarian banks' reaction to the 2008 crisis was twofold. A 60% drop in interbank market activity after 2008 along with an increase in total regulatory capital marked a withdraw from uncollateralized markets in Hungary. Low total transactional volumes were observed in 2009 and 2010, while the market showed positive signs in 2011 with close to pre-crisis transaction volumes, and a 70% increase in regulatory capital from 2008 to 2011 to defend against counterparty defaults.

Parallel to changes in market activity, banks' average exposure to their most frequent counterparties increased drastically in 2008 and 2009, partly because the Hungarian interbank network became more central after the crisis. This tendency can be considered negative if we expect a large shock to hit the network, as the risk of contagion through idiosyncratic shocks is higher when exposures to individual banks are higher. The risk of contagion decreases, however, in case multiple small shocks are expected, as large banks are unlikely to default in this scenario. Changes in term structure throughout the 9 years were not substantial.

In order to evaluate systemic risk in the Hungarian interbank market, domino effects were simulated for every year between 2003 and 2011. Results show, that the Hungarian interbank market was not prone to contagion during this period, with no defaults due to

contagion at LGD=100%. Capital losses to the banking system were negligible, average capital losses were below 0.6% and capital losses in the worst case scenario were below 6% of total buffer capital.

Trial simulations were conducted on the Hungarian interbank network, assuming a large decrease in capital in order to have contagion in the network. Trial simulations provided an environment to analyze contagion in different network structures. One main lesson from these simulations was that the importance of major lenders and major borrowers in propagating contagion is not systematically different throughout the 9 years. Capital losses related to banks are rather determined by average interbank exposure, and position in the network.

Trial simulations on networks with different interconnectedness showed, that the number of contagious scenarios differs significantly for more connected networks. These differences, are not found to be systematic, and the exact source of differences requires further research. Surprisingly, capital losses were not affected substantially by increasing interconnectedness. This suggests, that in small networks, with a relatively low number of contagious defaults (the highest was 6 defaults in 21 scenarios), capital losses are mainly driven by the total amount of interbank exposures and buffer capital in the network.

These findings have interesting implications for policymaking and further research. Simulating domino effects between 2003 and 2011, I conclude that systemic risk is low in the Hungarian market, and the network is resilient to contagion. An important result of this paper is that restricting the activity of major lenders and major borrowers in the network has equal importance in decreasing systemic risk. Explaining changes in the importance of large banks, however, requires further research. Results from trial simulations suggest that increasing interconnectedness in a small network, where few contagious scenarios occur, does not change

capital losses significantly. This suggests, that limiting banks' interbank exposures towards key

counterparties does not affect overall systemic risk in the network.

Appendix

<u>A.1:</u> The following Matlab code was used for simulation purposes

```matlab
clear all
clc

data_x=xlsread('Input file','Exposures');
data_c=xlsread('Input file','Buffer capital');

lgd=1;
shock_volume=120;

excel_mentes_mappa='Output folder';

default_banks=nan(data_c(end,1),2*data_c(end,1));
data_c_new=kron(data_c(:,2),ones(1,data_c(end,1)));

for i=1:data_c(end,1)
    if data_c(i,2)<=shock_volume

        data_c_new(i,i)=0;
        default_banks(1,2*(i-1)+1:2*i)=[0,i];
        effected_banks=sort(data_x(data_x(:,2)==i,1));

        n=1;
        m=1;
        for j=1:length(effected_banks)

data_c_new(effected_banks(j),i)=max(0,data_c_new(effected_banks(j),i)-
lgd*data_x(data_x(:,1)==effected_banks(j) & data_x(:,2)==i,3));
            if data_c_new(effected_banks(j),i)==0
                default_banks(1+n,2*(i-1)+1:2*i)=[1,effected_banks(j)]; %
                n=n+1;
            end
        end


        for j=1:data_c(end,1)-1
            if n==m
                break
            else default_banks_num=n-m;
                m_seged=n;
                for k=1:default_banks_num

effected_banks=sort(data_x(data_x(:,2)==default_banks(m+k,2*i),1)); %
                    for h=1:length(effected_banks)

data_c_new(effected_banks(h),i)=max(0,data_c_new(effected_banks(h),i)-
lgd*data_x(data_x(:,1)==effected_banks(h) &
data_x(:,2)==default_banks(m+k,2*i),3));
                        if data_c_new(effected_banks(h),i)==0 &&
isempty(default_banks(default_banks(:,2*i)==effected_banks(h),2*i))
                            default_banks(1+n,2*(i-
1)+1:2*i)=[j+1,effected_banks(h)];
                            n=n+1;
```

```matlab
                    end
                end
            end
            m=m_seged;
        end
    end
end
end


excel_mentes_nev=strcat(excel_mentes_mappa,'results_lgd_',num2str(lgd),'_so
kk_',num2str(shock_volume),'.xlsx');
xlswrite(excel_mentes_nev,default_banks,'Defaulted banks');
xlswrite(excel_mentes_nev,data_c_new,'Capital losses');
```

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2013). Systemic Risk and Stability in Financial Networks. *NBER Working Paper, National Bureau of Economic Research*.

Allen, F., & Gale, D. (2000). Financial Contagion. *Journal of Political Economy* , 108 (1): 1-33.

Blume, L., Easley, D., Kleinberg, J., Kleinberg, R., & Tardos, É. (2011). Network formation in the presence of contagious risk. *Proceedings of the 12th ACM Conference on Electronic Commerce*, (pp. 1-10). ACM.

Caballero, R. J., & Simsek, A. (2013). Fire sales in a model of complexity. *The Journal of Finance*, 68(6), 2549-2587.

Dasgupta, A. (2004). Financial contagion through capital connections: A model of the origin and spread of bank panics. *Journal of the European Economic Association*, 2(6), 1049-1084.

Degryse, H., & Nguyen, G. (2007). Interbank Exposures: An Empirical Examination of Systemic Risk in the Belgian Banking System. *International Journal of Central Banking*, 3(2), 123-171.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *The journal of political economy*, 401-419.

Fecht, F. (2004). On the stability of different financial systems. *Journal of the European Economic Association*, 2(6), 969-1014.

Freixas, X., Parigi, B. M., & Rochet, J. C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of money, credit and banking*, 611-638.

Furfine, C. H. (2003). Interbank exposures: quantifying the risk of contagion. *Journal of money, credit and banking*, 111-128.

Hungarian National Bank. (2003-2011). *Aranykönyvek.* Retrieved from Website of the Hungarian National Bank: http://felugyelet.mnb.hu/bal_menu/jelentesek_statisztikak/statisztikak/aranykonyv

Hungarian National Bank, F. S. (2003-2011). *Collection of Financial Stability Reports.* Retrieved from Website of the Hungarian National Bank: http://www.mnb.hu/Kiadvanyok/mnbhu_stabil/jelentes-a-penzgyi-stabilitasrol-2013-ig

Landler, M. (2008, September 30). *The U.S. Financial Crisis Is Spreading to Europe*. Retrieved from The New York Times Online: http://www.nytimes.com/2008/10/01/business/worldbusiness/01global.html?_r=1&

Lublóy, Á. (2005). Domino effect in the Hungarian interbank market. *Hungarian Economic Review*, 52(4), 377-401.

Mistrulli, P. E. (2005). Interbank Lending Patterns and Financial Contagion. *Mimeo, Banca d'Italia*.

Shleifer, A., & Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, 47(4), 1343-1366.

Temzelides, T. (1997). Evolution, coordination, and banking panics. *Journal of Monetary Economics*, 40(1), 163-183.

Upper, C., & Worms, A. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review*, 48(4), 827-849.

Vivier-Lirimont, S. (2006). Contagion in interbank debt networks. *Working Paper*.

Wells, S. J. (2004). Financial interlinkages in the United Kingdom's interbank market and the risk of contagion. *Bank of England*, Working Paper n.230.