Doctoral School of Economics, Business and Informatics

THESIS SYNOPSIS

Róbert Szini

Network theory approaches in systemic risk modeling

Ph.D. Dissertation

Supervisor:
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Associate Professor

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Department of Operations Research and Actuarial Sciences

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Contents

1 Research and topic selection background

The dissertation focuses on systemic risk and contagion in financial networks. Systemic risk, as a key concept of financial stability, came to the forefront of economic studies in the last two decades of the twentieth century, and only then did the general concept of systemic risk become clearer. Although there are many different definitions of systemic risk, they all have in common that they refer to the fragility and instability of financial systems. According to the relevant literature (De Bandt and Hartmann (2000), Lublóy (2005)) the systemic risk is the risk that a series of events triggered by a particular event adversely affects one or more financial institutions or markets over time. In literature two subtype of systemic risk are distinguished. One of them is called as cyclical systemic risk which is in connection with the risk appetite of financial intermediaries and try to capture that willingness to take risks moves along with business cycles. The other one is called as structural systemic risk which try to capture crisis-amplifying effects stemming from the structure of financial networks and the riskiness of network participants. Contagion in financial networks is considered as a subfield of systemic risk related literature which is typically defined as the possibility that at least one other financial institutions goes bankrupt as a result of an initial shock affecting the economy. Given the importance of financial stability and the systemic risk sensitivity of banks, it is important to measure how shocks spread from one bank to another in the banking system.

The importance of the systemic risk and contagion in financial networks were also highlighted by the 2008 financial-liquidity crisis and triggered a series of micro- and macroprudential reforms in recent years. International studies on the lessons from the crisis (Brunnermeier et al. (2009), Nier (2009)) agree that microprudential regulation of individual financial institutions in itself does not provide sufficient control over systemic risk. Furthermore, the confidence in microprudential regulation as a key tool for ensuring the solvency of credit institutions has been shaken after the financial crisis due to inadequate systemic and contagion risk management. Thus, besides the subsequent tightening of microprudential regulation, much greater emphasis has been placed on strengthening of macroprudential regulation (Hanson et al. (2011)) and macroeconomic approaches in microeconomic analyzes and models (Gamba et al. (2014), Clark and Jokung (2015)).

The regulation which laid down the foundation of macroprudential policy and tools known today is the Basel III post-crisis regulatory reforms which was implemented into the EU legal system by Regulation No. 575/2013/EU. This regulation is commonly referred to as CRR which entered into force on 1 January 2014. Macroprudential policy aims to prevent the build-up of systemic risks arising from the operation of banks and the emergence of financial crisis, and to ensure that financial intermediary system adequately supports economic growth. Having regard to this regulatory problem which was triggered by the financial crisis itself, the macroprudential toolkit is still immature and there was only limited opportunity to measure its effectiveness both in Hungary and worldwide. At the same time both researchers and economic decision makers have strong interest in this topic due to its relevance. The common feature of the most well-known macroprudential tools is that they are primarily aimed at improving the shock resistance of each credit institution and minimizing the likelihood of systemic risk events, while less taking into account the role of each credit institution in financial networks and the possible contagion which source is the circular interbank credit agreements between them. The most widely and up-to-date tool for analyzing and modeling the structural form of systemic risk in complex financial systems is the network theory which is basically the central theme of the dissertation.

The purpose of the dissertation is twofold. Firstly I would like to analyze and compare the Hungarian unsecured interbank lending market and FX-swap market using tools from network theory for which databases of transactional level data for period 01.01.2012 to 31.12.2015 were provided by the Central Bank of Hungary. Although similar analysis on interbank markets using tools from network theory can be found in both foreign and domestic literature but these have been limited to only one market. The provided databases were anonymized but the artificial IDs of participants of FX-swap and unsecured interbank lending markets were the same which made it possible to compare many network features of the two markets. The novelty of the obtained results lies in the fact that neither the foreign nor the domestic literature examined two interbank markets at the same time with network theory tools which aimed to identify and compare the key players on the referred markets. Secondly the other research and analytical framework of the dissertation is related to the application of a model published by the European Central Bank in Working Paper form on Hungarian data which can identify the systemically important financial institutions and potentially vulnerable interbank market network structures to external shocks. The novelty of the model lies in the fact that interbank market participants were examined through a multi-layered network which can take into account that in reality financial institutions can connect to each other through several markets at the same time. In addition, the model relies on agent-based simulation techniques namely in case of an exogenous shock to the system, through a predefined set of rules and algorithms financial institutions can make decision over a number of periods to renew their short-term interbank loans and sell their securities to fulfill their obligations and regulatory requirements. With appropriate modifications to the model I identified systemically important Hungarian financial institutions which failure could cause most institutions to fail and I also defined those conditions that make networks potentially vulnerable to external shocks. Chapter 2 is meant to cover the applied methods and the results coming from comparing the Hungarian unsecured interbank lending market and FX-swap market using tools from network theory while Chapter 3 covers the introduction of the agent based multi-layered interbank network model with its results using data of Hungarian banks and banking groups. Chapter 1 is a general introduction to systemic risk and macroprudential policy and Chapter 4 concluded the dissertation.

2 Methods used in the dissertation

As mentioned in the previous chapter the dissertation focuses on structural systemic risk and contagion in financial networks which are most commonly analyzed by using tools from network theory and simulation techniques. Therefore in the dissertation I deal with tools from network theory to analyze and compare the Hungarian unsecured interbank lending market and FX-swap market while simulation techniques in an agent based multi-layered interbank network model were used to analyze contagion effect and conditions that make network potentially vulnerable to external shocks.

In Chapter 2 I introduce the basics of network theory and its tools. Before applying tools from network theory on real data, it has to be decided how long the time interval should be on which the transactional level data is aggregated. Daily or weekly (León et al. (2018)) financial networks are typically rare and disconnected therefore in the literature monthly or even quarterly (Craig and von Peter (2014), Fricke and Lux (2015)) level of aggregation is most often used. The Hungarian unsecured interbank lending market (Berlinger et al. (2017)) and FX-swap market (Banai et al. (2015)) were already analyzed separately before with different purposes using basically different tools and data from different time intervals but the level of aggregation was the same in both research papers. So keeping in mind that my results should be comparable to the earlier results on Hungarian markets I used monthly level of aggregation as of the mentioned previous papers. In my analysis I examined and compared not only the overall FX-swap and unsecured interbank lending markets using tools from network theory but also maturity based submarkets. The overall markets and submarkets were analyzed and compared using the following properties: size, ratio of the largest connected component and network size, average degree, average clustering coefficient, average betweenness coefficient and average closeness coefficient. Furthermore, the monthly network properties of overall and submarkets were also compared to properties of random networks (Erdős-Rényi). In order to test the existence of scale-free property of real monthly networks, power law distribution was fitted on degree distributions based on Newman (2005) and conclusions were drawn based on p-values.

Given that one of the aims of the dissertation is to identify and compare the key players of FX-swap and unsecured interbank lending markets several different methods and models were used. I identified the largest HUF and foreign currency liquidity providers (sources) and receivers (drains) in monthly networks of overall markets and submarkets and based on the following centrality measures the most important institutions (vertices) were identified according to their importance in arrays of relationships linking entities: degree, closeness, betweenness, eigenvector centrality (Bonacich (1972)) and PageRank algorithm (Brin and L. Page (1998)).

In financial network literature it is a relatively new observation that within a financial network a densely connected core and a periphery are usually well distinguished. While each institution in the core is typically willing to transact with any other institution in the core, the institutions in the periphery generally do not transact directly with each other but only through the core institutions (Fricke and Lux (2015), Berlinger et al. (2017)). From systemic risk point of view core banks are the important ones and have to be identified. Networks in which the core and the periphery are well distinguished usually show hierarchical modularity, according to which each participant specializes in different tasks (Barabási (2016)). In order to check the existence of hierarchical modularity in monthly networks of both markets I examined the dependence of the clustering coefficient on the node's degree based on Barabási (2016). Financial networks core-periphery features are usually confirmed by examining the assortativity of the network (León et al. (2018)). In order to determine the assortative or dissassortative characteristic of a network, the so-called degree correlation has to be analyzed which is the Pearson-correlation coefficient of degrees between pairs of linked nodes (Newman (2002)). Based on the literature (León et al. (2018)) financial networks proved to be disassortative suggesting core-periphery characteristic of a network. Accordingly, disassortative nature of monthly networks of both markets were also examined. Finally, financial institutions located in the core were identified and compared for both markets using a k-core decomposition algorithm (Seidman (1983)) and an asymmetric continuous core-periphery model (Boyd et al. (2010)).

In Chapter 3 I introduce a model published by the European Central Bank in Working Paper (Montagna and Kok (2016)) form which can identify the systemically important financial institutions and potentially vulnerable interbank market network structures to external shocks. As it was mentioned in the previous chapter the interbank market participants were examined through a multi-layered network in order to take into consideration that financial institutions can connect to each other through several markets at the same time. The first layer embodies interbank counterparty risk on long term interbank market while the second layer try to capture the funding risk on short term interbank market. The third layer is meant to reproduce the network of overlapping portfolios namely when two banks invest in the same mark-to-market financial securities. Then their balance sheets can be correlated which means that when one bank is forced to sell some securities and the resulting price decline from such fire sale will affect the balance sheets of the banks which hold the same asset. Furthermore, the model relies on agent-based simulation techniques which means that in case of an exogenous shock to the system financial institutions can make decision over a number of periods through a predefined set of rules and algorithms which determine how much of their short-term interbank loans is being renewed and how much of their securities is being sold to fulfill their obligations and regulatory requirements. The dynamics of the model are as follows. In each case, exogenous shock means the bankruptcy of a randomly selected bank which withdraws all its funds from short term interbank market and sells all its securities and then it tries to pay back its creditors. Firstly, the remaining banks face credit obligations if the defaulted bank was one of their short term creditors. Secondly, the price of the securities are determined endogenously in the model and due to fire sales prices can fall significantly which cause losses to banks holding similar securities and reduce their solvency capital equal to the losses. Thirdly, those remaining banks which were creditors of the defaulted bank on long term book the defaulted bank's whole credit obligation as losses which directly affect their capital. The remaining banks have to fulfill liquidity and capital requirements and if their other short term liquidity providers do not renew the currently provided short term interbank loans the banks face further credit obligations which also have to be fulfilled. Hence, the remaining banks will simultaneously decide how much of their funds from short term interbank market will be withdrawn and how much of their securities will be sold in order to fulfill their credit obligations and regulatory requirements. If a bank is not able to fulfill the capital or liquidity requirement or its credit obligation it defaults. After the default of a randomly selected bank the system will continue to evolve and the simulation stops when there is no new bankruptcy in a given step.

3 Main results

3.1 Comparing the Hungarian unsecured interbank lending and FX-swap markets using tools from network theory

The analysis of the financial markets using tools from network theory became the center of attention after the financial crisis which was mainly driven by a better understanding of financial market network structures and the identification of systemically important financial institutions. The global financial crisis following the Lehman-bankruptcy has shown that some market participants are key players in the sense that their defaults threaten the financial stability, so their identification and prudent management by the regulator are essential.

It has to be highlighted that there is relatively little foreign and domestic literature in which unsecured interbank lending and FX-swap markets were analyzed using tools from network theory. The reason is that transactional level data from market participants is either not collected or only to a limited extent by central banks. The closest Hungarian literature to my study is the following: Berlinger et al. (2011), Banai et al. (2015) and Berlinger et al. (2017). Berlinger et al. (2011) analyzed the Hungarian unsecured interbank lending market using similar tools from network theory which were also applied in the dissertation and its goal was to examine the change in well-known metrics from network theory before and after the financial crisis in order to describe its emergence and the early stages of the recovery. Banai et al. (2015) examined the monthly networks of Hungarian FX-swap markets between 2005 and 2014. The article focuses on the evolution of emphasized network metrics, particularly during the crisis period but identifying the key players was not in focus. Berlinger et al. (2017) analyzed the Hungarian unsecured interbank lending market again but the article focused on identifying the key players with an asymmetric continuous core-periphery model. From the foreign literature Iazzetta and Manna (2009), Soramäki et al. (2006) and Simaan et al. (2020) should also be highlighted analyzing the unsecured interbank lending markets using tools from network theory. In case of FX-swap market similar to Banai et al. (2015) I did not find any foreign literature which focused on analyzing this market using network theory based tools. In summary, the novelty of the dissertation compared to the mentioned Hungarian and foreign literature lies in the following facts:

- There is no analysis in either the Hungarian nor in the foreign literature in which two markets were analyzed and compared using tools from network theory on the same time interval.
- Due to matching IDs in the given databases it was possible to identify and compare the key players of the two markets.
- In addition to Berlinger et al. (2011) and Berlinger et al. (2017) key players on Hun-

garian unsecured interbank lending market were identified using centrality measures and k-core decomposition algorithm.

- In addition to Banai et al. (2015) key players on the Hungarian FX-swap market were identified using centrality measures, a k-core decomposition algorithm and an asymmetric continuous core-periphery model. Furthermore, hierarchical modularity and disassortative nature of networks on Hungarian FX-swap market were also tested for the first time.

In the following, I summarize the results of the analysis based on tools from network theory by topics and applied methods. Each analysis was based on monthly networks of Hungarian FX-swap and unsecured interbank lending markets between 01.01.2012 to 31.12.2015.

Network metrics

I compared the well-known network metrics and their evolution in the indicated time interval for both FX-swap and unsecured interbank lending markets monthly networks. The analysis was also extended to maturity based submarkets. The overall markets and submarkets were analyzed and compared using the following properties: size, ratio of the largest connected component and network size, average degree, average clustering coefficient, average betweenness coefficient and average closeness coefficient. Based on the previous metrics, the following conclusions can be drawn.

- The number of nodes in networks of both markets can be considered as stable over time but monthly networks of FX-market have more than twice as many nodes on average as the unsecured interbank market which is in connection with the foreign players on FX-swap markets. The size of networks decreases with increasing maturity in both markets.
- In case of the FX-swap submarket of domestic players, all the monthly networks are connected. However, in case of unsecured interbank market the monthly networks for a total of 4 months out of 48 months were not connected, while this is true for 15 months related to the monthly networks of FX-swap market. Monthly networks of FX-swap submarket with a maturity over one month and of non-overnight unsecured submarket are typically not connected.
- The average degree of monthly networks of unsecured market is more than twice as much as of FX-swap market on average which is in connection with the low degree of foreign market participants on FX-swap market. However, the average degree of monthly networks of unsecured market and FX-swap submarket of domestic players moves approximately together. Average degree of monthly networks decreases with

increasing maturity in both markets. Moreover, networks of FX-swap submarket with a maturity over one month and of non-overnight unsecured submarket have the least connection on average.

- The average clustering coefficient of monthly networks of FX-swap market is significantly lower compared to unsecured interbank market. This means that for FX-swap market the probability that two randomly selected neighbors of a randomly selected node are connected is significantly lower compared to unsecured market. Furthermore, the average clustering coefficient of monthly networks of unsecured market and FX-swap submarket of domestic players moves approximately together. Average clustering coefficient of monthly networks significantly decreases with increasing maturity in both markets. Average clustering coefficient is the lowest in case of networks of FX-swap submarket with a maturity over one month and of non-overnight unsecured submarket.
- Based on the average betweenness metrics, the least central node are likely to be in the monthly networks of FX-swap market, while most are likely to be in networks of FX-swap submarket of domestic players. In case of unsecured market, the average betweenness metrics is between the metrics of the mentioned market and its submarket for each month. These results are confirmed by the evolution of average closeness metrics over time. The number of central nodes in monthly networks increases with increasing maturity in both markets but in case of FX-swap submarket with a maturity over one month and of non-overnight unsecured submarket the metrics are too volatile to draw conclusions from.

Relationship with random networks and scale-free property

In order to check whether the monthly networks of FX-swap market, unsecured interbank market and their maturity based submarkets can be considered as random networks I simulated random networks to every monthly networks using their basic properties. In case of FX-swap market and its maturity based submarkets I took into consideration the fact that there can be no connection between two foreign market participants. I compared the simulated random networks with monthly networks of the mentioned markets and submarkets using the average clustering coefficients and the number of connections of the five nodes with the highest degree. The following conclusions can be drawn.

- Based on the analysis, monthly networks are significantly different from random networks for both markets which means that monthly networks have meaningful structures.
- Monthly networks of FX-swap market differ the most from random networks while the networks of unsecured interbank market differ from random networks to a lesser extent compared to results in case of FX-swap market.

- In case of the maturity based submarkets the difference from random networks seems to decrease with increasing maturity for both markets. Furthermore, as the maturity increases, the small-world property is less and less typical for monthly networks.

Real networks can rarely be captured by random networks because real networks usually have far more nodes with high degree compared to random networks which can be considered as hubs. Furthermore, in real networks, some high degree nodes are typically associated with many low degree vertices that are also not captured by a random network. However, the aforementioned features of real networks can be captured by scale-free networks so I examined the scale-free property of monthly networks of both markets. According to Newman (2005) andClauset et al. (2009) I fitted power-law distribution to the degree distribution of the monthly networks for both markets and calculated the p-value of Kolmogorov-Smirnov statistics in order to check the adequacy of the fitted distributions. Furthermore, I also checked that the estimated parameters of the fitted power-law distributions were between 2 and 3 according to Barabási (2016). The following conclusions can be drawn.

- Based on the p-value of the Kolmogorov-Smirnov tests the null hypothesis that the degree distribution follows a power-law distribution cannot be rejected for all monthly networks of FX-swap market while it can be rejected for a total of 5 months out of 48 in case of the unsecured interbank market. Accordingly monthly networks can be considered as scale-free for both markets, whereas for FX-swap market this feature is stronger.
- The estimated parameters of the fitted power-law distributions are typically close to 2, however it is important to take into account that these networks are small and the parameters were estimated on a small sample.
- In case of the maturity based submarkets the scale-free property gets stronger with increasing maturity however, this result should be treated with caution as the networks of these submarkets are composed of very few market participants.

Key players of FX-swap and unsecured interbank markets

Firstly, in order to compare the key players in the two markets and in their maturity based submarkets I identified the largest HUF and foreign currency liquidity providers (sources) and receivers (drains) in monthly networks. Based on the analysis the following conclusions can be drawn.

- There is no significant difference in the number of drains in the monthly networks of FX-swap and unsecured interbank markets. However, fewer domestic players can be found in the FX-swap market which means that greater proportion of the domestic players can be considered as drains than on the unsecured market.

- The number of sources is the highest in case of FX-swap market which is not surprising due to the foreign FX liquidity providers. At the same time, on average more market participants are present in the monthly networks of unsecured market than in the monthly networks of FX-swap submarket of domestic players. This means that the number of domestic sources in networks of FX-swap market is significantly lower than in networks of unsecured market.
- In case of unsecured market as maturity increases, the average number of domestic drains decreases which means that more market participants need short-term HUF funding than in the long term. On the contrary, the average number of domestic drains increases as the maturity increases in case of the FX-swap market which means that more market participants need FX liquidity on the long term than in the short term. Furthermore, the number of domestic sources decreases as the maturity increases for both markets.

In both markets and in their maturity based submarkets I identified the TOP5 sources and drains during the whole period (01.2012-12.2015). Based on the analysis the following conclusions can be drawn.

- Comparing the TOP players of the two markets, it can be seen that there is no overlap between the TOP drains which means that not the largest HUF liquidity borrowers are the largest FX liquidity borrowers and vice versa.
- It is interesting to note that there is only one common market participant in the FX-swap submarket of domestic players and in the unsecured interbank market which means that not the same domestic players are the largest HUF and FX liquidity providers.

According to the literature I quantified the well-known centrality measures in monthly networks of both markets in order to identify and compare those institutions which are significant from systemic risk point of view. The following measures were calculated: degree, closeness, betweenness, eigenvector centrality (Bonacich (1972)) and PageRank algorithm (Brin and L. Page (1998)). Based on the analysis the following conclusions can be drawn.

- In case of the unsecured interbank market the overlap of significant institutions in the full market and in the maturity based submarkets is strong furthermore, according to the in-degree and out-degree metrics significant institutions tend to function as hubs due to their high number of inbound and outbound connections. I found two institutions which are key players based on all metrics and one of them is the largest liquidity provider in the non-overnight market while the other one is the largest liquidity borrower in the overnight market.
- In case of the FX-swap market the overlap of significant institutions in the full market and in the maturity based submarkets is strong but similar to the unsecured interbank

market on long term the degree of overlap decreases. Based on the in-degree metrics it can be seen that FX liquidity borrowers which have at least one foreign source are also connected to domestic partners in order to diversify their FX liquidity needs. I found three institutions which are key players based on all metrics and one of them has the most connection based on in- and out-degree metrics. There is a key player which is the only domestic institutions among the TOP5 banks which provide FX liquidity. The last one has higher out-degree metrics compared to the second one which means that the second institution provide FX liquidity to fewer domestic players but in larger volumes while the third one is likely to provide FX liquidity in smaller volumes to more domestic players.

- The comparison of the key players in the two markets shows that similar domestic market participants are the largest in terms of providing HUF and FX liquidity in the domestic market while there is only one common domestic key player in terms of HUF and FX liquidity borrowing. This means that domestic liquidity providers which tend to function as hubs are likely to provide HUF and FX liquidity for different institutions.

Core-periphery structure of the monthly networks

In the literature it can be considered as a relatively new observation that in financial networks a densely interconnected core and a periphery are usually well distinguished. That is, while each core bank is typically willing to transact with any other core bank, the peripheral banks generally do not directly transact with each other, only through the core banks. Considering the above, the identification of core banks is important from systemic risk point of view (Craig and von Peter (2014), Fricke and Lux (2015)). According to the literature examining the core-periphery structure of financial networks, these networks are typically characterized by a kind of hierarchical modularity, according to which each player specializes in different tasks. Based on the literature (Barabási (2016)) hierarchical network models are those scale-free networks in which nested hierarchical communities can be found. In these models, several smaller communities can be identified in the structure of the network, which together form a larger community, and then these larger communities form even larger communities, that is, a kind of nested hierarchical structure. The measurable sign of the hierarchical structure is the dependence of the clustering coefficient on the degree. That is, the higher the degree of a given node (the more connections it has), the lower the clustering coefficient (the less the connections between its neighbors). To check the nested hierarchical structure of the monthly networks of FX-swap and unsecured interbank markets I fitted linear regressions on the logarithm of the clustering coefficients using the logarithm of degrees as an explanatory variable for each monthly network and compared the estimated coefficient with -1 (Barabási (2016)). Based on the analysis the following conclusions can be drawn.

- The negative coefficients and their values around minus one justify that further analysis of the communities and possible core-periphery characteristics of the markets and sub-markets are needed.
- The average of the estimated coefficient shows an increasing trend over maturity but reliable conclusions can be drawn only for the short term submarkets due to low number of observations.
- Based on the estimated parameters the fitted linear regression in case of FX-swap market is steeper than of the unsecured interbank market which means that the hierarchical structure of the FX-swap market is more observable than that of unsecured market.

Before examining communities, I analyzed the preference of monthly networks nodes to attach to others in order to capture their assortative/disassortative nature. The core-periphery nature of financial networks has been confirmed by the study of assortativity (León et al. (2018)). Based on their results, the examined financial network proved to be disassortative, suggesting a core-periphery character, since their basic assumption is that market players on the periphery typically do not trade directly with each other, only through core players. Disassortative nature captures just this phenomenon as nodes with higher degree are likely to connect to nodes with lower degree. In order to determine the assortative/disassortative nature of a network, the so-called degree correlation has to be analyzed which is the Pearson correlation of degree between pairs on linked nodes. I analyzed the degree correlation for each monthly networks of the FX-swap and unsecured interbank markets and of their submarkets and based on the results the following conclusions can be drawn.

- The average degree correlation is negative for both markets and for their submarkets which means that the disassortative nature of monthly networks is confirmed.
- The results obtained when examining the hierarchical structure of networks are consistent with the degree-correlation results: in case of the FX-swap market the degree-correlation is significantly lower than of the unsecured market which indicates stronger disassortativity. This means that in case of the FX-swap market, the average degree of the neighbors of a high degree node is lower than that of the unsecured market.
- In terms of maturity breakdown, the degree correlation is lower for short term submarkets, which means that disassortativity is stronger for short term submarkets.

Based on the results obtained from the analysis of degree correlation and hierarchical modularity further analysis of the core-periphery structure of the monthly networks of each market and submarket is necessary. To identify the financial institutions in the core I used two different methods. One method was to analyze the k-core of the monthly networks while the other one was the estimation of an asymmetric continuous core-periphery model. Based on the literature the k-core of a graph is the maximum connected subgraph in which every vertex has at least k degrees. In practice, beside analyzing k-cores the so-called coreness indicator for every vertex is usually determined. The coreness of a vertex is k if it belongs to the k-core but not to the (k+1)-core (Seidman (1983)). I calculated the coreness indicator for each node in monthly networks of both markets and of their submarkets and identified the TOP5 players based on their average coreness indicator. According to the results the following conclusions can be drawn.

- The average of the coreness indicators of the TOP5 player decreases with increasing maturity in case of both markets which means that as the maturity increases, the core of the graph is less likely to contain numerous high degree vertices.
- Based on the average of the coreness indicator of the TOP5 player, the core of the unsecured interbank market contains more vertices than the FX-swap market which is probably due to the higher density of the unsecured networks. The results also indicate that in the FX-swap market fewer key players can be found in the monthly networks.
- According to the in- and out-coreness indicators which can take into consideration the direction of financing the size of the core decreases in case of the unsecured market while the core of the FX-swap market does not change significantly.
- Based on the comparison of the TOP5 player using the coreness, in-coreness and out-coreness indicators it can be seen that the core of the monthly networks of the FX-swap market typically contain 6-8 domestic players which are closely connected to each other and FX liquidity is provided mutually among themselves. In case of the unsecured market, since the coreness and in-coreness results are overlapping, while the out-coreness indicator overlaps with three institutions, it can be said that players in the core are willing to accept HUF liquidity from each other, but there are two additional players which provide HUF liquidity to core banks however, they need less HUF funds from the core banks.

Beside the analysis of the k-cores, I estimated asymmetric continuous core-periphery models on the monthly networks of both markets and their submarkets whereby the coreness indicator can be any real value between 0 and 1. To estimate asymmetric continuous core-periphery models I applied the method published by Boyd et al. (2010). Based on the results the following conclusions can be drawn.

- The average of the coreness indicators of the TOP5 player is extremely close to 1 in case of both markets which indicates a stable core presence but when looking at maturity based submarkets, it can be seen that the average of the coreness indicators decreases with increasing maturity. This means that the core is less stable in longer term submarkets which suggest that vertices in the cores are more likely to exchange in longer term submarkets.

- The asymmetric continuous core-periphery models can capture the largest sources and drains better than the k-core method based on the u- and v-coreness indicators. The k-core method is more suited to identify the highly connected players which can be considered as hubs in networks.

3.2 Identifying systemically important financial institutions and vulnerable network structures with an agent based multi-layered interbank network model

Following the financial crisis, it has been proven that the topology of the financial networks may change significantly as a result of an external shock to the system and a close link between financial market liquidity and network characteristics has been revealed. In light of the above, the propagation of shocks in financial networks and the dynamics of the network structure changes over time has become an important research area. As it was mentioned earlier the novelty of the model what was introduced and applied in the dissertation based on Montagna and Kok (2016) lies in the fact that interbank market participants were examined through a multi-layered network and the model relies on agent-based simulation techniques. This model with multi-layered network can take into account that in reality financial institutions can connect to each other through several markets at the same time which means that shock propagation is done simultaneously across these layers amplifying the initial shock. In the reviewed literature except Montagna and Kok (2016), only single-layered networks were used which means that banks were supposed to connect to each other on only a single market (Allen and Gale (2000), Bluhm and Krahnen (2011) and Georg (2011)). Applying multi-layered networks can lead to better understanding of the contagion effect in financial networks. Furthermore, due to the model relies on agent-based simulation techniques predefined set of rules and algorithms can be used to model the behavior of the financial institutions over a number of periods to an exogenous shock. In accordance with the above, these financial institutions make decision to renew their short-term interbank loans and sell their securities to fulfill their obligations and regulatory requirements.

The data of Hungarian banks and banking groups used in the model comes from multiple sources. I collected balance sheet data from the Aranykönyv published by Central Bank of Hungary as of 12.31.2018 while the source of the total assets and liabilities from the interbank market was the supplementary annexes of income statements published by Hungarian banks and banking groups individually as of 12.31.2018. I also collected Risk Weighted Assets (RWA) and Capital Adequacy Ratios (CAR) of the Hungarian banks and banking groups which was obtained from the Pillar 3 disclosures published by the market participants individually.

The following list summarizes the differences between the original model and the model used in the dissertation.

1. The asset and liability side of the financial institutions are slightly different in the applied model due to the overall interbank loans and borrowings indicated in the supplementary annexes of income statements contain asset and liabilities related to parent companies and to the Central Bank of Hungary. Accordingly, in order to get accurate results I corrected the overall interbank assets and liabilities with assets and liabilities related to affiliated companies and the Central Bank of Hungary.
2. Due to assets and liabilities related to affiliated companies and the Central Bank of Hungary were indicated in the equations of the total assets and liabilities separately, the applied regulatory capital and liquidity constraints were modified compared to those used by Montagna and Kok (2016).
3. Solvency capital was used on the liability side of the financial institutions instead of equity according to CRR Article 92 (2) c). For Montagna and Kok (2016) solvency capitals of the analyzed financial institutions were not available.
4. I calculated the general risk weight for securities as the average of the portfolio level risk weight of the TOP5 financial institutions in my sample and these portfolio level risk weights were calculated as the weighted average of the CRR based risk weights of securities held in portfolios of the TOP5 institutions. For Montagna and Kok (2016) the calculated risk weighted assets of securities held by institutions were available from which average portfolio level risk weights can be easily calculated.
5. Montagna and Kok (2016) did not take into account the decrease of short term interbank liabilities after obligation fulfillment during the calculation of the number of securities to be sold in order to meet the liquidity requirement. Furthermore, the decrease of capital requirement due to the sold securities was not properly treated during the calculation of the number of securities to be sold in order to meet the capital requirement. Both errors were corrected in the dissertation.
6. For both Montagna and Kok (2016) and me the overall short and long term interbank assets and liabilities for each financial institutions were available which means that short and long term interbank assets have to be allocated between the institutions in order to create interbank networks. The authors estimated probability matrices based on data from a document published by the European Banking Authority which presents the results of a stress test on major EU banks. Given that, due to only one Hungarian bank has participated in the EU-wide stress test this source was not applicable to create similar probability matrices. Therefore, I developed a methodology to estimate probability matrices in order to simulate networks related to the short and long term interbank market layers in the model. This methodology ensures that the generated networks have the typical characteristics of financial market networks, such as scale-free property (Fricke and Lux (2015)), disassortative nature (León et al. (2018)) and lower network density at longer maturity (Berlinger et al. (2011)).

In the following I summarize the new results obtained with the introduced agent based multi-layered interbank network model. Using the model four topics were investigated and accordingly the results are discussed separately.

The role of network layers in the model

In order to see the role of networks in different layers and their ability to amplify the propagation of shocks and thus increase the likelihood of contagion, I run the simulation in several ways. In case of the first run I assumed that financial institutions interact with each other only in the first layer, while in the second and the third runs only the second or the third layer was active. In such cases financial institutions face only one type of counterparty risk[1], liquidity risk[2] and risk related to overlapping securities portfolios[3]. In addition, I run the simulation even with pairs of active layers. In Table 1, the Active layers column shows in which layer contagion is possible and Table 1 shows the distribution of the number of defaulted financial institutions by active layers. Each row of Table 1 shows the distribution of the results of 50-50 thousand simulations.

Active layers	1	2	3	4	5	6	7	8	9	10
1-2-3	97.707%	2.012%	0.066%	0.169%	0.018%	0.021%	0.001%	0.005%	0%	0.001%
2-3	97.722%	2.013%	0.070%	0.151%	0.013%	0.025%	0.001%	0.004%	0.001%	0%
1-3	97.879%	1.882%	0.064%	0.154%	0.004%	0.014%	0%	0.003%	0%	0%
3	98.187%	1.582%	0.051%	0.096%	0.076%	0.008%	0%	0%	0%	0%

Table 1. Distribution of the number of defaulted financial institutions by active layers

The following conclusions can be drawn for the Hungarian financial institutions based on the results above.

- For any combination of active layers, the probability that the bankruptcy of one financial institution also causes the bankruptcy of at least one other bank is very low in the model which is in line with the results obtained by Montagna and Kok (2016).
- The likelihood of a bank failing to be followed by further bankruptcies is the highest if all three layers are active at the same time and in this case bankruptcies are most likely to occur in extreme numbers. This means that in single layer based models the contagion effect could be underestimated compared to multi-layer based models.
- In Table 1 active layer combinations in which the third layer is inactive are not included due to if I assume that securities portfolios are independent i.e. layer 3 is inactive then no bank failure can trigger further bankruptcies in the model. This is partly contradictory to that obtained by Montagna and Kok (2016) because the

[1] long term interbank market network, layer 1

[2] short term interbank market network, layer 2

[3] layer 3

authors could simulate further bankruptcies even if layer 3 was not active. The difference between the results can be explained by the following facts:

- Overall short and long term interbank assets and liabilities for each financial institutions were corrected with assets and liabilities related to affiliated companies and the Central Bank of Hungary in my calculation while Montagna and Kok (2016) did not mention any correction. Hence, the corrected interbank assets and liabilities compared to the balance sheet totals are lower in average than in case of the author's calculation.
- In case of Hungarian financial institutions, the market value of securities held in their balance sheets significantly exceeded the volume of the corrected interbank assets and liabilities. In case of EU large banks examined by Montagna and Kok (2016) interbank assets and liabilities are likely to give a greater portion of the balance sheet compared to Hungarian banks.
- Larger banks are likely to be more active on interbank market. While the authors examined EU large banks, in my case only the OTP Group is considered to be large on EU scale.

• Given that the model on Hungarian data is driven by the layer of overlapping portfolios which has negative impact on the solvency capital and hence the capital adequacy, if layer 1 is active beside layer 3 instead of layer 2 the contagion through the overlapping portfolios more significantly amplified. The reason behind this is that losses on long term interbank market also reduces solvency capital in the same way as losses related to overlapping securities portfolios while layer 2 is most likely to negatively affect liquidity. In other words, if layer 1 and 3 are active in the model a bank failure is more likely to cause further bankruptcies than if layer 2 is active beside layer 3 but in rare cases layer 2 can amplify the contagion in layer 3 through liquidity problems to such an extent which leads to more frequent bankruptcies in extreme numbers.

Systemically significant financial institutions

According to Montagna and Kok (2016), I measure the systemic importance of a financial institution by how many other financial institutions can fail due to its bankruptcy. Based on 100 thousand simulation Hungarian banks/banking groups can be ranked according to the maximum number of failures of other banks caused by the bankruptcy of a given bank. Table 2 summarizes the results of the simulation.

Maximum number of bankruptcy triggered	0	1	3	4	5	9
Number of banks	6	4	5	1	2	1

Table 2. The maximum number of bankruptcies triggered by a failure of a given bank

It can be seen that the failure of 6 out of the 19 examined financial institutions cannot cause further failures in the system which is realistic considering that the majority of the financial institutions in my sample are very small players on the Hungarian market. It can also be seen from Table 2 that there is only one player which default could cause up to 9 further failures. Furthermore, those institutions that are capable of causing further bankruptcies of 4, 5 or 9 banks can be considered as systemically important. Based on Table 2, there are a total of 4 such banks/banking groups in my sample. While the high number of further bankruptcies in case of a failure of a given bank may be due to a very special network structure from the point of view of that initial defaulted bank which has just been captured by the simulation, the average number of bankruptcies caused by the failure of a given bank in the system carries additional information in light of the 100 thousand possible network structures.

Table 3 summarizes the maximum number of bankruptcies triggered by a failure of a given bank and the average number of default events per 100 thousand simulations.

Banking group	The maximum number of bankruptcies triggered	Average number of default events
OTP group	9	1.285
UniCredit group	5	1.042
MKB group	5	1.038
K&H group	4	1.033
Erste group	3	1.052
Integration of saving cooperatives	3	1.039
Raiffeisen group	3	1.032
CIB group	3	1.009
Budapest Bank group	3	1.008

Table 3. The maximum number of bankruptcies triggered by a failure of a given bank and the average number of default events per banking group

Table 3 shows that both indicators are the highest in case of the OTP group which is in line with preliminary expectations as the OTP Group is by far the largest on balance sheet total and securities portfolio basis, furthermore it is one of the most active players on the interbank market. In terms of the maximum number of bankruptcies triggered UniCredit and MKB group follow the OTP group, while in case of the average number of bankruptcies Erste group is ahead of both groups. This is because, as of 31.12.2018 the Erste group's securities portfolio is the second largest among the 19 banking group in the sample, while it is far below UniCredit or MKB in terms of corrected interbank assets and liabilities. As the results mentioned above show that the model quantified on Hungarian data is highly dependent on the overlapping securities portfolios, the bankruptcy of a bank with larger portfolio of securities has, on average, a greater impact on the system than the bankruptcy of a more active interbank market participant. However, based on the mentioned results above the likelihood of contagion in interbank markets are high, so in case of a fragile simulated network structure the bankruptcy of an active interbank market participant could result in further bankruptcies in extreme numbers due to contagion. So the high average number of default events in case of the Erste group is explained by high volume of its securities portfolio, while the high maximum number of triggered bankruptcies indicators in connection with the failure of UniCredit and MKB groups are due to more active interbank market participation.

Fragile network structures

The agent based multi-layered interbank network model is also capable of identifying those network structures that weaken the system's shock resistance and amplify the effects of an initial shock. On the one hand, we know that the bankruptcy of a fraction of the banks examined can trigger further bankruptcies, hence it is advisable to analyze those network structures which are the most sensitive to the failure of the largest systemically important banks. Obviously, extreme number of defaults occurs when a systemically important bank goes bankrupt first and the simulated network is just that which is more vulnerable to the failure of this bank. On the other hand, rather than examining such extremely rare cases, systemic risk investigations tend to identify network structures that are critical to more than only one bank. From systemic risk point of view, since a systemic collapse is more likely to occur in a network critical to multiple banks than when we consider the most rare event to simulate the default of the most risky bank in a network structure most sensitive to the bankruptcy of this bank, so the examination of the former is more important. Based on Montagna and Kok (2016) the fragility of a multi-layered network can be measured as the average of bankruptcies caused by the failures of network members. In my calculations, I simulated 200 thousand multi-layered networks for which I calculated the average number of bankruptcies caused by the failure of each examined financial institution in my sample. Figure 1 shows the distribution of the average number of bankruptcies caused.

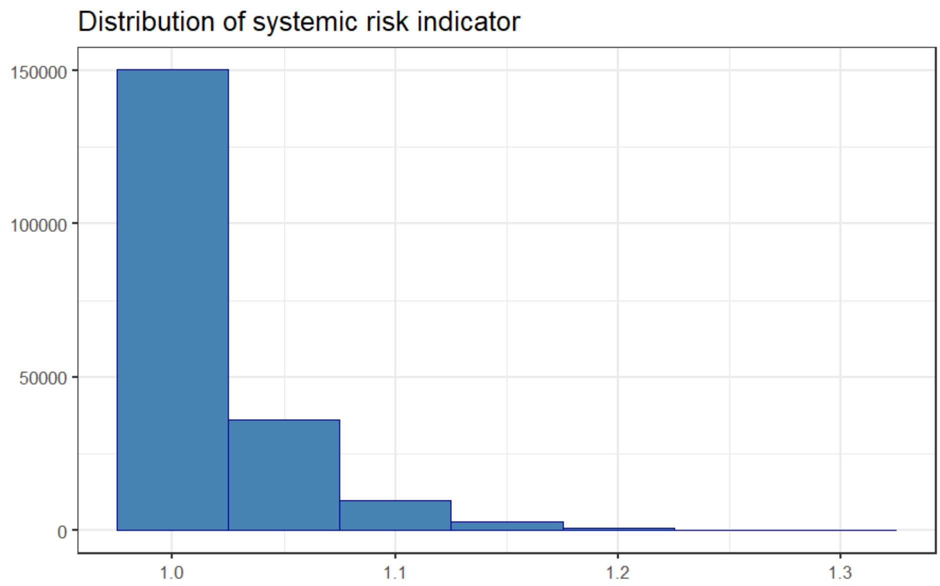

Figure 1. Distribution of systemic risk indicator

Figure 1 shows that for most of the simulated networks (75.1%), the systemic risk indicator will be 1, which means that the failure of any of the 19 examined financial institutions will not cause further bankruptcies. This means that, for 24.9% of the 200 thousand simulated network, the failure of at least one bank will result in bankruptcy of at least one other bank. The maximum value of the systemic risk indicator in my simulation was 1.3518 which means that in case of the most fragile network structure, the initial failure of any market participant causes 1.3518 bankruptcies on average. From a systemic risk point of view, the network structures with the highest indicators are of interest, so during the simulation I saved the networks with the highest indicators (separately for short and long term interbank markets and overlapping portfolio layers) to compare them with network structures where the failure of any market participant does not lead to further bankruptcy. Table 4 summarizes the key metrics for each layer of a multi-layered network with maximum (1.3158) and minimum (1) systemic risk indicators.

Network	Average overlap	Densitiy	Degree correlation	Average degree	Maximum degree
Securities (max)	0.1385	0.7836	-0.1348	28.21	36
Securities (min)	0.0936	0.5321	-0.1605	19.15	30
Short term interbank (max)	-	0.1578	-0.3307	5.68	11
Short term interbank (min)	-	0.1695	-0.3741	6.11	13
Long term interbank (max)	-	0.0789	-0.1773	2.84	6
Long term interbank (min)	-	0.1198	-0.0218	4.31	8

Table 4. Key metrics of networks with minimum and maximum systemic risk indicators

In the following, I draw general conclusions from Table 4, which network properties distinguish the most vulnerable network structure from systemic risk point of view from those in which no bank failure could cause further bankruptcy. I draw these conclusions not only on the basis of the two multi-layered networks in the Table, but also on the basis of further analysis of vulnerable and non-vulnerable networks.

1. In case of the layer related to the overlapping securities portfolios, it can be concluded that fragile networks from systemic risk point of view are denser and thus overlaps in the securities portfolios of market participants are higher compared to the non-fragile one. It means that in case of a default event more banks may suffer losses which will decrease their solvency capitals. Because of higher density, a more fragile network will naturally have a higher average degree value, but the degree correlation is lower, which suggests that more fragile networks show less disassortative nature. This means that the portfolios of market participants with higher and lower degree overlap to a lesser extent.
2. In case of the layer related to the short term interbank market, it can be concluded that key players provide short term liquidity to smaller banks to a lesser extent in fragile networks from systemic point of view. It means that smaller banks are likely to be more exposed to liquidity risk due to the failure of smaller institutions. Furthermore, the degree and density metrics show that short term interbank lending is more concentrated in fragile networks.
3. In case of the layer related to the long term interbank market, it can be concluded that in fragile networks long term interbank lending is more concentrated and in the long run key players are likely to provide liquidity to smaller institutions to a greater extent. Thus, in the event of bankruptcy of smaller banks, key players write off more of their solvency capitals.

The role of the number of securities in the model

All the results and analyzes presented so far have been carried out with 30 securities in the model in accordance with Montagna and Kok (2016), each of which is held by each market participants with $p = 0.2$ probability in their securities portfolio. With regard to the role of the securities in the model, firstly I examined how the overlapping nature of the securities portfolios of the examined institutions changes as function of the number of securities available in the model. To answer this question, I ran the model 50-50 thousand times using different number of securities and calculated the average overlap value depending on the number of securities. Figure 2 shows the average overlap parameter of securities portfolios as a function of the number of securities used in the model.

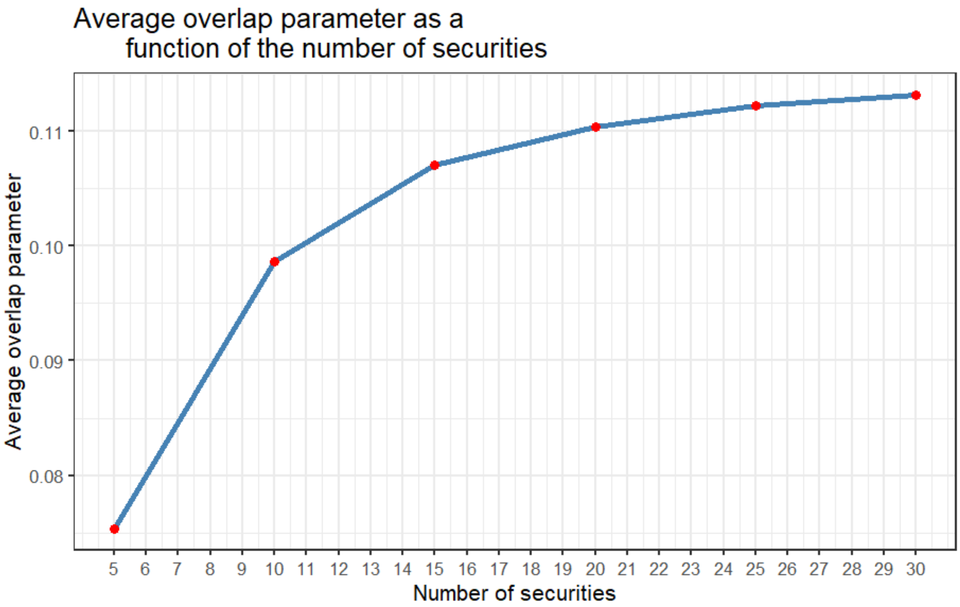

Figure 2. Average overlap parameter as a function of the number of securities

From Figure 2, it can be seen that as banks in the model hold more securities in their portfolios, the average overlap of banks's securities portfolios increases, but at a slower pace. That is, the overlap of securities portfolios with the number of securities does not increase linearly, but the growth declines over time. We may suppose that the greater the overlap in securities portfolios, the greater the risk of contagion, but in the light of the above, it is not entirely clear which securities number and overlap rate will maximize the number of failing banks in the system. This question is answered in the followings. I am looking for an answer to the question of how the number of bankruptcies changes depending on the number of securities and the degree of overlap. To answer the question, I also ran the model 50-50 thousand times using different number of securities and calculated the average overlap per simulation, and determined the number of defaulted banks in the given simulation. That is, for each different number of securities, 50 thousand average overlap values and the number of defaulted banks in 50 thousand simulations are calculated. I then rounded the average overlap rates to two decimal places and aggregated the simulation results using the rounded values for each different number of securities and calculated the average number of defaulted banks during the aggregation by the average overlap values. Figure 3 shows the average number of defaulted banks as a function of the different number of securities used in the model and the average overlap values.

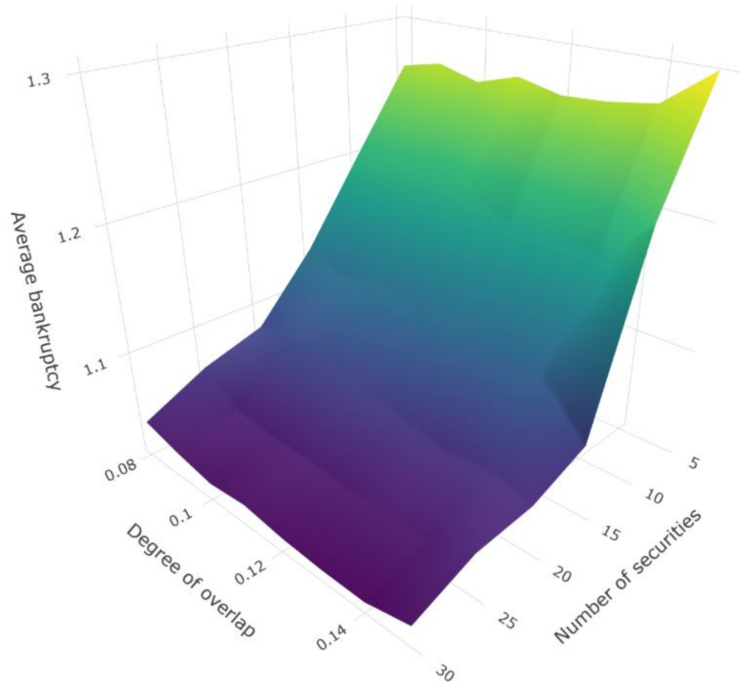

Figure 3. The average number of bankruptcies as function of the degree of overlap and the number of securities

Figure 3 above shows that the less the number of securities held by market participants in their securities portfolios, the higher the average bankruptcy. This is a consequence of the fact that the less the securities held by the banks, the greater the volume invested in a given security, which increases concentration and reduces diversification across securities portfolios. Figure 3 also shows that the average overlap of securities portfolios does not have significant impact on the average number of bankruptcies. Furthermore, it can also be seen that the average number of bankruptcies reaches its maximum where the average overlap is the highest and the number of securities is the lowest. Given that the relationship between average overlap and average bankruptcy is not intuitive based on the above figure, it is likely that in the vast majority of simulations the failure of a particular bank is not followed by another bank, hence the average bankruptcy cannot capture extreme events, so I examined this phenomenon further. Figure 4 shows the maximum bankruptcy instead of the average bankruptcy as a function of the average overlap and the number of securities.

Based on Figure 4, I get a similar result in terms of number of securities and maximum bankruptcy as before for the average bankruptcy, that is, the fewer securities that can be held in securities portfolios, the higher the average and maximum bankruptcy in the model. At the same time, a much more interesting picture of average overlap and maximum bankruptcy can be seen, meaning that the highest maximum bankruptcy is typically highest if the degree of overlap is moderate. This phenomenon is stronger the more securities the banks can hold. Presumably, with a low average overlap, the risk of contagion is lower, meaning that in the event of a bank failing, the decrease of the market value of the securities

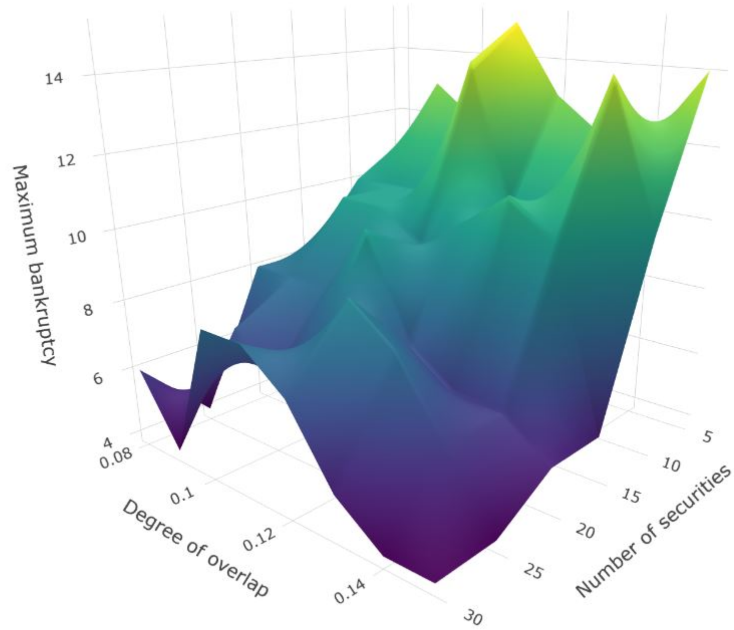

Figure 4. The maximum number of bankruptcies as function of the degree of overlap and the number of securities

held by that bank will have much less impact on solvency capitals of other banks. In case of high average overlap, it is likely that the securities portfolios of the banks overlaps with fewer and fewer other players however, in case of overlapping portfolios the degree of overlap is increasing. As a result, a bank failure means much greater loss for banks with much more similar securities portfolios than before, while other players have less loss due to less overlap. Thus, in case of high number of securities and high average overlaps the bankruptcy of a given bank affects fewer banks, but it is much more severe than in case of average overlaps.

In other words, the larger the number of securities available in the model, the greater the diversification effect and the average and maximum bankruptcies are reduced. Furthermore, from a systemic risk point of view, the mid-level average overlaps are the most dangerous, since contagion is less likely in case of lower average overlaps. However, in case of high overlaps, groups with similar securities portfolios are formed so when a bank fails, the loss increases within the group of the given bank and decreases outside of the group, meaning that fewer banks bear the greater part of the loss, thereby the maximum bankruptcy is lower.

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