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The Implications of Financial Network Architecture on the Stability of a Banking System

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Abstract

The structure of interbank connections affects financial system's resilience to shocks. This thesis determines the implications of network's architecture on stability of a banking system. A framework for structural analysis established in Elliott, Golub and Jackson (2014) is applied to the financial network model from Gourieroux, Heam and Monfort (2012) in order to examine performance of various network structures under two shock scenarios. The model used in the present research is calibrated to match data for a Swedish banking system (at the end of 2016). The results suggest that under an idiosyncratic shock regime, a mid-range level of diversification creates the most prone to default environment as banks are exposed to a significant propagation risk due to a bankruptcy of individual institutions, while a complete network structure shows good resilience. However, under a systemic shock regime, the complete network structure is the most susceptible to contagion. These findings support claims that diversified networks exhibit *robust-yet-fragile* tendencies, as concluded in Gai and Kapadia (2010).

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1 Introduction

As recovering from a financial crisis is a costly and protracted process,[1] financial regulators are continuously attempting to establish a regulatory framework (such as the Basel Accords) that would help to prevent crises. The introduction of Basel I was a milestone as it established a common regulatory framework adapted in virtually all countries with active international financial institutions.[2] Later it was followed by a revised framework referred to as Basel II, that was due to be implemented before the events of 2008. The global financial crisis of 2008 has taken a toll on the majority of the developed economies and highlighted shortcomings of the existing regulatory framework. It has showed that analysing financial entities without considering their interconnectivity can create a false sense of stability as the systemic risk might not be sufficiently accounted for.[3] In Brunnermeier *et al.* (2009) the authors argue that prior to the crisis, the regulatory framework was aiming at preventing failures of individual financial institutions and further macroprudential measures are necessary to address systemic risk. Similar conclusions regarding the necessity of capturing and reducing systemic risk were made in Claessens (2015).[4] Once implemented, the Basel III regulatory framework is set to add the system-wide, systemic risk-based framework to the existing firm-specific approach.[5]

The structure of the financial market plays an important role in shaping of the systemic risk as it affects the potential spread of losses among financial entities in the system.[6] The global financial crisis of 2008 demonstrated that the existing interdependencies may in fact amplify losses in the financial system[7] and made it clear that a proper assessment of the potential risk of contagion is a necessity in a current situation of globalised and highly interconnected financial markets. Consequently, following the global financial crisis more attention was directed towards further understanding and quantification of the impact of network structures on the stability of the financial system.

An important stream of research on the systemic risk consists of analyses which focus on characterising the best network structures given different types of shocks (e.g. idiosyncratic default of an individual institution or a systemic shock to the financial system) and contagion channels, through a process of numerical simulations. In Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) the authors identified the best and the worst network structures under moderate and large shock regimes, by simulating network's responses to shocks in a stylised model. They showed that for a mild shock, the best struc-

[1] E.g. Reinhart and Rogoff (2014) shows that within five to six year after the onset of the financial crisis of 2008, only the United States and Germany managed to reach their 2007-2008 peaks in income per capita out of all countries undergoing systemic crisis.

[2] See Basel Committee on Banking Supervision (2014).

[3] See Acharya *et al.* (2017).

[4] Galati and Moessner (2013) provides an overview of research on the topic of macroprudential policy, while Hanson, Kashyap and Stein (2011) discusses a potential design of macroprudential regulations.

[5] See Hannoun (2010).

[6] See Yellen (2013) and Plosser (2009).

[7] See Gai and Kapadia (2010).

ture is a complete network, whereas in case of a large shock it becomes the most vulnerable structure. Gai and Kapadia (2010) explored how the impact of contagion depends on the type of shock used and how it is influenced by various alterations of the network structure. Their results indicated that diversified financial systems exhibit a *robust-yet-fragile* tendency.[8] A complex approach towards the analysis of implications of various network structures is presented in Elliott, Golub and Jackson (2014). In their research, they introduced concepts of integration (level of dependency on other institutions) and diversification (total number of connections to counterparts) of institutions in a financial system. Application of these two concepts in a model guarantees a considerable level of flexibility with respect to generating and simulations of different network structures. Furthermore, they employed a stylised model of organisations' cross-holdings of shares to examine the impact of diversification and integration on the stability of the system. Their results showed that diversification increased the fragility of the system in its middle ranges, while for a fully diversified network the systemic risk was limited, and that high levels of integration caused a decline in a number of defaults.

The aforementioned analyses are focused mainly on obtaining generalised results regarding the influence of various network architectures on the systemic risk in a financial system. A considerable part of the literature on financial networks and systemic risk concentrates on the empirical testing of various contagion channels and shock propagation mechanisms (such as debt and shareholding exposures, or assets' "fire sales"). Based on the available data, authors attempt to identify exposure channels that serve as shock transmitters and accommodate further spread of losses in financial systems. Upper (2007) provides a comprehensive survey on empirical literature that uses counterfactual simulations calibrated to imitate specific financial networks.

The main purpose of the present research is to bridge the gap between counterfactual, empirical simulations of prespecified financial systems and general analysis on the impact of different network structures on the systemic risk. The previously described framework established in Elliott, Golub and Jackson (2014) offers a flexible and tractable method of generating different network structures. However, the shock propagation mechanism employed in that paper does not include typically used exposure channels such as interbank lending or assets' market prices. Hence, to put that framework for structural analysis to the test, a shock propagation mechanism developed in Gourieroux, Heam and Monfort (2012) is applied in the present research. In their paper, Gourieroux, Heam and Monfort developed a network model that considers debt and share holding channels of contagion,[9] and calibrated it (using data for the French banking system) to conduct a counterfactual simulation of the implications

[8]The term *robust-yet-fragile* describes a financial network that is resilient when facing moderate shocks, however, is highly susceptible to default and serves as a shock transmitter and amplifier under more adverse scenarios. Similar conclusions regarding the *robust-yet-fragile* feature of financial systems were drawn in e.g. Haldane (2009).

[9]The model presented in Gourieroux, Heam and Monfort (2012) is particularly useful for the implementation in the structural analysis framework as it considers a contagion through shareholdings (similarly to Elliott, Golub and Jackson (2014)), allowing for a better comparability of results.

of idiosyncratic shock on the probability of default of institutions in the system. They concluded that interconnectivity can efficiently lower the probability of default due to diversification of risk, however, pairwise defaults occur more frequently compared to the system with no connections.

Combining these two frameworks allows for a full structural analysis of the implications of network architecture on a spread of losses through two shock propagation channels.[10] Therefore, it gives an opportunity to further investigate the influence of the network architecture under complex model settings with two propagation channels as well as to compare the outcomes of a simulation to those obtained in Gai and Kapadia (2010), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Elliott, Golub and Jackson (2014). Finally, to further augment the analysis, the network model of the banking system is tested under two types of shocks: idiosyncratic and systemic.

After establishing the extended framework for the structural analysis, three main research questions arise:

1. Do the results on the impact of diversification and integration on the stability of the system hold under the new, more complex network model?
2. What kind of network structure guarantees the lowest probability of default under idiosyncratic and systemic shocks?
3. Is the *robust-yet-fragile* tendency present in the modelled network?

In order to add the empirical component into the present research and to calibrate the network model, the framework for structural analysis is applied to the case of the Swedish banking system. The aim is to provide answers to the general questions stated above based on the counterfactual simulation as well as to benchmark the actual structure of a banking system in Sweden (obtained from the data as described in section 4 of the thesis) against other network structures generated using the combined framework. That way, it is possible to gain some insights regarding the best and the worst network structure for the Swedish case under different types of shocks and to prove the usefulness of the framework from Elliott, Golub and Jackson (2014) in a more complex model setting. To my knowledge this is the first study that applies the above mentioned framework for structural analysis to a model with debt and shareholding contagion channels in order to derive insights on implications of network architecture on the systemic risk, based on the case of the Swedish financial system.

In the past three decades the Swedish economy suffered from two major financial crises. The fiscal bailout cost of the financial crisis in the 1990s was estimated at around 4% of the Swedish GDP

[10] As stated in Degryse and Nquyen (2007), a financial contagion occurs as a product of materialisation of two risk factors: the risk that at least one institution in the network is affected by a shock (likelihood of bearing losses) and the risk of a further propagation of the shock through the system (potential impact on the network). The focus of this thesis is on the latter.

according to Boyd, Kwak and Bruce (2005). The global financial crisis of 2008 was not as harsh on Sweden as it was on some other developed economies (Swedish economy did not fall into long-lasting recession following the crisis[11]).[12] However, it showed that there are certain shortcomings in the banking supervision as it did not account for the macroeconomic aspects enough.[13]

Over the last few years the Swedish economy grew steadily, while the unemployment continuously decreased. However, the indebtedness of Swedish households went up as the aggregate debt-to-income ratio for Swedish households increased to 180% in 2016 and the credit growth among households and non-financial companies remained high (fostered by low interest rate and peaking house prices in Sweden).[14]

The Swedish banking system is large (its total assets amount to around 400% of Sweden's GDP) and made up of around 120 banks and credit institutions. However, the four major banks account for approximately 85% of the total amount of loans and deposits in Sweden (and about 330% of Sweden's GDP), dominating the market.[15] As concluded in a report prepared by the Swedish Financial Supervisory Authority (Finansinspektionen (2017)), the resilience of the domestic banks is satisfactory as they fulfil capital and liquidity requirements and have higher profitability than their European counterparts. However, a large portion of financing of the Swedish banks comes from foreign markets exposing them to volatility on the international capital markets. Additionally, a substantial share of their assets consists of mortgages and other loans connected to real estate sector, making them vulnerable to any potential turbulences on the housing market. Furthermore, numerous reports from both domestic and international organisations[16] are stressing that the Swedish banking system is significantly concentrated and interconnected, which emphasises the importance of accounting for the systemic risk entirely.

In order to simplify the simulation of the network model, the present research is limited only to the four major institutions: Nordea, SEB, Swedbank and SHB. Among these banks, Nordea is by far the largest measured in total assets, followed by SHB, SEB and Swedbank. Although they all conduct their business internationally (primarily in other Nordic countries and Baltic states, with Nordea having a majority of its operations outside of Sweden), they are all headquartered and incorporated in Sweden, thus making it responsible for their supervision. The data used for the calibration of the model were extracted mainly from the institutions' annual financial statements (for the end of 2016).

The main results of the present research are as follows. Under the idiosyncratic shock regime,

[11]See European Commission (2012).

[12]Österholm (2010) quantifies the impact of the global financial crisis on the Swedish economy, showing its negative effects on the growth of the real GDP in Sweden.

[13]See Öberg (2009).

[14]Similar factors played important role in the development of the financial crisis in 1990s, as described in Englund (2015).

[15]See Finansinspektionen (2017).

[16]See e.g. Swedish Riksbank (2017), European Commission (2016), or International Monetary Fund (2016).

full diversification of the system leads to a lower probability of default compared to the case with no connections, while moderate levels of diversification create the most vulnerable environment. Greater integration of the system causes an increase in the total number of defaults observed. In the case of the systemic shock regime, increase in diversification and integration levels always drives the probability of default up. The model exhibits the *robust-yet-fragile* tendency as once the initial losses are large enough, the network amplifies shocks further, resulting in additional cases of default.

The rest of the thesis is organised in a following way. Section 2 contains a detailed review of existing literature in the field of modelling of shock propagation mechanisms and analyses of financial networks. Section 3 provides details on the network model, framework for structural analysis and the procedure used for the simulation of the responses of the model to idiosyncratic and systemic shocks. Section 4 describes the data used in the simulation and presents the structure of exposure matrices derived from the data. Section 5 contains the results of the numerical simulation. In Section 6 the results and their validity are discussed and further extensions of the research are proposed, while Section 7 concludes the thesis.

2 Literature review

The focus of this section is to review the existing literature on the topic of financial networks, with a particular focus on mechanisms for shock amplification and propagation, in order to provide a solid understanding of the developments in the field of network analyses. Following Upper (2011), we distinguish two main types of contagion channels in the banking system, that is: liability side and asset side channels.

In the present research, we focus solely on channels of contagion connected to the asset side of balance sheet.[17] Asset side contagion channels are further divided into direct and indirect effect channels. The former includes, among others, the two channels of shock propagation used in this thesis, namely interbank lending and equity cross-holdings. The latter includes exposures to assets' prices.

Much of the literature on financial networks was built on the seminal paper by Eisenberg and Noe (2001). In that paper, the authors modelled in-network exposures through interbank lending channel and proved the existence of a unique "clearing payment vector" in the system. Furthermore, they developed a "*fictitious default algorithm*" that computes the clearing vectors and produces information on exposures of the entities in the system to the systemic risk. Another paper with a similar approach to modelling of contagion channel is Allen and Gale (2000), where authors proposed a model analysing

[17] Examples of liability side contagion channels as listed in Upper (2011) are: common pool of liquidity (Diamond and Rajan (2005), Brunnermeier and Pedersen (2009)), information about asset quality (Acharya and Yorulmazer (2008)), or fear of direct effects (Dasgupta (2004), Freixas, Parigi and Rochet (2000)).

impact of devaluation of interbank claims due to a banking crisis, on other financial institutions in the system. In addition, this paper introduced concepts of *complete* and *incomplete* network structures[18] and the authors observed that the former form of the network exhibits greater robustness to financial crises than the latter. Variations of the interbank lending contagion channel are also used as shock propagation mechanisms in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Gai, Haldane and Kapadia (2011).

An example of the implementation of interbank lending and equity cross-holding channels can be found in Gourieroux, Heam and Monfort (2012). Building on the model by Eisenberg and Noe (2001), Gourieroux, Heam and Monfort additionally included a propagation mechanism through the net value of institutions in the network. In their paper, they demonstrated how to set up and solve the model as well as show implications of the French network structure on banks' resilience. The results they obtained indicate that individual defaults of banks are less frequent under the modelled structure, however, pairwise defaults occur more often. The equity cross-holdings shock propagation channel was also used in Elliott, Golub and Jackson (2014), to present the implications of integration and diversification of exposures in the system on its stability.

Cifuentes, Ferrucci and Shin (2005) extended the model of Eisenberg and Noe (2001) to account for the systemic risk arising from the exposure to market prices of assets (an example of an indirect effect of a shock to the financial system). They introduced a framework for analysis of the impact of changes in assets' market price, due to the "fire sales" phenomenon, on the stability of financial institutions and presented the algorithm that solves for the equilibrium price of assets. In their paper, Cifuentes, Ferrucci and Shin showed that mark-to-market rule can induce further losses in the financial system in case a "fire sale" occurs. In Gauthier, Lehar and Souissi (2012), authors employed a similar framework to conduct a counterfactual simulation of the response of the Canadian banking system to initial shocks. Their findings suggested that adding a systemic perspective to banking regulations can significantly enhance the financial stability. Gai and Kapadia (2010) included interbank lending and "fire sales" contagion channels in their model to investigate how different network structures cope with idiosyncratic and aggregate shocks. They showed that a financial network exhibits *robust-yet-fragile* tendency. Similar approach to modelling of indirect shock propagation mechanisms can be also found in Chen, Liu and Yao (2014) and Greenwood, Landier and Thesmar (2015).

3 Model of the banking system

A model of the interbank network is constructed in order to determine the consequences of two types of shocks on the system. After the introduction of a shock to the network, the model finds a fixed point

[18] Allen and Gale established basic concepts of network structure, frequently referred to in many subsequent papers.

solution to the system of equations through an iterative algorithm. The model of the banking network can be used to determine how different structures of the banking network contribute to the overall probability of default of banks in the system. To pin down influences of different network structures, there are two channels of contagion applied in the present research:

1. Equity cross-holding;
2. Interbank lending.[19]

These channels of contagion enable analysis of the stability of various structures of a banking system as it faces different types of shocks. In the present analysis there are two types of shocks considered:

1. Systemic shock, that is a randomised, negative shock to the institution's asset side that has a direct negative impact on all banks;[20]
2. Idiosyncratic shock, that is a randomised shock (may be either negative or positive as it is normally distributed around zero) to the asset side of institutions.[21]

Testing the outcomes of different shocks allows for the assessment of the performance of network structures in normal times (the case of idiosyncratic shock) and during a severe crisis (the example of systemic shock). Thus, the present analysis provides some valuable insights on the resilience of various structures of a banking network.

The network model implemented in this research was developed in the Gourieroux, Heam and Monfort (2012). Their model provides a mechanism that returns net values of all institutions in the system (hence, indicates which banks are in a default) given initial shocks imposed on the network and lays a foundation for the present analysis. However, in Gourieroux, Heam and Monfort (2012) authors applied their model to a single, prespecified network without considering any potential variations of the interbank exposures and their possible consequences. Therefore, to conduct a full structural testing, it is imperative to come up with an appropriate framework that enables running the model on different structures of the banking system.

A solution to that issue are concepts of integration and diversification of networks developed in Elliott, Golub, Jackson (2014). These concepts may serve as means to obtain different forms of the interbank exposures and therefore allow for the analysis of networks varying in the number of direct

[19]In this thesis, different terms are used to refer to these two propagation channels. For the equity cross-holding channel: shareholding, net value exposure. For the interbank lending channel: debt exposure, liability exposure.

[20]Systemic shock may be seen as, for example, a consequence of a crisis on the housing market, when a significant number of mortgage loans are not performing.

[21]Idiosyncratic shock can be interpreted as a result of bad investment choices (when negative) or some additional profit (when positive). In the current framework, under the idiosyncratic shock some banks might experience certain losses, while other could make a profit.

connections (diversification) and in the size of the total exposures (integration). In the present analysis the concepts of integration and diversification are both adapted into the model taken from Gourieroux, Heam, Monfort (2012) in order to test the resilience of a banking system to shocks under different network structures.

The following paragraphs contain a summary of the structure of banks' balance sheets, a detailed description of the model, further characterisation of shocks applied as well as discuss how different network structures are obtained and simulated.

3.1 Balance sheet

For the purpose of the analysis a simplified bank's balance sheet is considered, as described in Gourieroux, Heam and Monfort (2012). There are $N = \{1,...,n\}$ institutions in the system which are interconnected through stocks and debts. Balance sheet of institution i consists of the asset side A_i and the liability side L_i (also referred to as the debt of i). The former comprises of the sum of exposures towards other institutions' liabilities (such as value of securities and bonds issued by bank j and held by institution i as well as loans granted to j by i, denoted as a portion of j's total liabilities to which i is eligible, equal to $\gamma_{i,j}L_j$), sum of exposures to the net values of institutions in the system (through a shareholding, denoted as a portion of net value of bank j owned by institution i, equal to $\pi_{i,j}Y_j$) and exogenous assets Ax_i (other assets such as loans to corporations, household mortgages etc.). The latter has only one element, which is the total liability of institution i, L_i, equal to the contractual value L_i^* when bank is not in default and subject to a potential decrease in case of a bankruptcy. A product of a difference between asset and liability sides is the net value Y_i (also referred to as the equity of i).

Asset	Liability
$\pi_{i,1}Y_1$	L_i
$\vdots$	
$\pi_{i,n}Y_n$	
$\gamma_{i,1}L_1$	
$\vdots$	
$\gamma_{i,n}L_n$	
Ax_i	
A_i	L_i

Table 1: Balance Sheet of institution i.
Source: Gourieroux, Heam and Monfort (2012).

As the focus of the analysis is on the solvency constraints and liquidity aspects are not of interest in the present research, different maturities of debt are not considered in the model. Table 1 shows the balance sheet of institution i as described above.

3.2 Network model

In the present model, before any shocks are introduced to the system and all institutions are solvent, the following accounting relationships hold for all i = 1,...,n:

$$\begin{cases} L_i = L_i^* \\ Y_i = A_i - L_i \\ \quad = \sum_{j=1}^{n}(\pi_{i,j}Y_j) \ + \ \sum_{j=1}^{n}(\gamma_{i,j}L_i^*) \ - \ L_i^* \ + \ Ax_i \end{cases} \tag{3.1}$$

In the present framework all shocks are applied to the system through the exogenous asset component Ax. As a consequence of a shock the initial exogenous asset value Ax^0 changes into Ax.[22] After the introduction of a shock, the system is no longer in its initial state. A decrease in the value of exogenous assets inevitably leads to a fall of the net values of institutions affected by the shock. Hence, it is possible that a given institution might not be able to cover its contractual debt and its net value might decrease to zero. In that situation, a default of a bank occurs. The net values of institutions and the values of their total debts after the application of a shock are solutions of the system:

$$\begin{cases} Y_i = max\{A_i - L_i, 0\} \\ L_i = min\{A_i, L_i^*\} \end{cases} \tag{3.2}$$

The first equation in the system (3.2) allows for the potential default (in case of $A_i \leq L_i$) and returns the resulting net value of institution i. It also considers a limited liability of shareholders (up to the value of Y_i in the worst case scenario). The second equation indicates the amount of debt (equal to A_i/L_i^*) that may be recovered by debtholders in case of a bankruptcy of institution i. System (3.2) implies the seniority of debtholders with respect to shareholders, as the net value is the first to be wiped out in case of a default.

Combining systems (3.1) and (3.2) produces:

$$\begin{cases} Y_i = max\{\sum_{j=1}^{n}(\pi_{i,j}Y_j) + \sum_{j=1}^{n}(\gamma_{i,j}L_i^*) + Ax_i - L_i, 0\} \\ L_i = min\{\sum_{j=1}^{n}(\pi_{i,j}Y_j) \ + \ \sum_{j=1}^{n}(\gamma_{i,j}L_i^*) \ + \ Ax_i, L_i^*\} \end{cases} \tag{3.3}$$

The solution of the system (3.3) are two consistent sets of values $Y = (Y_1, ..., Y_n)$' and $L = (L_1, ..., L_n)$'. Furthermore, the resulting values of Y and L provide information regarding the defaulted institutions

[22]Shocks are described in details in section 3.6.

($Y_i = 0$, $L_i < L_i^*$), the institutions which remained solvent ($Y_i > 0, L_i = L_i^*$) and the net and liability values of all institutions in the system.

In order to analyse the model described by the system (3.3), it is necessary to ensure that a solution to this system exists and is unique. After Gourieroux, Heam and Monfort (2012), let us formulate the following proposition:

Proposition 1. If $\pi_{i,j} \geq 0, \gamma_{i,j} \geq 0, \forall_{i,j}, \sum_{i=1}^{n} \pi_{i.j} < 1, \forall_{i,j}, \sum_{i=1}^{n} \gamma_{i.j} < 1, \forall_j$, the solution of the system (3.3) (equilibrium values of Y and L) exists and is unique for any choice of non-negative exogenous assets Ax_i and total liabilities L_i^* (for $i = 1, ..., n$).

The proof of the Proposition 1 is found in Gourieroux, Heam and Monfort (2012).[23] The solution of the system (3.3) provides the equilibrium values of institutions' net values Y and liabilities L, depending on the specification of the financial system $S = \{\Pi, \Gamma, L^*, Ax\}$, where $\Pi = (\pi_{i,j})$ and $\Gamma = (\gamma_{i,j})$ are the (n, n) equity and debt exposure matrices, respectively.

3.3 Default analysis

Once shocks are introduced to the system and the respective outcomes are computed according to the equations in the system (3.3), there are three different states in the equilibrium that an institution can reach:

1. Survival (S);
2. Fundamental Default (FD);
3. Contagious Default (CD).

In the survival state, a bank does not default as its reserves are sufficient to cover any potential losses from the initial shock as well as those arising from the equity cross-holding and debt exposures. As it was mentioned before, a bank faces bankruptcy once its net value drops to zero ($Y_i \leq 0$ due to the losses caused by shock and propagation effect). The survival state is defined by the following inequality:

$$\sum_{j=1}^{n}(\pi_{i,j}Y_j) + \sum_{j=1}^{n}(\gamma_{i,j}L_j) + Ax_i > L_i \tag{3.4}$$

As long as the condition (3.4) is satisfied, institution i will remain solvent, its net value will take a positive value ($Y_i > 0$) and its actual liabilities will be equal to the nominal ones ($L_i = L_i^*$).

The fundamental default state occurs when a net value of an institution drops to zero due to a

[23] For proof see Appendix 2 in Gourieroux, Heam and Monfort (2012).

direct effect of a shock. Let us use the following notation to define a direct effect of a shock:

$$Ax_i^0 - Ax_i = \Delta A_i \tag{3.5}$$

Therefore, the necessary condition for the fundamental default state to occur is following:

$$\Delta A_i \geq Y_i \tag{3.6}$$

Finally, the contagious default state occurs once institution i survives a direct impact of a shock but defaults due to a contagion effect, through one of the exposure channels. The necessary conditions for that state to occur are following:

$$\begin{cases} \Delta A_i < Y_i \\ \Delta A_i + \sum_{j=1}^{n}(\pi_{i,j}Y_j^0) - \sum_{j=1}^{n}(\pi_{i,j}Y_j) + \sum_{j=1}^{n}(\gamma_{i,j}L_j^*) - \sum_{j=1}^{n}(\gamma_{i,j}L_j) \geq Y_i \end{cases} \tag{3.7}$$

As the framework for the analysis of the network model is set, let us discuss the measures of outcome that are employed to compare the results. The main measure is the probability of default of each institution. In each scenario,[24] a bank can either survive a shock and a consequent propagation effect or default. Dividing the number of defaults for a given bank across all scenarios by the total number of scenarios provides a simple measure of the probability of default. In case of n different scenarios a simple way to express the method of calculating a probability of default is:

$$PD_i = \sum_{i=1}^{n}(\mathbb{1}_{Y_i \leq 0})/n \tag{3.8}$$

where $\mathbb{1}_A$ denotes an indicator function of A. That measure shows individual, unconditional probabilities of default of each institution in the network.

Apart from individual probabilities of default, probabilities of joint default (default of institution i due to a contagion effect conditional on the default of institution j) are also of interest. By computing those, one can assess the systemic importance of each bank in the system, that is determine which institution can cause the most damage (or increase the probability of default of other institutions the most) in case of its default. As the focus of the thesis is to analyse the network structures, it is important to understand which institutions are prone to default and may pull other banks down with them.

Additionally, the model allows for calculations of the total net value of non-defaulted banks and the

[24]Scenarios refer to a series of random draws of shock values that are being used to compute probabilities of default in each setting of the model. More information on scenarios is provided in the Section 3.7.

total value of debts of all institutions after including all negative effects. Those values might be used as a mean to compare different structures of banking network, where higher values of debt and net values indicate that losses experienced in a given system are lower. The total net value of non-defaulted institutions is given by:

$$\hat{Y} = \sum_{i=1}^{n} Y_i, \tag{3.9}$$

which is a measure essential for shareholders. The total value of debts of all institutions is computed from the following equation:

$$\hat{L} = \sum_{i=1}^{n} L_i, \tag{3.10}$$

which is a measure important for bondholders. By examining the outcomes for these two measures, it is possible to draw conclusions regarding the overall effects of shocks. They can be used as measures supplementary to probabilities of default, as they inform about the "depth" of losses.

3.4 Example of contagion

Illustrating how the network model and shock propagation channels work might be helpful to understand the mechanics behind it. Let us assume that there is a simple system with only two institutions (bank 1 and bank 2). The balance sheets of institutions in this example are following:

- Bank 1: $\pi_{1,1} = \pi_{1,2} = \gamma_{1,1} = 0$, $\gamma_{1,2} = 20\%$, $L_1^* = 150$ and $Ax_1 = 200$,
- Bank 2: $\pi_{2,1} = 50\%$, $\pi_{2,2} = \gamma_{2,1} = \gamma_{2,2} = 0$, $L_2^* = 150$ and $Ax_2 = 130$.

Net values of both institutions can be obtained from the second equation in (3.1) and are equal to 80 and 20 respectively.[25] Now, let us assume that due to some adverse event, exogenous asset components (Ax_1 and Ax_2) of both institutions decrease by 10%. The effects of the aforementioned event can be divided into two parts: direct and contagion. The direct effect of the decrease of exogenous asset components is a decline in net values (to 60 and 7 respectively[26]).

The contagion effect applies differently to both institutions. Bank 1 is exposed only to the debt of its counterpart (only affected when Bank 2 defaults on its liabilities), while Bank 2 owns half of the Bank 1's equity (affected whenever the net value of Bank 1 changes). Due to the decrease of the net value of Bank 1 (from 80 to 60), the asset side of the Bank 2's balance sheet is affected. Its net value falls below zero (due to the contagion effect, the asset side of Bank 2 declines in value by 10) and Bank 2 is in the default state. At this point Bank 2 is not able to pay back all its debts ($L_2 < L_2^*$) and as

[25]For Bank 1: 200 + 20% * 150 - 150 = 80, Bank 2: 130 + 50% * 80 - 150 = 20.
[26]For Bank 1: 200 * 90% + 20% * 150 - 150 = 60, Bank 2: 130 * 90% + 50% * 80 - 150 = 7.

a consequence Bank 1 does not recover the full amount owed by Bank 2. Present value of the Bank 2's liabilities can be computed from the second equation in (3.3). Bank 1's loss due to the interbank exposure is equal to 0.6 as the recovery rate is equal to A_2/L_2^*.[27] Bank 1's net value declines to 59.4 and it is in the survival state.

3.5 Network structure

A pivotal element of the present analysis is the stability of a banking system subject to different structures of the interbank network. In order to bring the structural element into the analysis, concepts of network diversification and integration developed in Elliott, Golub and Jackson (2014) are introduced.

3.5.1 Integration and diversification

In Elliott, Golub and Jackson (2014) the authors were investigating the impact of different levels of integration and diversification on the stability of a financial system. These concepts allow for the testing of a broader number of different network structures and comparison among them, hence their usefulness for the analysis of the resilience of a banking system.

At first, it is necessary to understand the idea behind integration and diversification before diving into the mathematical representation and implementation of those. The intuition behind those concepts is as follows. Integration refers to the size of the total in-network exposure of the analysed institutions. The increase of integration of institution i means that its total in-network exposure increases, whereas the decrease of integration has the opposite effect. Diversification defines a number of banks to which the institution i is connected. Higher diversification means that the same amount of in-network exposure of bank i is divided among more institutions. On a contrary, a decrease in diversification of a bank indicates that its exposure is divided among less counterparts. By setting different levels of both these measures, one can obtain a number of various network structures with diverse quantity of connections and sizes of in-network exposures.

A more formal representation is as follows. As previously, there are n institutions that make up a set $N = \{1,...,n\}$. In the present analysis there are two sources of the interconnectedness: debt and equity exposures. Throughout the thesis, it is assumed that both contagion channels have the same structural features (it excludes cases when e.g. diversification of debt channel increases while diversification of equity channel decreases). Therefore, let us assume for a notational purpose that there is one combined source of exposure, denoted by E. That produces a following equality:

$$E_{i,j} = \gamma_{i,j} L_j^* + \pi_{i,j} Y_j, \tag{3.11}$$

[27] As $A_2 = 147$, $L_2^* = 150$ and the value of interbank claim of Bank 1 was equal to 30. Thus it recovers 29.4.

where $E_{i,j}$ denotes the total exposure from both sources of institution i to the institution j. Additionally, it follows that $E_i = \sum_{j=1}^{n}(E_{i,j})$ (denoting the total exposure of institution i to all banks in the system) and $E = \sum_{i=1}^{n}(E_i)$ (denoting the total in-network exposure of all institutions). After Elliott, Golub and Jackson (2014), let us formally define integration and diversification of the network.

Following the notation introduced above, an increase of integration of institutions in the system (assuming that diversification remains unchanged) would lead to a higher exposure through at least some of the existing connection. The system E' is *more integrated* than system E if and only if:

1. $E'_{i,j} \geq E_{i,j}$ for all i, j, and
2. $E'_{i,j} > E_{i,j}$ for some i, j.

Thus, integration captures the size of institutions' total in-network exposure.

The banking system becomes *more diversified* when the total in-network exposure of a given institution is divided among more counterparts. Formally, the system E' is *more diversified* than system E if and only if:

1. $E'_{i,j} \leq E_{i,j}$ for all i, j such that $E_{i,j} > 0$, with some ordered pair (i, j) for which the inequality is strict, and
2. $E'_{i,j} > E_{i,j} = 0$ for some (i, j).

Hence, diversification represents the spread of institutions' in-network exposures.

3.5.2 Analysis of structures

For the purpose of the present analysis, various levels of both diversification and integration are used. The base case structure of the model is the one obtained from the real data[28] and it is tested against other potential network structures obtained through a process of simulation.

Analysis of different levels of diversification requires a tractable and flexible method of generating networks. A random graph model offers an ability to impose some structure on the distribution of potential interbank lending and equity exposure matrices. Through a simulation process, the random graph model generates networks with desired characteristic that allow for inferences with high probability.[29]

Let us define fixed matrices $\mathbf{G}$ and $\mathbf{H}$ with all entries equal to either 0 or 1. They are referred to as *network matrices* of unweighted, directed graphs. Matrices $\mathbf{G}$ and $\mathbf{H}$ represent the network of interbank lending and equity exposures respectively. When institution i has a claim on institution j's debt, then $G_{i,j} = 1$. Similarly, $H_{i,j} = 1$ means that institution i owns some shares of institution j. To obtain the *exposure matrices*, it is necessary to determine the amount of the exposure for which each

[28] The real data, original network is complete in terms of debt exposures and close to complete in terms of equity exposures, where complete network refers to the structure defined in Allen, Gale (2000). The real data network is further described in section 4.

[29] See Elliott, Golub, Jackson (2014)

direct link accounts for. Institution i is exposed to a portion of institution j's liabilities equal to:

$$\gamma_{i,j} = (\frac{ED_i * G_{i,j} * SA_j}{\sum_{j=1}^{n}(G_{i,j} * SA_j)})/L_j, \tag{3.12}$$

where ED_i denotes the total exposure of institution i to liabilities of all other institutions in the system, $G_{i,j}$ is a network matrix representing interbank lending network as defined earlier, SA_j indicates the total assets of institution j in Sweden and L_j is the total value of institution j's liabilities. Therefore, the exposure of institution i is divided among $dd_i = \sum_{j=1}^{n} G_{i,j}$ (where dd_i is the degree of connectivity of institution i in terms of debt exposures) other institutions to which i is connected proportionally to the size of each institution's assets in Sweden.[30]

The same procedure applies to the equity exposures. Institution i is exposed to a portion of institution j's equity equal to:

$$\pi_{i,j} = (\frac{EE_i * H_{i,j} * SA_j}{\sum_{j=1}^{n}(H_{i,j} * SA_j)})/Y_j, \tag{3.13}$$

where EE_i denotes the total exposure to equity of institution i divided among $de_i = \sum_{j=1}^{n} H_{i,j}$ institutions (proportionally to the size of each institution's assets in Sweden), $H_{i,j}$ is a network matrix describing the network of equity exposures and Y_j is the total net value of institution j.

Hence, in order to set different levels of diversification it is necessary to change the degrees of connectivity of institution i (dd_i and de_i), where a higher degree is characteristic for more connected networks. Testing various sizes of integration in the system requires some alterations of the total exposures of institution i (ED_i and EE_i), where an increase in values of those measures increases the integration of institution i. By adjusting those four variables, it is possible to obtain a broad number of different structures of the network and compare their performance (in terms of defaults, total assets and total losses) when shocks are applied.

3.5.3 Disconnected institutions

In the framework described in the previous section there is an important issue that arises in certain situations. When an institution has no direct links to any other institution in the system its exposure must be channeled differently.

A good way of doing that is fixing values of a given exposure to zero and increasing the value of exogenous assets by the respective amount (one could treat it as cashing shares or bonds held and "reinvesting" them,[31] ultimately turning exposure value into additional exogenous assets). In this way,

[30] In Elliott, Golub and Jackson (2014) authors assumed that exposure are divided evenly among all organisations, here I allow for more heterogeneity among exposure values.

[31] Intuitively, if an institution decides to cancel its investment in e.g. bonds of other banks in the system, it will likely

it is possible to "switch off" a channel of contagion without meddling with the aggregate values on the balance sheet. Considering that a magnitude of shocks depends directly on the size of exogenous assets (greater value of exogenous assets translates to a greater change of the net value as a consequence of shock), disconnecting an institution leads to na increase of sensitivity of that particular institution to the initial shock.[32]

To analyse institution i that has no outgoing links in the network, one could set $\sum_{j=1}^{n}\gamma_{i,j}=0$ and $\sum_{j=1}^{n}\pi_{i,j}=0$ (in case when $dd_i=de_i=0$, if one of the degree measures was different from 0, a sum of a row in the respective matrix of exposures should be different from 0). If the initial system is described as $S^0=\{\Pi,\Gamma,L^*,Ax^0\}$, cashing institution i's stocks and bonds of other banks produces two systems $\widetilde{S_i^0}=\{0,0,L_i^*,\widetilde{Ax_i^0}\}$ and $\widetilde{S_j^0}=\{\Pi,\Gamma,L_j^*,Ax_j^0\}$, where $\widetilde{Ax_i^0}=\Pi_i*Y^0+\Gamma_i*L^*+Ax_i^0=Y_i^0+L_i^*$, for all $j\neq i$. The equilibrium values are then calculated for the new situation. The same procedure could be applied should there be no connections in the network (the case of completely disconnected network). In that case, the only effects of shocks would be direct.

3.6 Shocks

As it was previously mentioned there are two types of shocks considered in the present analysis, both aimed to provide valuable insights on the consequences of different network structures on the stability of a banking system. Firstly, let us focus on the idiosyncratic shock followed by the description of the systemic shock.

3.6.1 Idiosyncratic shock

The first type of shock used in the analysis is an idiosyncratic shock to the system. It is modelled as a randomised change of value of the exogenous assets of each individual institution from Ax^0 to Ax. Shocks are introduced to the system similarly to the approach used in Gourieroux, Heam and Monfort (2012). Shocks to each institution in the system take randomly drawn values, normally distributed around 0. Shocks are derived according to the following formula:

$$log(Ax_i)=log(Ax_i^0)+u_i,\ i=1,...,n, \tag{3.14}$$

where u_i is a stochastic value with $E(u)=0.00, V(u)=\sigma^2, \sigma=0.025$. The value of the standard deviation was calibrated to ensure that there is a certain amount of defaults in the system, so that a comparison among structures is possible. As the Swedish banks are in general resilient, standard

utilise that unused resources in some other way, e.g. grant mortgage loans to households.

[32]The same rule applies to the integration analysis. Once an integration is decreased, a part of the exposure amount is turned into exogenous assets, eventually making any shock more severe (similarly, increasing integration leads to a decrease in a magnitude of shocks).

deviation of the shock had to be large enough for some institutions to default in at least some of the cases.

The idiosyncratic shock assigns randomly either a loss or a profit to each institution in the system. Hence, as a results of the shock the value of exogenous assets of a given bank may either increase or decrease with equal probabilities. Any potential losses and gains can be interpret as effects of some underlying characteristics of each institution.[33]

The idiosyncratic shock as described here bears some resemblance to the shocks introduced in Gai and Kapadia (2010) and Elliott, Golub and Jackson (2014). Idiosyncratic shock can also be seen as a variation of a small shock regime used in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015).

Based on the network model used in the present research one may anticipate that more diversified banking system lowers the probability of defaults, as any potential losses to a given institution are divided among higher number of counterparts. Hence, in a more connected network, even in case of a single default, any further cascades of bankruptcies and joint defaults should be rare. The total losses resulting from the occurrence of a negative shock are expected to be smaller in a network with more links compared to a less diversified system.

3.6.2 Systemic shock

The second type of shock considered is a systemic shock. It has a system wide negative impact on the value of institutions' exogenous assets components. It can be perceived as a financial crisis that causes losses of all banks in the system. One example of such situation could be an outbreak of a crisis on the housing market, leading to severe losses on mortgage loans. The magnitude of losses would depend on the size of individual banks' exposures to that specific type of loans as well as on institution specific characteristics (such as required collateral, risk aversion and etc.).

The systemic shock is introduced in the model in the same way as the idiosyncratic shock described above, however, the values are normally distributed around a negative value instead of 0. Both the mean and the standard deviation of shocks are calibrated based on historic data. Figure 1 shows a percentage of non-performing loans to gross loans for Sweden between 1998 and 2014, and standard deviation from that time series was used for the calibration of volatility of the systemic shock.[34] The mean for the systemic shock was chosen based on the information obtained from Englund (2015), where the author estimated that in the peak of Swedish banking crisis credit losses were reaching up to 7.5% of total loans. Therefore, setting a mean value of losses due to a shock to approximately 4% seems plausible, considering that we discuss a case of an adverse scenario. The shock causes a decrease

[33] E.g. riskiness of a business model.

[34] Although it is not a perfect proxy for the deviation of potential shocks, it gives some realistic approximation of a variation in loan losses, which constitute a substantial part of exogenous assets component for the Swedish banks.

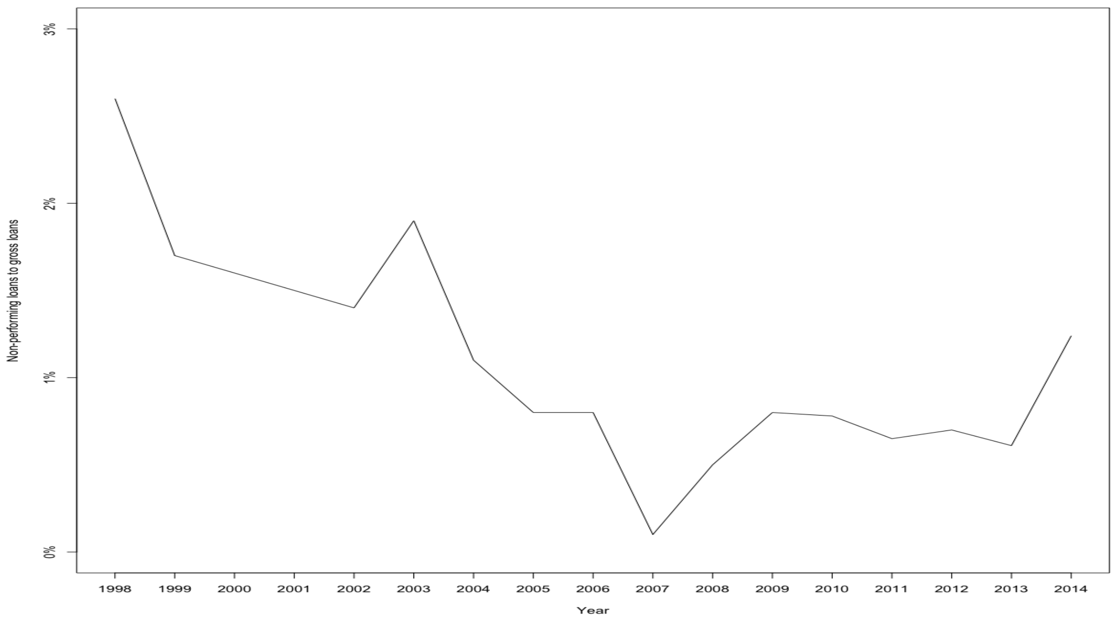

Figure 1: Bank non-performing loans to gross loans in Sweden.
Source: The Federal Reserve Bank of St. Louis.

of the value of exogenous assets component according to the following formula:

$$log(Ax_i) = log(Ax_i^0) + u_i,\ i = 1, ..., n, \tag{3.15}$$

where u_i is a stochastic value with $E(u) = -0.04, V(u) = \sigma^2, \sigma = 0.0062$. This type of shock can be compared to the one introduced in Gauthier, Lehar and Souissi (2012)[35] as well as to a large shock regime in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015).

Intuitively, as all institutions are subject to certain losses under systemic shock scenario the more connections are established in the network, the less resilient should be the banking system. Many fundamental defaults may occur in the system and a large number of links can cause a further propagation of losses. It is likely that joint defaults take place much more frequently than under the idiosyncratic shock. Lastly, as the number of defaults in the system goes up, the total loss in terms of the aggregate net value of all institutions in the network would be expected to be significantly larger than under the other shock.

[35]Though in their paper authors obtained credit losses through a very detailed modelling procedure, whereas in the present research the focus is on the propagation mechanisms rather than on modelling of shocks.

3.7 Simulation

Once the framework for the network analysis is established, it is time to describe the simulation procedure used to obtain the results on the stability of the Swedish banking system under different network structures.

To find a solution to the system (3.3), a variant of the *fictitious default algorithm* first described in Eisenberg and Noe (2001) is used. After the introduction of a shock into the system, institutions' net values are computed. If a significant alteration of the net values is reported, the algorithm starts another iteration and the effects of changes in the net values and of any potential defaults on liabilities affect the system. The algorithm iterates until there are no new defaults reported and the difference between net value of each institution between two consecutive iterations is negligible.

This simulation is conducted for both types of shocks analysed in the present research. Shocks are randomised and there are 2500 sets drawn for each shock scenario according to equations (3.14) and (3.15).

In order to obtain different levels of diversification of the network structure, the random graph model is used. In the variant implemented in the present thesis,[36] a network is generated by connecting nodes (in this case nodes stand for institutions) randomly according to a prespecified rule. The mechanism generating network matrices **G** and **H** is described by function *G(n,p)*, where n denotes number of nodes and p is an independent probability of establishing each connection. By adjusting values of the probability of generating a connection between two nodes, one can achieve a desired level of diversification of the network. For a given level of the probability, the *average directed degree of connectivity* is the expected number of outgoing links from each institution, denoted by d. In the course of the simulation, probability p is set to obtain values of *average directed degree of connectivity* ranging from 0 (disconnected network) to 4 (complete network), according to the following rules: *d/(n-1)* for matrix **G** and d/n for matrix **H**.[37] For each of the levels, there are 2500 various structures drawn that satisfy these *average directed degree of connectivity*.[38]

Finally, to bring the integration analysis to the picture all the previously drawn structures are considered using different sizes of total exposures of institutions in the system. The original sizes of integration is the one obtained from the data (ED_i and EE_i) and to test different levels of integration, exposure variables are multiplied by the following set of factors: $\{0.5, 0.8, 0.9, 1, 1.1, 1.2, 1.5, 2, 2.5\}$.

The fictitious default algorithm computes the resulting default probabilities as well as the total net

[36] One of the alternatives of the model described in Erdös and Rényi (1959) and Erdös and Rényi (1960).

[37] Different rules apply due to the fact that in matrix **G** self exposures are not permitted, while in matrix **H** it is allowed for an institution to keep its own shares. Therefore, there is a different quantity of possible links to be generated for both matrices and hence they require different rules.

[38] Random draw of large number of structures that meet the required degree distribution enables interferences based on the results of the simulation.

value and total losses for each scenario described above.

4 Data

The analysis of the banking sector requires a large portion of data, typically difficult to gather. A good source of data regarding banks' balance sheets are regularly filled financial statements, which provide useful information on financial institutions' activities.

For the purpose of the present research the public financial statements of the biggest banks in Sweden were analysed to allow for a reconstruction of the simplified balance sheets of these institutions. The gathered data consists of aggregate values for different types of exposures within Sweden. Information on maturities of banks' liabilities were omitted as that is beyond the scope of the present analysis.

As the Swedish banking sector is very concentrated with four major banks accounting for around 85% of total assets,[39] the focus of the analysis is only on the biggest institutions: SEB, Swedbank, Nordea and Handelsbanken.[40] The data were gathered for the end of 2016 from the annual financial statements published by each of the four banks.

4.1 Exposure matrices

The information gathered from banks' financial statements was used to construct exposure matrices Γ and Π essential to the model. These two matrices describe the original structure of the Swedish banking system. The original structure is being used as a benchmark in the analysis of the stability of different network architectures.

4.1.1 Equity cross-holding exposure matrix

Exposure matrix Π was obtained directly from the financial statement (as the largest shareholders of a given bank are named).[41] Each institution can have links to every other bank as well as to itself (an institution can hold its own shares). The equity cross-holding exposure matrix obtained explicitly

[39]See Sveriges Riksbank (2017).

[40]It is assumed that there are only four banks in Sweden and they account for 100% of the total assets in Sweden. Other institutions are omitted due to lower significance.

[41]Only major links were considered as information on the financial statement typically includes only the biggest shareholders. Therefore, the size of exposures is likely to be understated.

from the data is following:

$$\Pi = \begin{bmatrix} 0.0080 & 0.0100 & 0.0000 & 0.0000 \\ 0.0110 & 0.0290 & 0.0190 & 0.0062 \\ 0.0240 & 0.0420 & 0.0630 & 0.0316 \\ 0.0110 & 0.0100 & 0.0000 & 0.0134 \end{bmatrix},$$

where each entry informs about a fraction of an institution's equity (or net value) held by others.

4.1.2 Interbank lending exposure matrix

It is not as straightforward to come up with exposure matrix Γ. In this case, there are no precise data publicly available. In financial statements one can only find aggregated data for each bank's exposures and based on that generate desired matrix of exposures.

Commonly used method of establishing unknown interbank exposures are information criterion methods such as entropy maximisation algorithm, described in Blien, Graef (1998).[42] Another approach to obtain the exposure matrices is to employ a mechanism that assigns values to each link in the network according to a prespecified rule. In Gauthier, Lehar and Souissi (2012) it was showed that assigning interbank claims according to the size of total assets of each bank gives similar results to the entropy maximisation algorithm. Hence, to simplify the simulation process a prespecified rule is applied in this thesis. The mechanism implemented in the present research assigns values to each link in the network according to the respective sizes of the assets in Sweden of each interconnected institution.

Another question to be resolved is the structure of the original interbank lending exposure matrix. As it was pointed out, there are no precise data regarding amount of exposure as well as counterparts involved. In numerous reports[43] it is stated that the main vulnerabilities of the Swedish banking system are its high concentration and interconnectedness. Based on that knowledge, an assumption is made that each bank is exposed (have some debt claims such as bonds, securities or loans granted) to every other institution in the network.[44]

[42]Method used for example in Gourieroux, Heam and Monfort (2012) and Gauthier, Lehar and Souissi (2012).
[43]See e.g. Sveriges Riksbank (2017), International Monetary Fund (2016), European Commission (2016), Finansinspektionen (2017).
[44]The same assumption was made in Gourieroux, Heam and Monfort (2012).

Considering these assumptions, the following interbank lending exposure matrix, Γ, is obtained:

$$\Gamma = \begin{bmatrix} 0.0000 & 0.0149 & 0.0151 & 0.0109 \\ 0.0033 & 0.0000 & 0.0100 & 0.0072 \\ 0.0012 & 0.0037 & 0.0000 & 0.0027 \\ 0.0020 & 0.0059 & 0.0060 & 0.0000 \end{bmatrix},$$

where each entry refers to a portion of banks' total liabilities that other institutions have claims on. The values on the main diagonal show the size of the self-exposure. As the data were gathered for the consolidated banking groups, there is no self-lending available.

5 Results

As the network model and the framework for the structural analysis are set and the data required for the simulation are described, it is time to move on to the results of the numerical simulation. The aim of the simulation is to increase the understanding regarding the actual interactions between structural factors and to determine their influence on the stability of individual banks and of the system as a whole. The outcomes of the simulation show the impact of idiosyncratic and systemic shocks on the banking network across a number of generated structures. The results are given in terms of probabilities of default of institutions in the system (as defined previously) and values of variables such as the net values and the actual liabilities of banks in the network. However, as the results of the numerical simulation depend heavily on its calibration, it is important to focus on the tendencies and interactions obtained from the simulation, rather than resulting values in absolute terms.

At first, the results of the simulation after the introduction of the idiosyncratic shock are presented, followed by the description of responses of the modelled network to the systemic shock. In both cases the original network structure obtained from the data (as described in section 4) is tested against a version without any connections, followed by an in-depth structural analysis of the performance of networks with various integration and diversification levels.

5.1 Idiosyncratic shock

The case of an idiosyncratic shock is based on the example analysed in Gourieroux, Heam and Monfort (2012), where random institution specific shocks with a mean equal to 0 and a given standard deviation were applied to the network model. Tested scenarios may provide some insights regarding the potential advantages of a diversified network structure due to a certain level of positive feedback effect from other institutions (through the net value exposure channel) and diversification of losses among banks in the financial system.

5.1.1 Original and disconnected networks

The first step on a way to understand the implications of different network structures on the overall stability of the banking system is to pin down the exact consequences of the original network structure[45] compared to the case of a disconnected network, where there are no links among institutions.

Table 2 contains probabilities of default (from this moment on referred to as PD) of institutions in the system, subject to idiosyncratic shock. PD values where obtained by dividing number of occurrences of defaults across all the simulated shock scenarios. The outcomes were computed for both the original and the disconnected networks and the resulting total PD were further divided based on their origins (fundamental or contagious[46]).

Institution Names	**Original network**			**Disconnected network**			**Difference in total PD**
	Fund.	Cont.	Tot.	Fund.	Cont.	Tot.	
Nordea	1.12	0.08	1.20	1.32	-	1.32	-0.12 pp
SEB	1.52	0.24	1.76	1.72	-	1.72	0.04 pp
Swedbank	0.40	0.44	0.84	0.52	-	0.52	0.32 pp
Handelsbanken	1.40	0.04	1.44	1.48	-	1.48	-0.04 pp
Average	1.11	0.20	1.31	1.26	-	1.26	0.05 pp

Table 2: PD of banks in simulation, divided into fundamental, contagion and total PD. PD showed as percentages, difference in PD in percentage points.

As it can be seen, for Nordea and Handelsbanken the obtained PD are lower for the original network compared to the disconnected case, whereas other institutions were defaulting more frequently under the original network. On average a default of an institution is more likely to occur in the original network rather than in a case when banks are disconnected.

Decreased PD for two banks in the original case compared to the disconnected network is likely to be a result of different severities of fundamental shocks between these two networks. Due to the underlying assumption regarding the disconnected institutions, fundamental defaults take place more frequently in the disconnected network case.[47] As contagious defaults are rare for Nordea and Handelsbanken, their overall PD are lower for the original network compared to the disconnected one.

In the original network under the idiosyncratic shock there are no occurrences of joint defaults. It indicates that although the PD through the contagion channels are higher than 0, bankruptcies usually

[45] Network structure introduced in section 4.1.

[46] As defined in section 3.3.

[47] In section 3.6.3 it was assumed, that whenever an institution has no outgoing connections of some sort, it reinvest a respective "unused" amount and increases its exogenous assets Ax that are subject to shock. Hence, once an institution becomes disconnected its exposure towards other institutions is equal to zero, however, its direct exposure to a shock increases.

occur for a single bank at a time, without tipping other institutions over. This result is consistent with the intuition explained in section 3.6.1. As the original network is almost fully connected, a single case of a default due to the idiosyncratic shock does not cause an outburst of a wider banking crisis and losses are contained.

Institution Names	**Original network**		**Disconnected network**		**Difference in values**	
	NV	LV	NV	LV	NV	LV
Nordea	313.56	5570.82	313.63	5570.78	-0.07	0.05
SEB	141.61	2479.28	141.54	2479.28	0.07	-0.01
Swedbank	129.50	2024.38	129.27	2024.41	0.23	-0.03
Handelsbanken	138.92	2490.90	138.88	2490.89	0.03	0.01
Total	723.59	12565.38	723.33	12565.37	0.26	0.01

Table 3: Average net values (NV) and liability values (LV) of institutions across all shocks and their differences between networks, in billions of SEK.

Finally, by examining net and liability values of institutions presented in table 3, one can learn more about the influence of shocks on banks under different network structures. Although the differences in average amounts of net and liability values between networks are not substantial, it is worth mentioning that despite higher total PD for the original network, net values obtained from the simulation on that structure are greater compared to the disconnected network. It indicates that despite being more prone to defaults, the average loss for the original system was smaller compared to the disconnected network. It may be a result of a combination of positive in-network feedback through the net value exposure channel,[48] greater direct effect of shocks on the disconnected network (due to its additional portion of exposure to the initial shock compared to a diversified system) and diversification of losses inflicted by negative shocks.

5.1.2 Structural analysis

Once the differences between the original and the disconnected networks are highlighted, it is time to bring up full structural analysis. As already explained in the simulation section, different network structures were obtained through a process of solving the model for a range of values for diversification and integration. The results are as follows.

Figure 2 shows how the average PD of institutions in the system differs for various levels of integration and diversification. For the disconnected system (diversification equal to 0) the average PD is equal to 1.26%. Once some connections start to form (diversification greater than 0), the average PD of a bank in the network goes up. After exceeding certain threshold level of diversification, the

[48] That effect may occur when some institutions are profiting as a result of a positive shock and the increase of their net value positively affects other banks connected to them through the equity exposure channel.

average PD starts to decline to 1.24%.

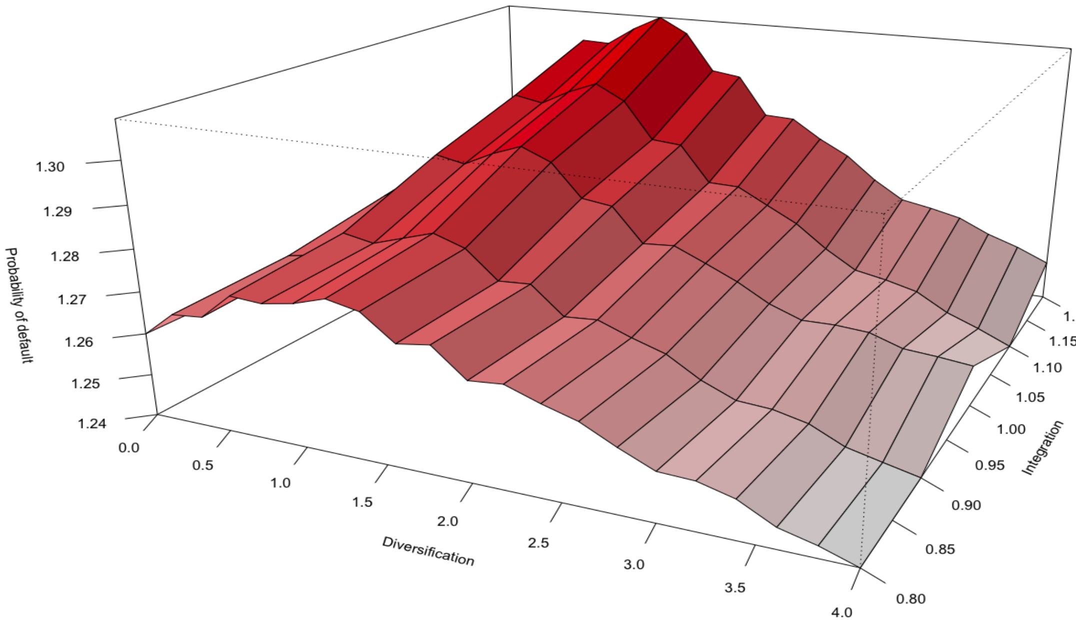

Figure 2: Average PD (in percentages) in the system for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network.

The results of the simulation showed that when the number of outgoing links from each institution is relatively small, the number of defaults is significantly higher compared to a well-diversified network. It is due to the fact, that for the middle levels of diversification, the network is typically connected,[49] yet single exposures are still large enough to affect connected banks.

When the level of diversification surpasses the critical point, the average PD of banks in the system decreases and for the fully diversified network the PD is lower than in the disconnected network case. By examining plots of fundamental PD and contagion PD, one can get more understanding of the underlying factors that influence the distribution of PD in figure 2.[50] These two figures show that the contagious risk from well-diversified exposures is lesser than the risk arising from additional portion of exposure to the direct shock in case of a disconnected network.

In terms of the impact of different levels of integration on the average PD in the system, results indicate that an increase in integration (up to 120% of the original value of exposure) leads to a higher value of PD. Figure 3 shows the influence of integration once some more extreme values are considered.

[49] There is a path from any node to any other. By Theorem 4.1 in Jackson (2010), if the probability of establishing an individual connection, p, is larger than $\log(n)/n$, then the probability that the network is connected tends to 1. In the system considered in this thesis, the threshold for the connectedness is exceeded for the *average directed degree of connectivity* equal to 0.6 and 0.8 for matrices **G** and **H**, respectively.

[50] See Figure 5 and Figure 6 in the Appendix, respectively.

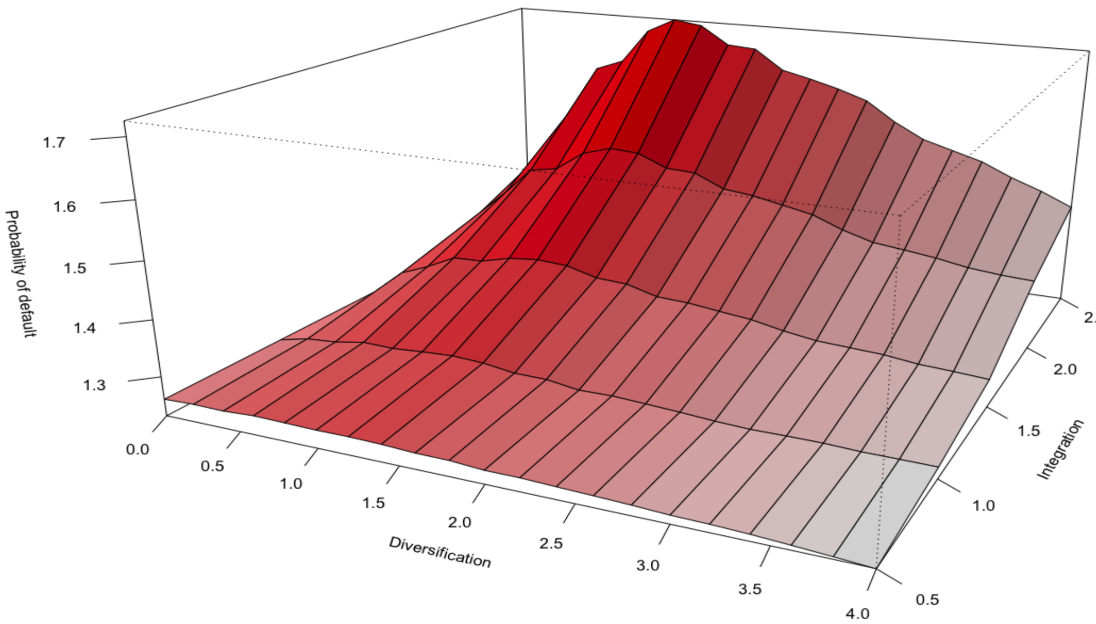

Figure 3: Average PD (in percentages) in the system for different values of integration (0.5 to 2.5) and diversification (0 to 4) of the network.

As it can be seen, in the present setting the impact of higher levels of integration on the resilience is clearly negative. Testing the influence of integration for its value greater than 2.5 (corresponding to 250% of the actual exposure) would be unrealistic, suggesting strictly negative implications of greater exposures on the resilience of the banking system.

Apart from investigating the implications of different levels of diversification and integration on the average values of PD in the system, it is also useful to examine their influence on each bank individually. Table 4 displays values of PD for individual banks for a few selected levels of integration and diversification. It turns out that Swedbank is the most sensitive to changes in integration levels, though its PD does not react much to shifts in diversification. On the other side of the spectrum is Nordea, which reacts to different setting of diversification the most (for integration equal to 1.2, change between diversification levels 1 and 3 is equal to 0.08 pp), whereas it is not severely affected by integration levels.

When it comes to the assessment of the systemic importance of institutions in the system, it is useful to analyse joint defaults of banks in the network. Table 5 shows PD of joint default of banks in the system. Results show that in this particular case, Handelsbanken and SEB appear to be the most influential institutions in the system as in some scenarios their defaults lead to further bankruptcies in the network. In this example, default of SEB caused Swedbank to default due to a contagion

Institution Names	Integration = 0.8 Diversification =			Integration = 1 Diversification =			Integration = 1.2 Diversification =		
	1	2	3	1	2	3	1	2	3
Nordea	1.22	1.19	1.18	1.20	1.16	1.15	1.20	1.14	1.12
SEB	1.74	1.72	1.70	1.74	1.73	1.71	1.74	1.73	1.71
Swedbank	0.67	0.69	0.69	0.75	0.75	0.74	0.83	0.84	0.80
Handelsbanken	1.46	1.44	1.44	1.46	1.43	1.42	1.45	1.42	1.42
Average	1.27	1.26	1.25	1.29	1.27	1.25	1.31	1.28	1.26

Table 4: PD of banks in simulation by integration and diversification levels. PD showed as percentages.

effect in more than 1% of scenarios. The occurrences of joint defaults are more frequent for the network characteristics presented in table 5 compared to the original (more diversified) system, which is consistent with the expectations that under the idiosyncratic shock scenario, higher connectivity causes a decline in the number of contagious defaults.

	Nordea	SEB	Swedbank	Handelsbanken
Nordea	-	0.00	0.00	0.00
SEB	0.00	-	1.08	0.43
Swedbank	0.00	0.00	-	0.00
Handelsbanken	0.40	0.30	0.00	-

Table 5: PD of joint default of banks in simulation for Integration = 1 and Diversification = 1. PD showed as percentages.

As it was stated before, low levels of diversification cause an increase of PD of institutions in the system. However, when it comes to the total net value of banks in the network, even low levels of diversification guarantee lower overall losses in the system compared to the disconnected case. As the diversification level increases, the total losses of all institutions in the simulation are decreasing. Though the difference between the complete and the disconnected networks amounts to approximately SEK 300 million. Hence, the effect of diversification of losses in the system does not seem to be substantial. In terms of integration, it does not significantly affect the amount of the total losses in the system. Figure 7 presents the distribution of the total net value of institutions in the network as a function of different diversification and integration levels.[51]

Similar finding applies to total liability values. As the diversification level increases, the total actual liabilities of institutions in the system are increasing.[52]

[51]See Figure 7 in Appendix.
[52]See Figure 8 in Appendix.

5.2 Systemic shock

As the response of the modelled network to the idiosyncratic shock is already analysed, let us move to the case of the systemic shock. Its aim is to test the resilience of the original network and various combinations of the structure to more adverse scenarios, such as e.g. mortgage loans crisis. The ultimate goal of the systemic shock is to discover how different network structures influence the stability of the system in the face of more severe losses.

5.2.1 Original and disconnected networks

Similarly to the analysis of the effects of idiosyncratic shock, let us start by comparing the results of the model for the original and the disconnected networks. This comparison provides some first insights into the performance of the basic network structures under the systemic shock scenario.

In table 6 one can find PD for individual banks in the network for both the original and the disconnected network cases. Similarly to the analysis of the idiosyncratic shock, probabilities of fundamental and contagious defaults were distinguished.

Institution Names	**Original network**			**Disconnected network**			**Difference in total PD**
	Fund.	Cont.	Tot.	Fund.	Cont.	Tot.	
Nordea	0.68	0.24	0.92	1.04	-	1.04	-0.12 pp
SEB	0.56	1.68	2.24	1.12	-	1.12	1.12 pp
Swedbank	0.00	2.32	2.32	0.00	-	0.00	2.32 pp
Handelsbanken	0.76	1.04	1.80	1.16	-	1.16	0.64 pp
Average	0.50	1.32	1.82	0.83	-	0.83	0.99 pp

Table 6: PD of banks in simulation, divided into fundamental, contagion and total PDs. PD showed as percentages, difference in PD in percentage points.

For all the banks except Nordea the disconnected network case guarantees lower levels of PD. In most of the cases, the difference between structures is larger than under the idiosyncratic shock scenario. One institution that clearly stands out is Swedbank, which does not default fundamentally in the simulation, however its total PD of default is the highest of all bank. These evidences indicate that when all institutions are subject to a negative shock, higher connectivity of the network does not increase the resilience but leads to a greater fragility of the system. Another interesting feature of the obtained results is that for the systemic shock the main component of the total PD are contagious defaults (except for Nordea), whereas in the case of idiosyncratic shock, the fundamental component was a dominating one for a majority of institutions.

In terms of the systemic importance of institutions in the network, the most significant banks are Nordea and SEB, while Swedbank is influenced the most by their potential defaults (as it defaults in

4.35% and 3.57% of cases when Nordea and SEB go bankrupt, respectively). There were no occurrences

	Nordea	SEB	Swedbank	Handelsbanken
Nordea	-	0.00	4.35	4.35
SEB	0.00	-	3.57	1.79
Swedbank	0.00	3.45	-	0.00
Handelsbanken	0.00	2.22	0.00	-

Table 7: PD of joint default of banks in simulation for the original network. PD showed as percentages.

of a joint default of SEB and Nordea, however, SEB's PD is affected by defaults of Swedbank and Handelsbanken. Finally, the most resilient bank turned out to be Nordea, which was unaffected by other banks' defaults. This last finding goes in line with the results presented in table 6, which indicated that Nordea was the least affected by the contagion channels. Not surprisingly, under the systemic shock joint defaults are by far more frequent compared to the idiosyncratic case as connectivity only induces further spread of losses.

When it comes to the average net values of institutions after the introduction of systemic shock, the obtained results are much lower than in the case of the idiosyncratic shock (which is line with higher PD of banks under the systemic shock). The difference between the combined net values of all institutions across the two networks tested is much higher under the systemic shock scenario. As expected, the total losses in the system are larger when contagion channels are considered compared to the case with fundamental effect alone. Surprisingly, despite bigger losses in terms of net value, the total value of liabilities is higher for the systemic shock scenario compared to the idiosyncratic case. It indicates that although there are more defaults in the system altogether, the severity of shocks on banks is not as extreme as in the case of the idiosyncratic shock (likely to be due to a higher standard deviation of the idiosyncratic shock).

Institution Names	**Original network**		**Disconnected network**		**Difference in values**	
	NV	LV	NV	LV	NV	LV
Nordea	80.12	5571.37	79.21	5571.35	0.92	0.02
SEB	32.52	2479.53	38.06	2479.62	-5.53	-0.09
Swedbank	27.54	2024.40	45.37	2024.50	-17.84	-0.10
Handelsbanken	30.52	2491.10	33.77	2491.14	-3.26	-0.04
Total	170.70	12566.4	196.41	12566.61	-25.71	-0.22

Table 8: Average Net values (NV) and Liability values (LV) of institutions across all shocks and their differences between networks, in billions of SEK.

5.2.2 Structural analysis

The next step is to compute the results for a range of diversification and integration levels and to examine how different network structures influence values of the measures used.

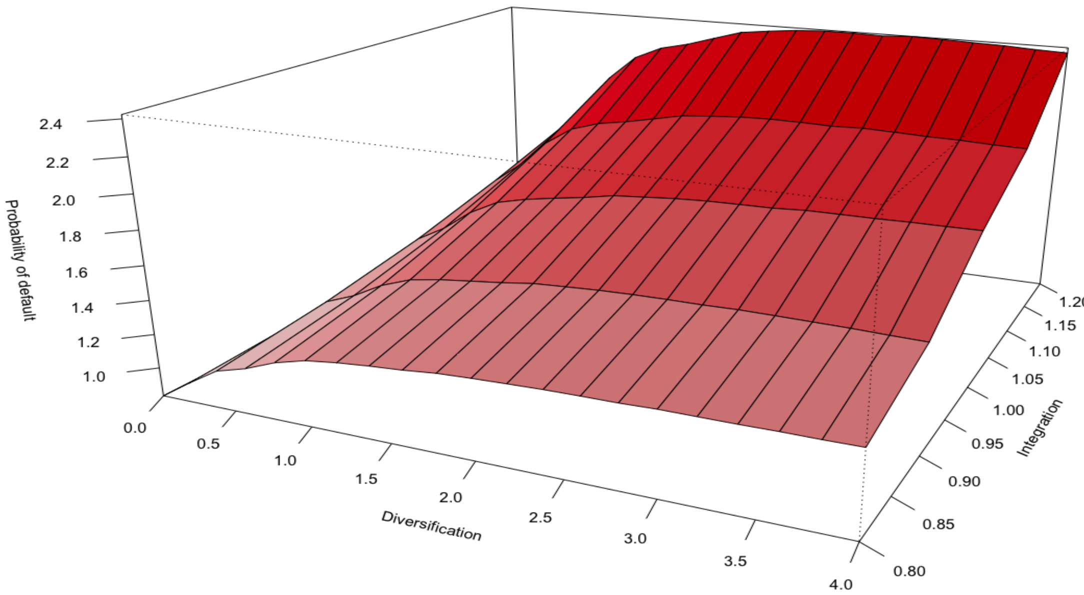

Figure 4: PD (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario.

Figure 4 shows the resulting average PD for a number of combinations of diversification and integration. The shape of a plot is much different comparing to the case of idiosyncratic shock. As it can be noticed, the more connections are established in the system due to increasing average directed degree of connectivity, the higher is the respective PD level. It suggests that once all banks in the network are affected by the shock, the benefits of diversification are no longer present. Figure 9 and figure 10 show the evolution of fundamental and contagious defaults.[53] Although the fundamental PD is once again decreasing as the diversification increases, the surge in the risk of contagion due to the higher connectedness is by far larger in magnitude.

In a moderate range, different levels of integration are having similar impact on PD as in the idiosyncratic case. The higher level of integration is applied, the more defaults are observed in the system. To complete the analysis of the implications of different structures on the average value of PD in the system, let us inspect the results for slightly more extreme levels of integration (just as it was done for the idiosyncratic shock). Figure 11 shows the impact of setting integration to values ranging

[53]See Figure 9 and Figure 10 in Appendix.

from 0.5 to 2.5.[54] Even for extreme cases when the total exposure of institutions in the system is equal to 250% of the original value, integration has nothing but negative effect on the stability. For the highest level of integration investigated, the average PD in the network goes up to 20%.

The average values of PD for the whole system showed in figure 4 and figure 11 indicate that the overall influence of a growing diversification and integration on the stability of the network is negative. Let us now take a look at the values of PD for individual institutions in some selected cases. Table 9 shows individual PD for banks in the system.

The first thing that stands out in table 9 are the values of PD for Nordea. As for all other banks an increase in integration has a negative effect on their resilience to shocks, Nordea's PD declines. Additionally, as it was previously inferred, a growing number of links in the system was causing the PD in the network to increase. However, in case of Nordea, growing diversification has the opposite effect. Those two evidences suggest, that Nordea is more susceptible to direct shock (which is more severe for lower levels of integration and diversification) compared to the contagion effect, whereas all other institutions are more prone to default due to the spread of losses.

Institution Names	Integration = 0.8 Diversification =			Integration = 1 Diversification =			Integration = 1.2 Diversification =		
	1	2	3	1	2	3	1	2	3
Nordea	0.97	0.90	0.89	0.96	0.87	0.87	0.94	0.83	0.81
SEB	1.70	1.83	1.89	2.01	2.17	2.22	2.37	2.56	2.62
Swedbank	0.69	0.85	0.85	1.60	1.99	2.08	3.32	4.10	4.15
Handelsbanken	1.50	1.61	1.61	1.67	1.81	1.84	1.89	2.07	2.11
Average	1.21	1.29	1.31	1.56	1.71	1.75	2.13	2.39	2.42

Table 9: PD of banks in simulation by integration and diversification levels. PD showed as percentages.

As expected, joint defaults are more frequent under the systemic shock compared to the idiosyncratic case. As all institutions are subject to a certain direct loss, there are more cases of defaults in total and consequently banks are more prone to contagious defaults. Based on the example presented in table 10, Nordea and Handelsbanken are by far the most systemically important institutions in the network. However, these results hold for low levels of diversification as the joint defaults showed for the original (more diversified) network[55] indicate that SEB has larger influence on the stability of the system compared to Handelsbanken (Nordea appears to be systemically important in both cases).

As for the total net value in the system, the results are as expected.[56] For low levels of diversification the PD is lower and the total net value is higher compared to more diversified networks. With an increase in PD, institutions are defaulting more frequently and hence the total loss in net value in more

[54] See Figure 11 in Appendix.
[55] Presented in table 7.
[56] See Figure 12 in Appendix.

	Nordea	SEB	Swedbank	Handelsbanken
Nordea	-	0.66	3.04	3.04
SEB	0.00	-	1.45	0.69
Swedbank	0.00	1.18	-	0.00
Handelsbanken	0.21	1.83	2.03	-

Table 10: PD of joint default of banks in simulation for Integration = 1 and Diversification = 1. PD showed as percentages.

connected networks is greater. In terms of the total liability value, there is no significant difference among different structures.[57]

5.3 Sensitivity of results

The results of the numerical simulations described above help to understand how different network structures and levels of integration influence the overall resilience of the banking system in the face of idiosyncratic and systemic shocks. As it was previously stated, the patterns and interactions revealed by the simulations are of interest in the present research (not the resulting values in the absolute terms). However, in order to complete the analysis of the impact of different shocks on various network structures it is also important to determine whether the obtained trends and relationships were just a result of a specific calibration or rather hold under alternative shock specifications. Additionally, it is informative to establish the effect of changes in the severity of shocks on the overall stability of the banking system.

To verify whether changes in calibration of shocks cause a drastic shift in the obtained patterns, the simulations of network's responses to idiosyncratic and systemic shocks were repeated for new severity levels of shocks. Figure 14 and figure 15 show the resulting values of the average PD in network obtained for idiosyncratic shock with a standard deviations equal to 0.02 and 0.03 respectively.[58] Although the values of PD are much different, the overall shape of graphs indicates that the general conclusions regarding the influence of network structures on the stability hold also for other calibrations of the idiosyncratic shock. By examining figure 16 and figure 17 we can also conclude that the general pattern holds as well for the various magnitudes of the systemic shocks.[59] The scope of defaults is different compared to the original shock values, however, the relationship between network structure and changes in PD remains similar. These results indicate that the robustness of the results is satisfactory as the main findings of the present research hold under different calibrations of shock values.

When it comes to assessing the impact of changes in the severity of shocks on the overall PD of banks in the system, it is not that straightforward. Intuitively, as the severity of shocks increases,

[57]See Figure 13 in Appendix.
[58]See Figure 14 and Figure 15 in Appendix.
[59]See Figure 16 and Figure 17 in Appendix.

the total number of defaults goes up. That simple intuition is confirmed by the results of simulations presented in figure 14, figure 15, figure 16 and figure 17. However, the relationship between the magnitude of shock and the number of bankruptcies is not linear in nature due to the existing interbank connections. Furthermore, mild shocks are not causing too much fuss as banks have some ability to absorb moderate losses. However, once the severity of shocks crosses a certain threshold, the number of defaulting institutions increases rapidly. Additionally, the impact of increasing severity of shocks on the stability of the banking system is not uniform across different types of shocks. The results obtained from the simulations suggest that under the systemic shock scenario, any increase in the severity of initial shocks leads to a greater rise in a number of default cases compared to the idiosyncratic shock scenario.

The outcomes of the sensitivity analysis indicate that the general results of the simulations hold under different specifications of shock scenarios. The results of the sensitivity analysis also confirm that a growing severity of shocks leads to an increase in the number of defaulting banks. However, in order to quantify this relationship and identify the threshold severity of shocks, for which their impact on the stability surges, it is necessary to conduct some further analyses and expand the simulation procedure.

6 Discussion

The findings of the present research suggest that under a moderate (idiosyncratic) shock regime, full diversification of the network results in a more resilient structure, whereas for the mid-range levels of connectivity banking system is the most susceptible to shocks. It indicates that in case of limited losses inflicted on the financial system, full diversification of exposures mitigates the overall systemic risk. This result is in line with Elliott, Golub and Jackson (2014), where authors referred to the mid-range levels of diversification as network's "sweet spot". It is also consistent with findings described in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), where it was showed that for mild shocks, more diversified network leads to a less fragile system, with complete network being the least prone to contagious default. The results obtained under the idiosyncratic shock scenario support the conclusion from Gai and Kapadia (2010) where the authors showed that the frequency of contagion is the highest for the medium levels of connectivity and falls to virtually nothing once a certain threshold is exceeded.

However, the results obtained in the present research do not support the findings from Elliott, Golub and Jackson (2014) regarding the implications of integration. In their paper, the authors argued that despite having a negative influence on the resilience of the system in low to medium range, high levels of integration lower the number of defaults in the simulation. Results of the present research indicate that any increase in integration level inevitably leads to a higher probability of default of institutions in the system, as the overall exposure of a given bank to losses of other institutions expands.

Surprisingly, the total net value of institutions in the system increases as the diversification of the network goes up. Even for the mild levels of connectivity (for which the probability of default is the highest) aggregated losses of all banks are lower compared to the disconnected case. Furthermore, the total net value of all institutions is the greatest for the highest level of integration. These evidences suggest that the unexpected results for the total net value may be attributed to a combination of the following factors: an additional portion of direct losses born by weakly diversified and integrated networks,[60] a positive feedback effect through the equity cross-holding propagation channel and a diversification of losses among banks in the system. However, in order to determine which factor plays the crucial role in shaping of the obtained net values it is necessary to isolate their effects.

The results obtained for the case of a stronger, systemic shock indicate that once the initial losses in the financial system are large enough, full diversification only leads to an amplification of the default risk. Under that shock regime, the greatest resilience of the network is achieved with the disconnected structure (no connections among institutions). This result is in line with findings in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Gai, Kapadia (2010) where authors showed that once a large enough shock takes place, highly diversified network only facilitates further financial contagion.

Furthermore, the results gathered from the counterfactual simulation of responses of the Swedish banking system to shocks suggest that the modelled network exhibits a *robust-yet-fragile* tendency (similarly to e.g. Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Gai, Kapadia (2010)). Under the idiosyncratic shock regime a fully diversified network structure limits the probability of default of institutions in the system, while for the systemic shock the complete network is the most vulnerable structure. The results on the total net value in the system provide further support for the authenticity of the *robust-yet-fragile* tendency. Under the systemic shock regime losses are the most significant for the fully connected network (while under the idiosyncratic shock, the complete network guarantees the lowest losses of the total net value) indicating that in a crisis scenario banking system serves purely as a shock transmitter and amplifier. Finally, the results on joint defaults and differences in individual probabilities of defaults between the original and the disconnected networks show that the systemic risk is in fact much elevated for a full-blown systemic shock compared to the idiosyncratic case. These outcomes confirm that the fragility of a more interconnected network increases significantly in a highly adverse scenario.

In terms of validity of the findings, cautious is advised. Gai, Kapadia (2010) and Upper (2007) list main issues with empirical testing of network models such as strong assumption regarding shock propagation channels and distribution of exposures or data related problems (e.g. lack of information

[60] Due to their greater exposition to the initial shock arising from the assumption described in Section 3.5.3.

on exact values of the actual interbank connections). In the present thesis, fixing the interbank exposures required certain assumptions regarding the structure of the original network and the exposure allocation rule. Hence, the resulting probabilities do not have direct financial or risk interpretations. Moreover, the assumption regarding the treatment of disconnected institutions[61] significantly affects the obtained results. Although this assumption is well justified in the present model, it modifies the direct effects of shocks depending on the network's structure, leading to greater direct losses for the cases of disconnected structures (the same effect is observed for networks with lower integration level). Therefore, the results obtained in the present research could be further validated and confirmed by testing them under different set of assumptions. However, the simulation outcomes support the findings observed in the literature and hold under different calibrations of shocks. Hence, the general results on the implications of network structures on the resilience of financial institutions under different shock regimes prove to be useful in further increasing of the understanding of financial networks.

The framework used in the present research proved to be useful in capturing impacts of different network structures on the stability of the financial system. Due to the data limitations some strong assumption were required. The approach described in this thesis could be employed to inform policy, however it requires obtaining more granular data on the interbank exposures. Additionally, applying an information criterion method (such as the entropy maximisation algorithm) to obtain exposure matrices could increase the quality of modelled exposures. Proper quantification of bilateral exposures in terms of lending, stocks and securities would considerably enhance the numerical simulation and result in more precise outcomes. Furthermore, in the current research different seniorities and maturities of debt were excluded. Considering these features of the liability side of bank's balance sheet would produce a more realistic model of a financial system, capturing the structure of bank's funding. Gourieroux, Heam and Monfort (2013) describes a method of extending the network model used in the present research to include multiple seniority levels of debt. Moreover, including additional contagion channel such as loss propagations through changes in the market prices of assets resulting from "fire sales" (as described in Cifuentes, Ferrucci and Shin (2005) or Greenwood, Landier and Thesmar (2015)) could be one of the potential extensions of the shock transmitting mechanism employed in the present framework. Finally, in order to obtain a complete framework for structural analysis of banking networks that would allow for more concrete inferences, it is necessary to implement an appropriate credit loss model. In the current research shock values were randomised based on the historic data, however, to improve the quality of results it is imperative to introduce more advanced framework for the modelling of losses (e.g. as presented in Gauthier, Lehar and Souissi (2012)).

[61] As described in Section 3.5.3.

7 Conclusion

The main purpose of the present research was to determine the implications of different network structures of the financial system on its resilience to shocks, based on the case of the Swedish banking sector. Additionally, this study was set to test the general results on the network architecture presented in the literature using the shock propagation mechanism described in Gourieroux, Heam and Monfort (2012), and to show the application of the framework for structural analysis introduced in Elliott, Golub and Jackson (2014) in a more complex model setting. The thesis established that the *robust-yet-fragile* tendency of a diversified financial system described in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Gai, Kapadia (2010) is exhibited in the network modelled in the present research. When a mild shock hits the economy the complete network is the most resilient structure. However, when the magnitude of shocks exceeds a certain threshold value, more connected systems are much more susceptible to defaults. Under a systemic shock regime the disconnected network proved to be the least prone to defaults as the losses do not propagate through the exposure channels. Finally, the present study confirmed the results on the impact of diversification described in Elliott, Golub and Jackson (2014). However, their suggestion that high levels of integration lead a decline in the number of defaults was not demonstrated by the results obtained in the present research.[62]

While the majority of results described in this research are in line with the findings outlined in the literature, further study is required to confirm these conclusions. In particular, obtaining more precise data on the interbank claims and exposures is necessary to enhance the model and to limit the number of assumptions needed in the present framework.

[62]In the range of integration levels considered in the study.

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Appendix

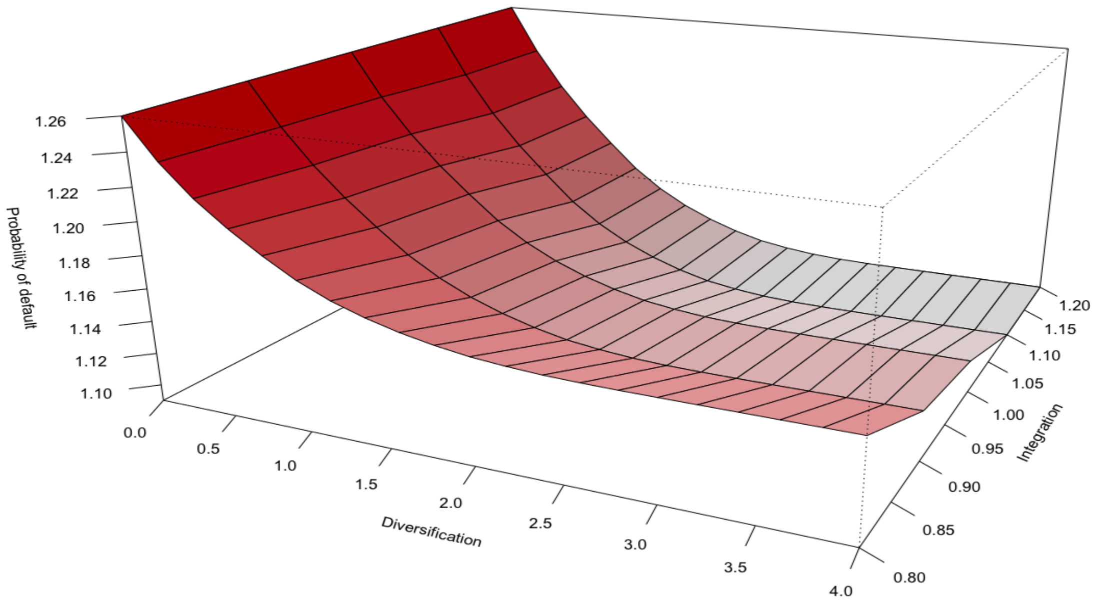

Figure 5: Probabilities of fundamental default (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario.

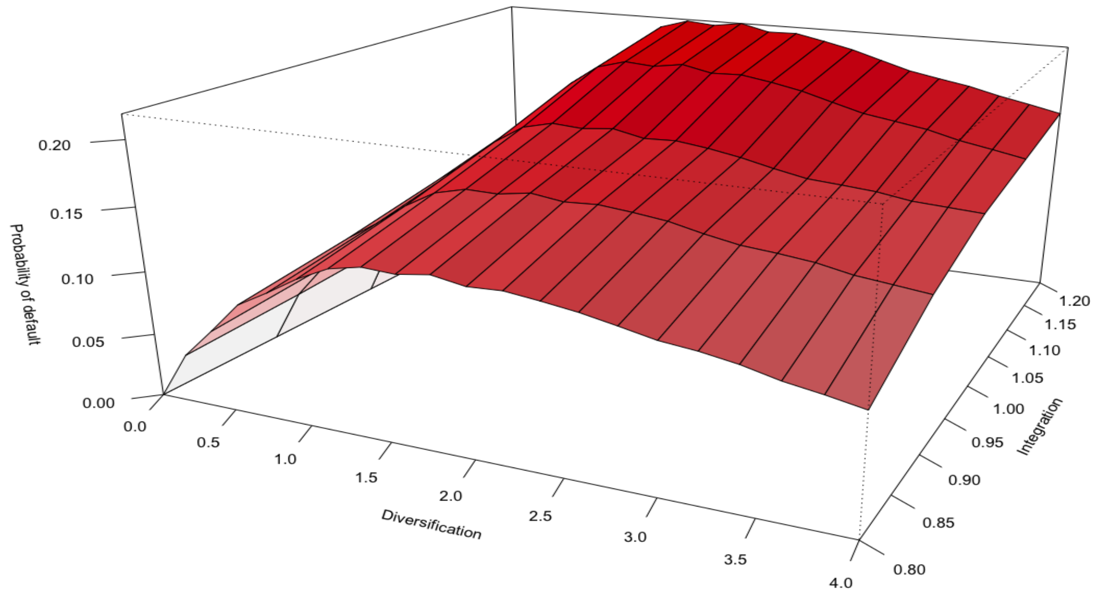

Figure 6: Probabilities of contagious default (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario.

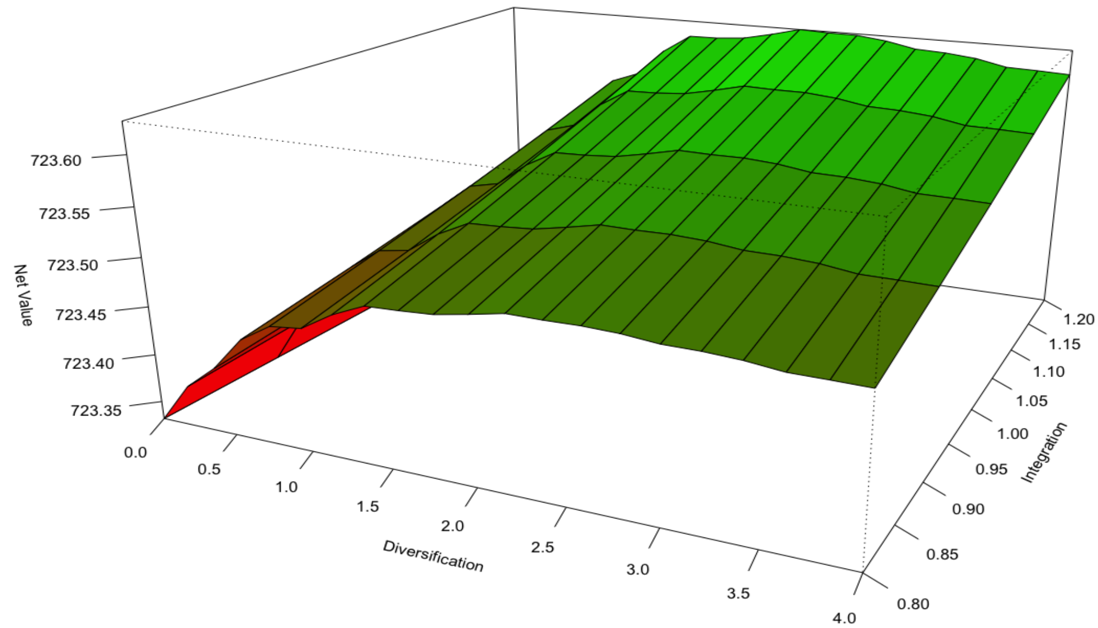

Figure 7: Total net value in the system for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario. Values showed in SEK billion.

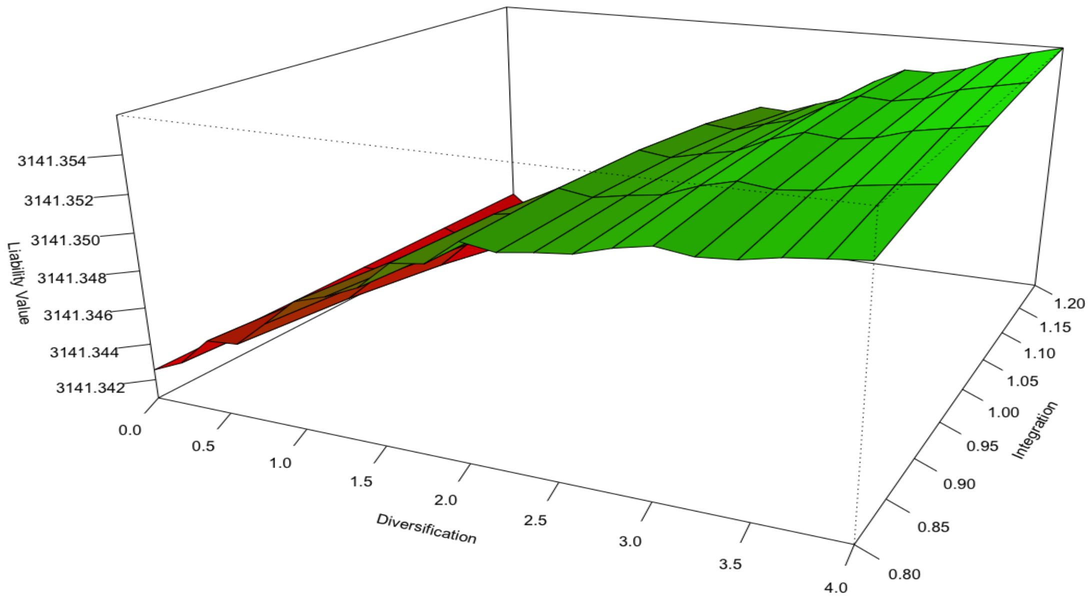

Figure 8: Total liability value in the system for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario. Values showed in SEK billion.

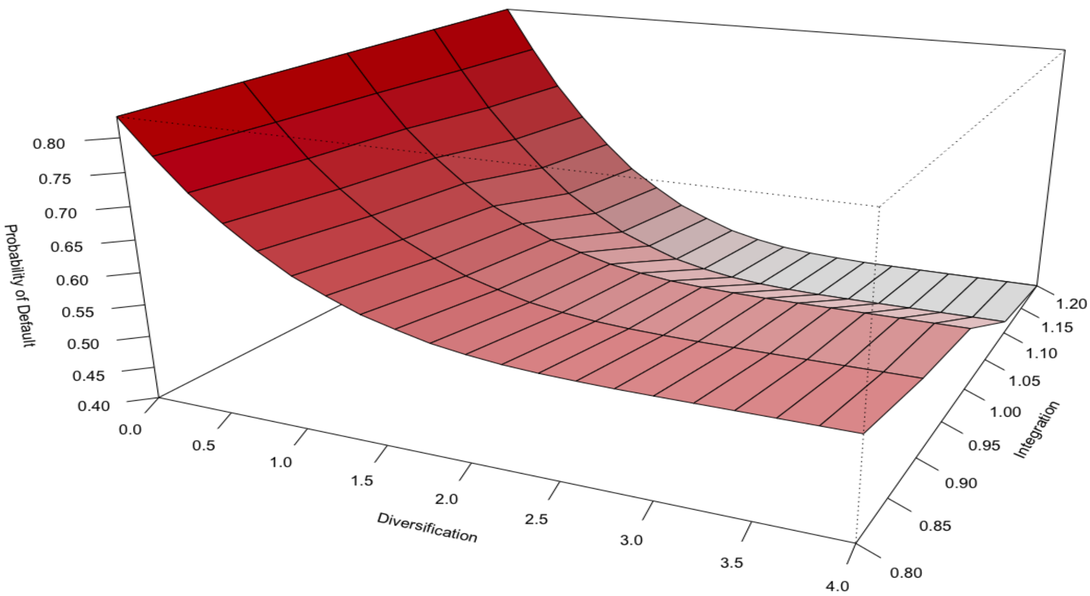

Figure 9: Probabilities of fundamental default (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario.

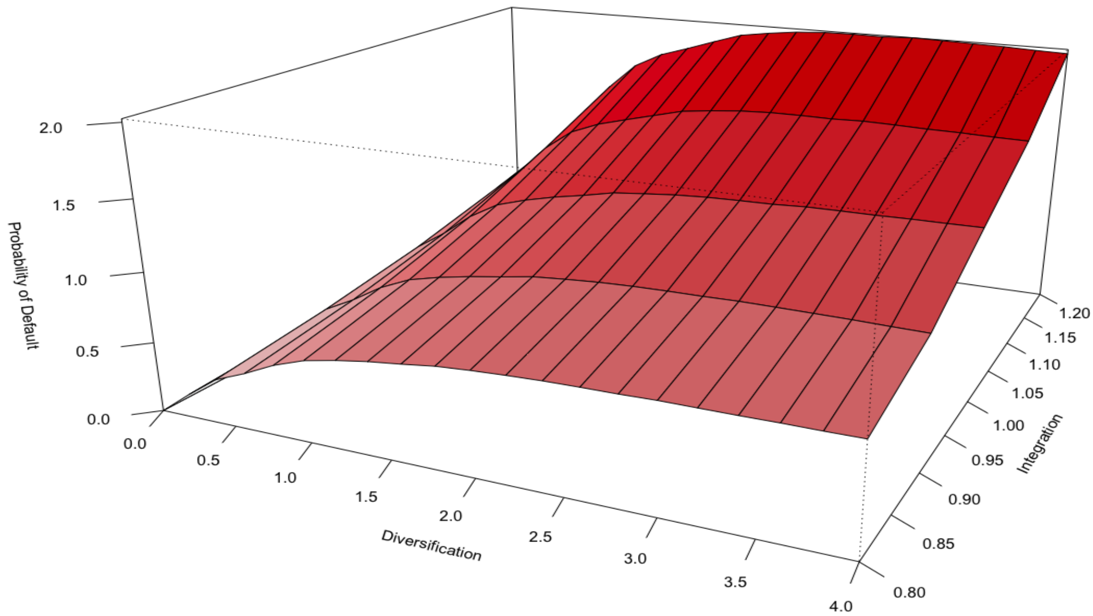

Figure 10: Probabilities of contagious default (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario.

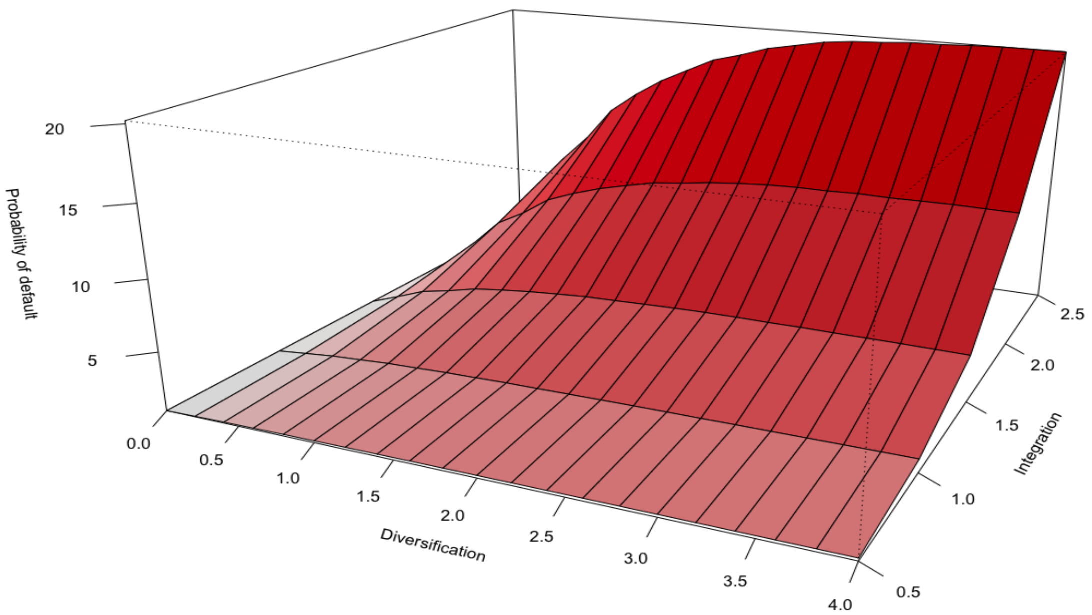

Figure 11: PD (in percentages) for different values of integration (0.5 to 2.5) and diversification (0 to 4) of the network under systemic shock scenario.

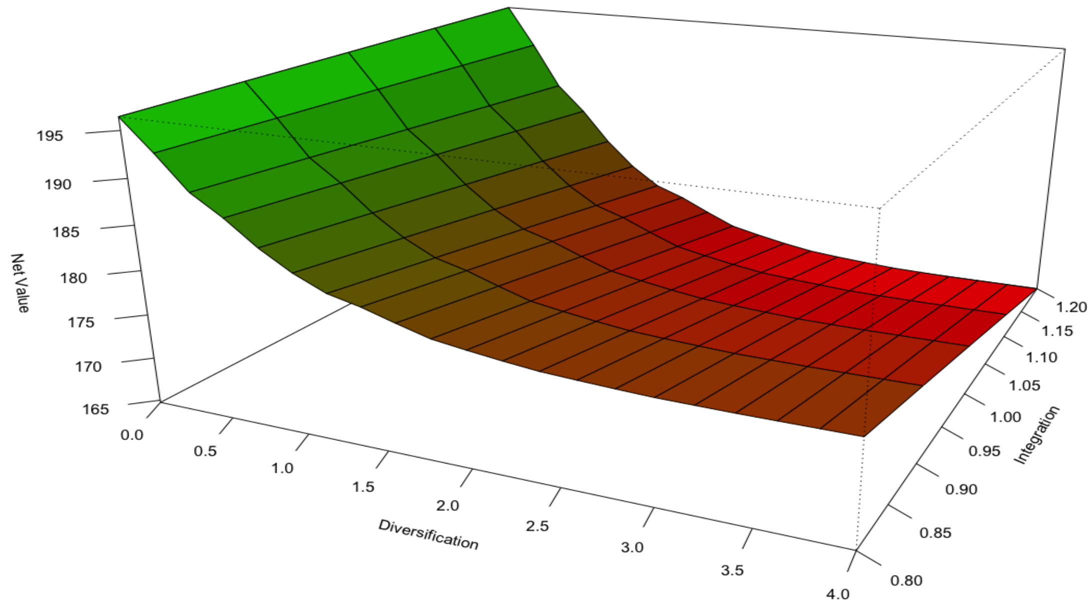

Figure 12: Total net value in the system for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario. Values showed in SEK billion.

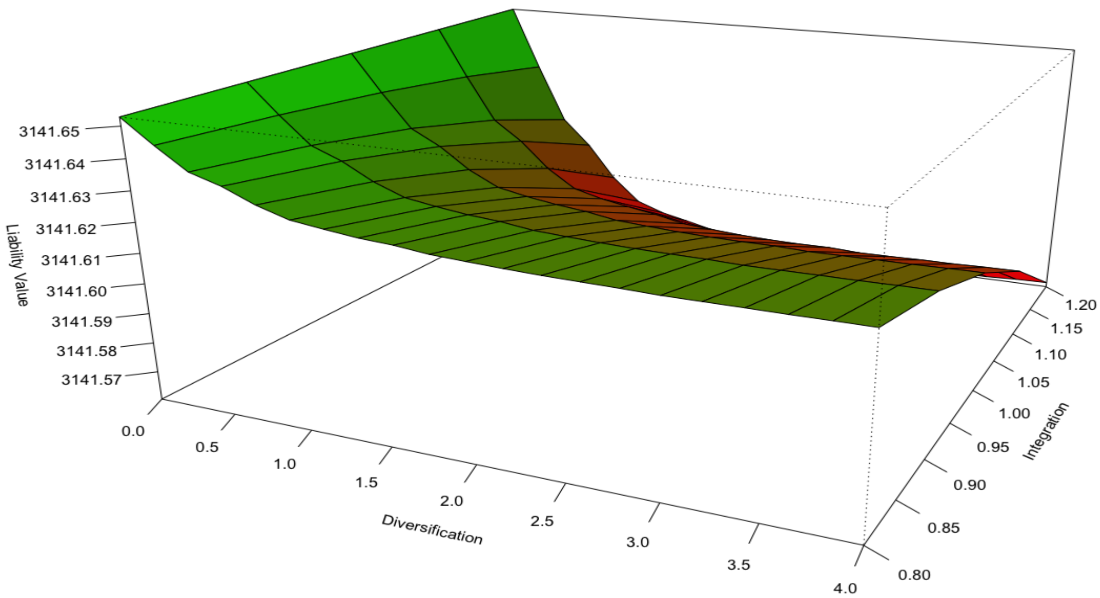

Figure 13: Total liability value in the system for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario. Values showed in SEK billion.

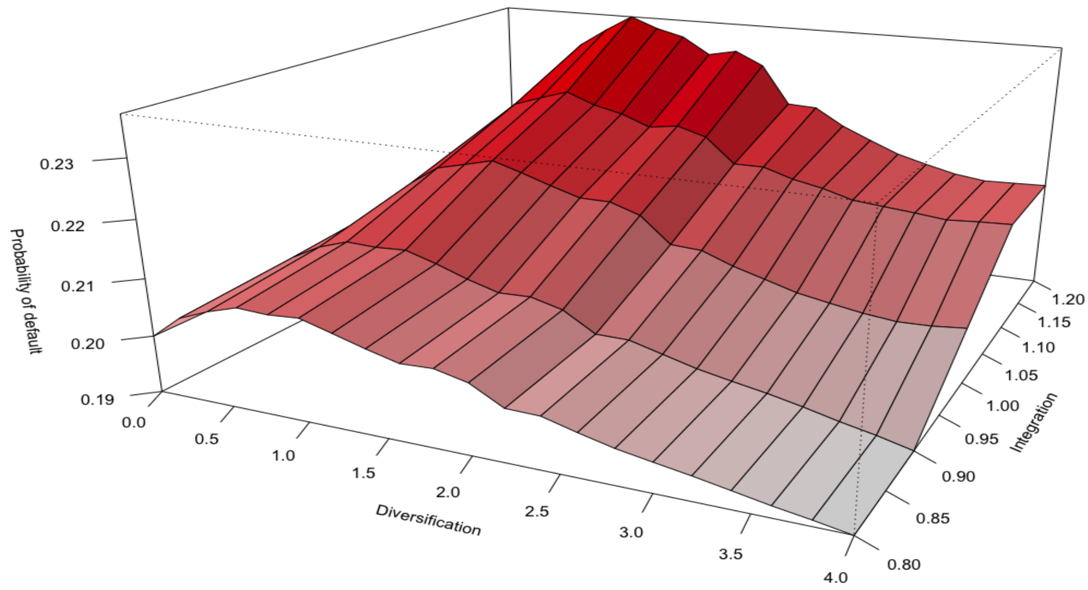

Figure 14: PD (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario for $E(u) = 0.00, \sigma = 0.02$.

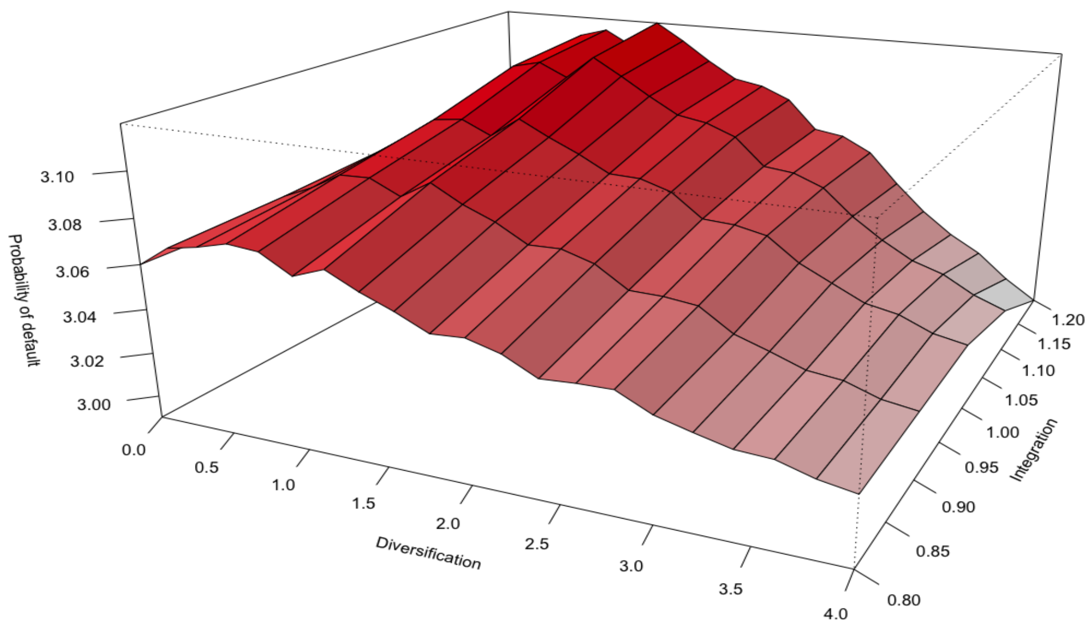

Figure 15: PD (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under idiosyncratic shock scenario for $E(u) = 0.00, \sigma = 0.03$.

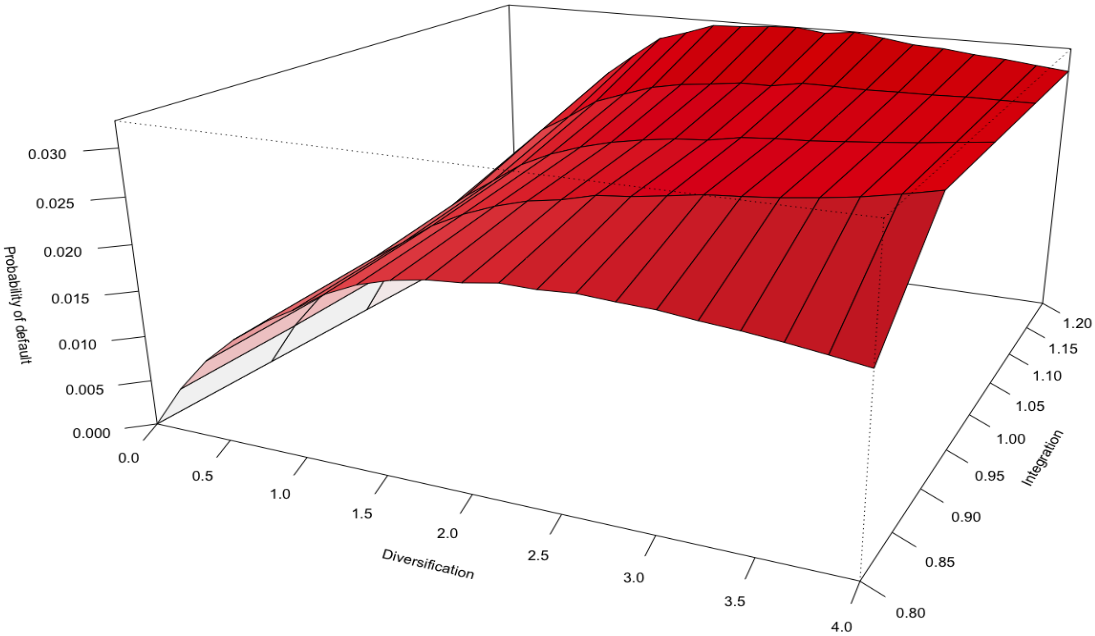

Figure 16: PD (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario for $E(u) = -0.03, \sigma = 0.0062$.

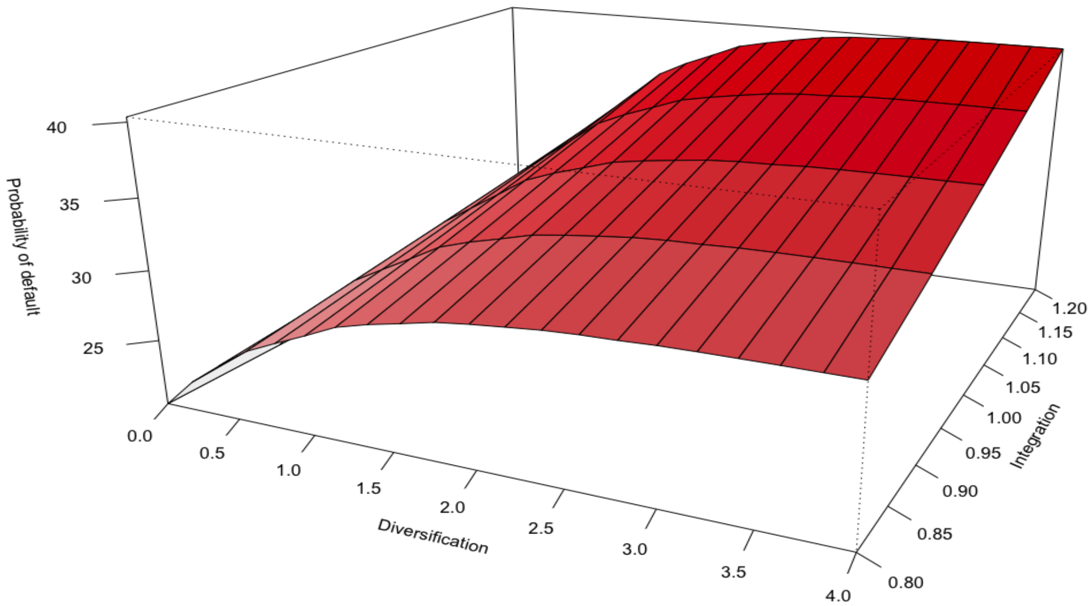

Figure 17: PD (in percentages) for different values of integration (0.8 to 1.2) and diversification (0 to 4) of the network under systemic shock scenario for $E(u) = -0.05, \sigma = 0.0062$.