Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Lecture with Computer Exercises:
Modelling and Simulating Social Systems with MATLAB

Project Report

Systemic risk in network model of financial shock spreading

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Kalinowski Paweł, Walser Dario, Park Sanggil

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Abstract

The systemic risk is one of the most interesting factors in evaluating resilience of banking systems. In this project, we estimate the stability of banking system as a function of number of banks failed by varying three main parameters: level of capitalization, size of interbank exposure, and degree of connectivity. Additionally, we study the percentage of lost deposits as a function of each parameter.

Through the modeling and implementation to Matlab simulation, we ask the fundamental questions in the following.

• How do parameter values affect the expected number of bank defaults and a percentage of lost deposits?
• How repeatable are the results for fixed parameters (variation between realizations)?
• Which model parameters can be influenced by regulators and what should they aim for?

Our work is mainly based on available literature (Nier et al.; 2007) - we follow up their approaches and we further investigate effect of three parameters on the percentage of lost deposits.

Individual contributions

All members participated to regular meetings and contributed to all parts of project. Especially, Kalinowski Paweł and Walser Dario were responsible for the Matlab simulations and Park Sanggil wrote the proposal and final report.

Introduction and Motivations

In the multiple bank system, systemic risk is the main concern for financial stability. Systemic risk could leverage failure of a single bank to a breakdown of banking system that affects the whole economy. Thus, it is crucial to examine the systemic risk nature. We investigate the resilience of the banking systems upon the effect of systemic risk by observing the effect of financial shock directed to one bank on number of failing bank under varying values of key model parameters.

To construct simplified model of the banking system we employ the network theory where each node corresponds to a bank and each link between the nodes represents a directional lending relationship. Our model initiates a financial shock at one bank and transmits overflow that cannot be paid via links to the lending banks, potentially causing them to fail and spreading the shock recursively through the network. This model is called "knock-on defaults". Parameters of the model are capitalization level, size of interbank susceptibility, and degree of connectivity.

The first parameter, capitalization level denotes the capacity of banks to absorb the financial shock. Thus, we examine the number of failure by varying the level of banks' net worth.

The second parameter is the size of interbank lending/borrowing in the total assets. We keep the absolute amount of the external assets constant and vary the percentage of interbank assets in the total assets.

The third parameter is the degree of concentration that is the interbank connectivity. We check the effect of the interbank connections against the number of failure in the banking system. We vary these three parameters and relate them with the number of defaults, describing resilience of banking systems. In addition, we investigate the effect of parameters on the number of defaults and the percentage of lost deposits.

Description of the Model

The set of structural parameters of the banking systems are as follows: (γ, θ, p, N, E).

γ: net worth as a percentage of total assets

θ: percentage of interbank assets in total assets

p: probability of any two nodes being connected (i.e. p_{ij} = a bank i has lent to another bank j)

N: number of banks (i.e. number of nodes)

E: total external assets of banking system (i.e. total loans made to ultimate investors)

The probability is the Erdös-Rènyi probability. Thus the network is generated randomly with N banks and p (e.g. N = 25 and p = 0.25).

The contents of banking systems are given in detail as follows:

- Individual bank's assets: $a_i = e_i + i_i$

  e = external assets (investor's borrowing)

  i = interbank assets (other banks' borrowing)

- Bank's liabilities: $l_i = c_i + d_i + b_i$

  c = net worth of a bank = $\gamma \cdot a$

  d = customer deposits

  b = interbank borrowing

- System level: $\beta = \frac{E}{A} = \frac{\text{external assets}}{\text{total assets}}$
- Aggregate assets of the whole banking system: A = E + I

  E = aggregate amount of external assets

  I = aggregate size of interbank exposures

- $\theta = 1 - \beta = 1 -$ (percentage of external assets in total assets)

  = percentage of interbank assets in total assets

  $I = \theta \cdot A$

- Z: total number of links
- w: bank-level size of any directional link

  $$w = \frac{I}{Z} = \frac{\text{aggregate size of interbank exposures}}{\text{total number of links}}$$

The conditions of the banking systems are given in the following.

- $e_i \geq b_i - i_i$

  External assets $\geq$ net interbank borrowing

  (interbank borrowing) – (other banks' borrowing)

  1st: $\tilde{e_i} + i_i = b_i$; external assets plus interbank lending equals its interbank borrowing

  2nd: $e_i = \tilde{e_i} + \hat{e_i}$; leftover in aggregate external assets is uniformly distributed among all banks. Thus, we will distribute the $(E - \sum_{i=1}^{N} \tilde{e_i})$ equally among all banks. $\hat{e_i} = \frac{E - \sum_{i=1}^{N} \tilde{e_i}}{N}$

Implementation

We fix the total external assets (E) to 100000 (as it's just numéraire, not affecting the results) and generate the network with 25 nodes (banks) and 0.20 Erdös-Rènyi probability of link existence between two nodes.

For the shocks and their transmission, we employ the following parameters. For the shocks and their transmission, we employ the following parameters.

- s_i: size of the initial shock

  The loss is firstly uptaken to the bank's net worth c_i, and then to its interbank liabilities b_i and lastly to its deposit d_i, which is the ultimate sink of the shock.

  k = number of creditor banks
  j = one of the creditor banks that have lent to bank i
  i = the bank which has been hit by the initial shock.

  If $s_i \geq c_i$, then the bank is failed
  If $(s_i - c_i) < b_i$, then the residual loss $(s_i - c_i)$ is transferred to creditor banks.
  The bank j takes a loss of $s_j = \frac{(s_i - c_i)}{k}$
  If $(s_i - c_i) > b_i$, then the residual loss $(s_i - c_i)$ cannot be transferred to creditor banks and the depositors take a loss of $(s_i - c_i - b_i)$.

  If $s_j \leq c_j$, then creditor bank j is survived from the shock transmitted. (i.e. bank j withstands the shock.)

Simulation Results and Discussion

First simulation: Bank capitalization level and contagion

Firstly, we perform a simulation to investigate the effect of banks' net worth (γ) on the resilience of the banking system. The capitalization level denotes the capacity of banks to absorb the financial shock using net worth without affecting other banks' assets/depositors' money. We examine the number of failure by varying the level of banks' net worth as shown in figure 1.

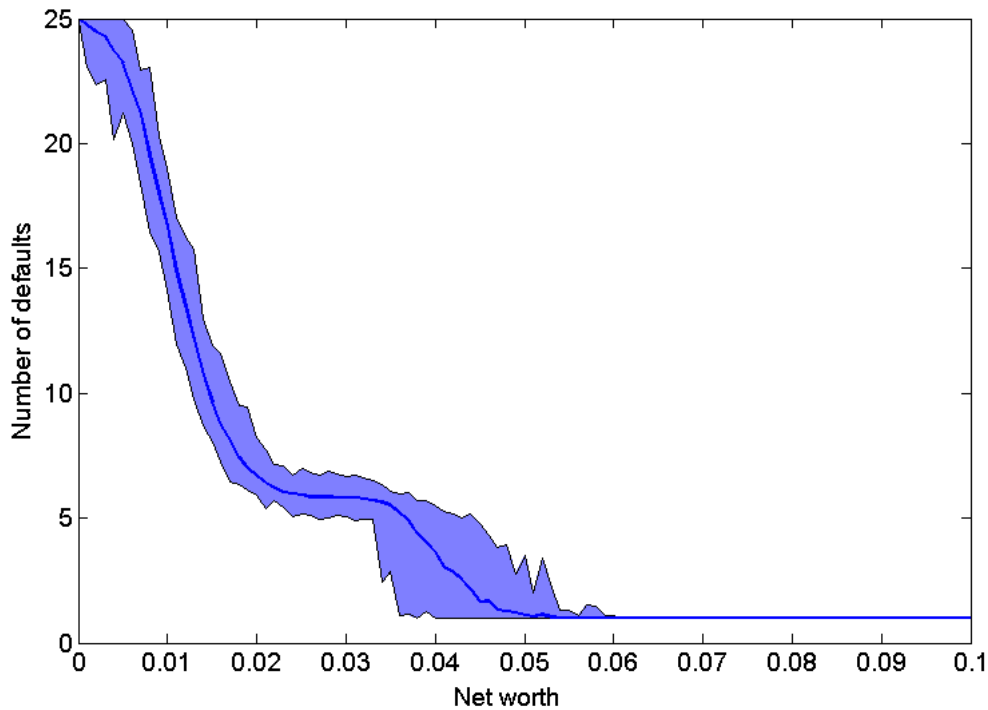

Figure 1. Number of defaults by varying the level of banks' net worth (γ)

We generate 100 banking systems for each combination of parameters. For each banking system, we shock each bank separately and save the average number of defaults over these 100 simulated situations. This is the number of defaults of this single banking system. Then, we plot the maximum/minimum and average number of defaults from100 independent systems, as a function of net worth. By averaging over the 25 banks of each system, we remove the effects of the first bank. The Erdös-Rènyi probability of connectivity between two banks is 0.20. Also, the percentage of interbank assets in total assets, θ, is fixed as 0.20. As shown in figure 1, we find the negative relationship between the number of defaults and the level of banks' net worth. With increase of the net worth, the number of defaults decreases. Until the value of net worth 2%, we observe the rapid decrease of the number of defaults. After 2%, the rate of decrease becomes more moderate than before. In addition, after approximately 5%, all the other banks can withstand the financial shock except the initial bank defaults. For the contagion of the banking system, the shock spreading is not linear function of the net worth.

Second simulation: Size of interbank lending/borrowing and contagion

In the second simulation, we check the effect of the size of interbank exposures against the number of failure in the banking system. The θ is a percentage of interbank assets (lending/borrowing) in total assets. We keep the absolute amount of the external assets constant and vary the percentage of interbank assets in the total assets. Also, we fix the

Erdös-Rènyi probability to 0.20 and thus the increase in interbank assets results in increase of the amount of interbank lending/borrowing relationship. It is an increase in weight (w) that is the size of any directional link between banks. In addition, the banks' net worth is varied, using values 0.01, 0.3 and 0.05. The results are shown in figure 2.

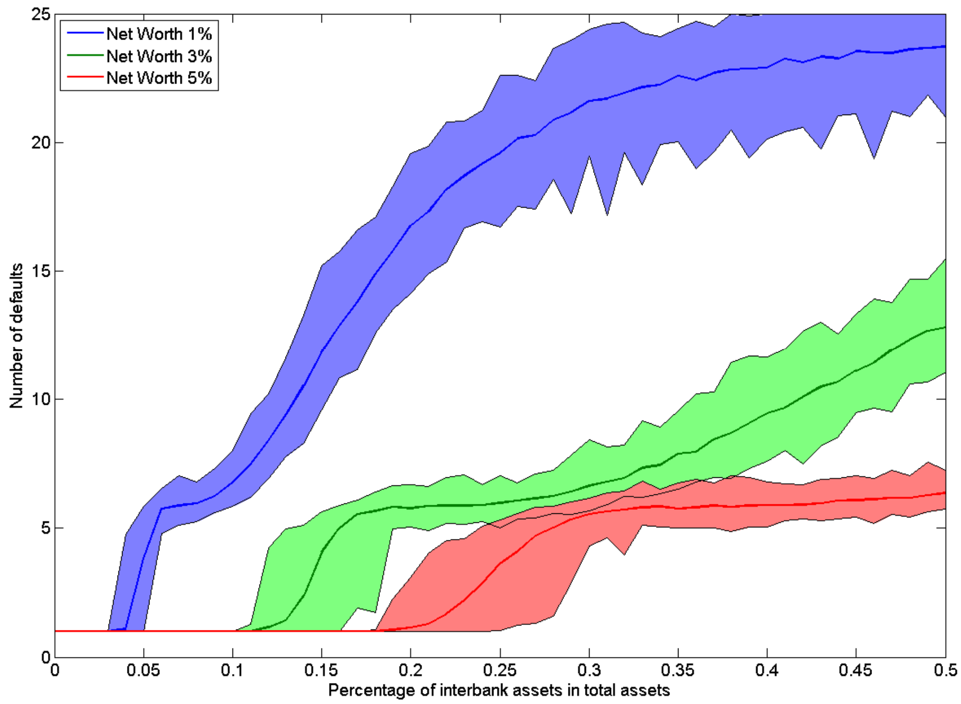

Figure 2. Number of defaults by varying the percentage of interbank assets (lending/borrowing) in total assets (θ)

As shown in figure 2, for the net worth 1%, the number of defaults starts to rise from around 4% of interbank assets in total assets. Also, for the net worth 3% and 5%, the number of defaults begins to rise from 10% and 18% of interbank assets in total assets, respectively. Thus, there is a certain value of **θ**, depending on the net worth, where the number of defaults starts to rise.

In summary, we observe no contagion for low levels of interbank assets. Below approximately 18% (net worth 5% case), no contagion effect is observed. After reaching 18%, number of defaults increases steeply. The shock spreads to creditor banks, but their net worth cannot rise fast enough to absorb the shock received. The number of default increases rapidly to 5. From the second simulation, we find that increase of interbank exposure lead to a contagion effect after passing the threshold value, 18% in case of 5% net worth.

Third simulation: Interbank connectivity and contagion

In the third simulation, we check the effect of the interbank connections against the number of failure in the banking system. Figure 3 shows the results.

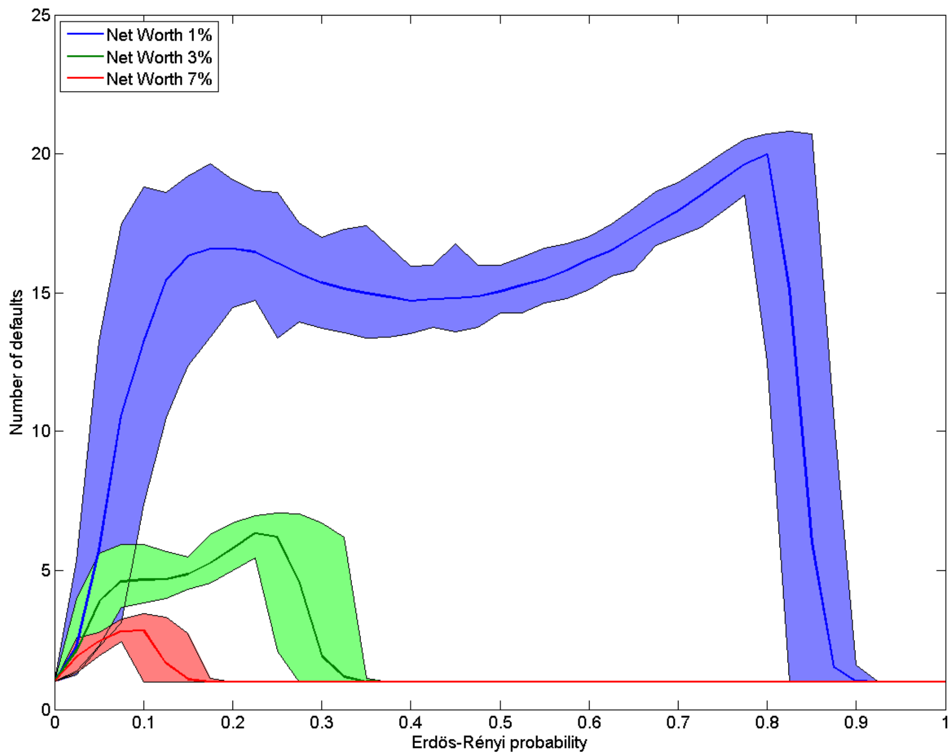

Figure 3. Number of defaults as a function of Erdös-Rènyi probability (p) and net worth (γ)

Interbank connection has two opposing effects. One is the role of shock-transmitter. Through the network, the shock is transmitted. The other is the shock-absorber. Also, through the network, the shock is shared and absorbed. We observe these two effects from the results shown in figure 3.

For very low levels of concentration, that is very low value of p, shock spreads fast through the network. The low levels of concentration acts as the shock-transmitter. For high levels of concentration, the number of defaults tends to decrease. The interbank connectivity plays the role of shock-absorber. The shock is more spread and absorbed by the network. Thus, we observe M-shaped graphs by two opposing roles of connectivity.

In addition, figure 3 shows the effect of the net worth on contagion. For the lowest net worth (1%) network, the shock spreads fast and only small amount of shock is absorbed by the net worth. Even in the high levels of connectivity, the number of default still keeps increasing. It indicates that the under-capitalized banking systems are susceptible to contagion even in the high levels of connectivity. However, for higher net worth (3% and 5%) networks, the shock is absorbed rapidly by the net worth. Thus, well-capitalized banking systems are robust against the shock.

Also, we observe that after certain p values, the shocks are completely absorbed. For the 1% net worth banking system, the threshold p value is 0.9 and approximately 0.34 and 0.15 for 3% and 7% net worth banking systems, respectively.

Additional simulation: Percentage of lost deposits versus three parameters (γ, θ, p)

(1) Percentage of lost deposits versus net worth (γ)

The simulation is done in the same way as the first simulation. We observe the percentage of lost consumer deposits instead of the number of defaults.

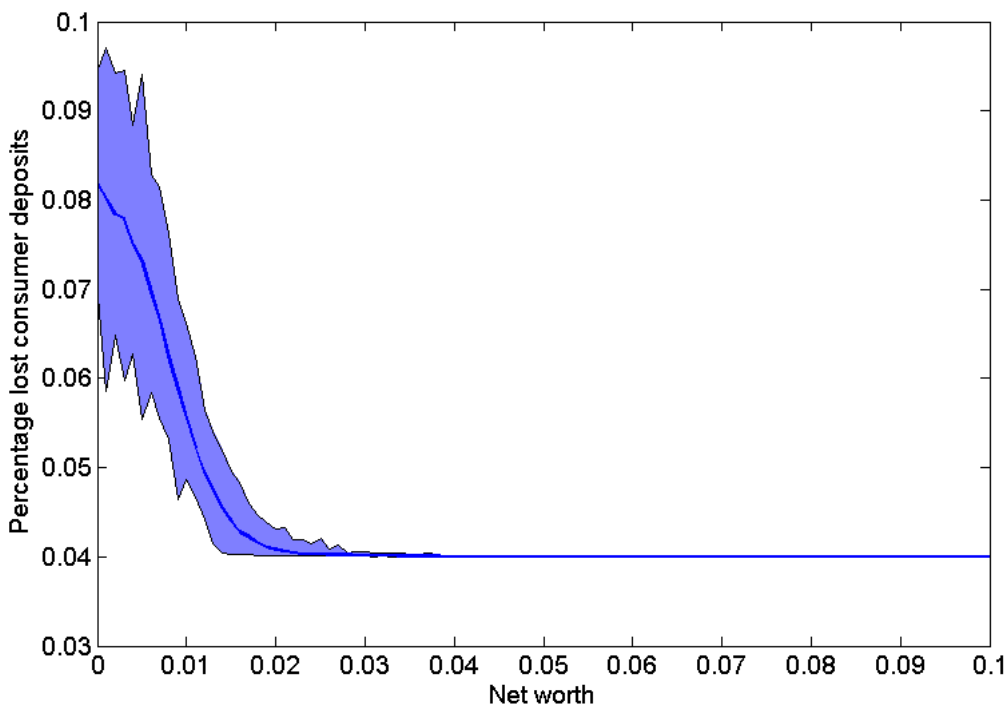

Figure 4. Percentage of lost deposits as a function of net worth

As shown in figure 4, the net worth about 2% reduces the amount of lost consumer deposits to about 4% (consumer deposits of the first bank – it's the minimum as whole liabilities of first bank are lost in initial shock, including deposits). Thus, well-capitalized banking systems (net worth more than 2%), the shock is fully absorbed by customer deposits.

(2) Percentage of lost deposits versus percentage of interbank assets in total assets (θ)

The simulation is done as the second simulation. We plot the percentage of lost consumer deposits instead of the number of defaults.

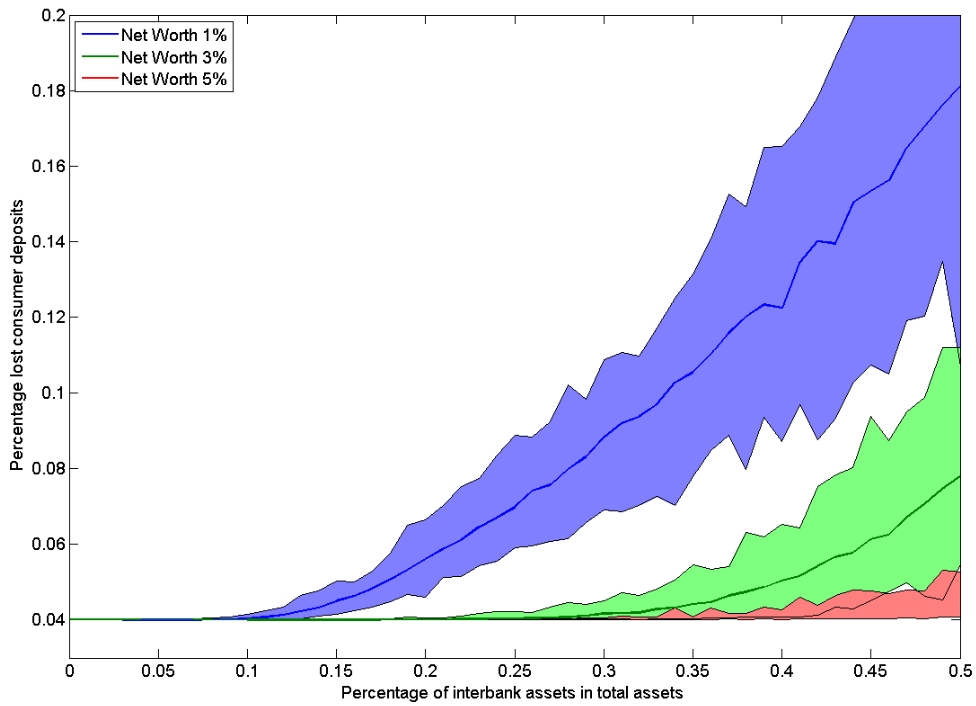

Figure 5. Percentage of lost deposits as a function of percentage of interbank assets in total assets

In case of the under-capitalized banking systems (1% net worth), more consumers' deposits is lost than in the case of well-capitalized banking systems (3% and 5% net worth).

(3) Percentage of lost deposits versus interbank connectivity (p)

The simulation is done same as the third simulation. We plot the percentage of lost consumer deposits instead of the number of defaults.

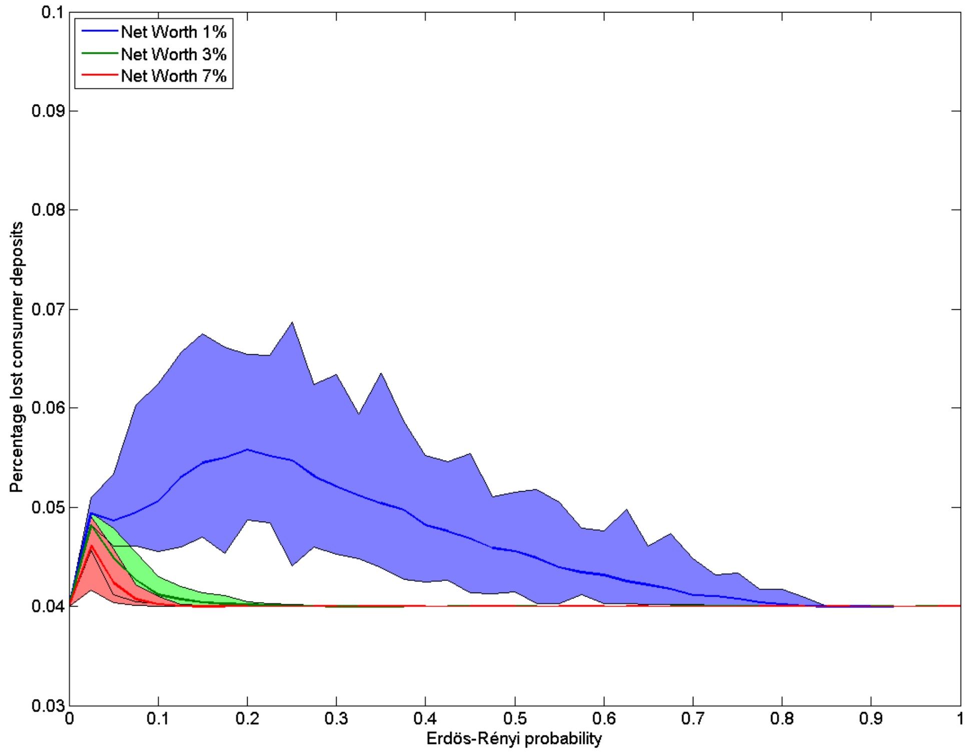

Figure 6. Percentage of lost deposits as a function of Erdös-Rènyi probability (p) and net worth (γ)

As shown in figure 6, for very low levels of concentration, the customer deposits are lost more than the high levels of concentration.

Summary and Outlook

We studied the effect of three parameters on the resilience of banking system. The parameters were capitalization level, size of interbank susceptibility, and degree of connectivity. Through multiple simulations, we calculated the average defaults as a function of three parameters. The results are summarized in the following.

Bank capitalization level and contagion

The shock spreading is negative relation with the net worth and it is not linear function of the net worth. We observe the two important thresholds, 2% and 5%. More than 5% net worth value, the shock is completely absorbed by the net worth. However, below 2%, very fast shock spreading is initiated. Thus, regulators should maintain the net worth value more than 5% to be safe from the systemic breakdown. At least 2% is required to reduce the threat of shock spreading.

Size of interbank lending/borrowing and contagion

We observe the threshold value of size of interbank exposure, 18%. After 18%, the shock spreads fast. Thus, regulators should keep the size of interbank lending/borrowing under 18% to prevent the systemic breakdown.

Interbank connectivity and contagion

We find the two opposing effects of connectivity. One is the shock-transmitter and the other is the shock-absorber. For the low levels of connections, the banking system is prone to breakdown but the resilience increases with the degree of connectivity. Also, well-capitalized (high net worth) banking system is more resilient against the shock than the under-capitalized (low net worth) banking system.

Additionally, we study the effect of three parameters on the percentage of lost customer deposits. Well-capitalized and high interconnect banking system absorbs the more shock by the customer deposits than the under-capitalized and low interconnect banking system.

Our modeling and simulation are mainly based on the literature (Nier et al.; 2007) and we further investigate the effects of each parameter on the lost deposits. This Matlab course allowed us to learn the Matlab modeling and apply it to financial system. For the future work, it is recommended to expand the investigation using different network generator.

References

Erlend Nier, Jing Yang, Tanju Yorulmazer, Amadeo Alentorn, Network models and financial stability, Journal of Economic Dynamics & Control 31 (2007) 2033-2060