

Krassimir Markov, Vitalii Velychko, Oleksy Voloshin
(editors)

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of
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Krassimir Markov, Vitalii Velychko, Oleksy Voloshin (ed.)

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A GRAPH MODEL OF SHOCKED FINANCIAL SYSTEM

Velina Slavova, Lyubomir Mirchev, Hristian Elefteridis

Abstract: We applied mathematical modeling in order to understand the behavior of the banking system as a network infrastructure. Based on graph modeling, we developed program modules for simulating the propagation of a financial shock over a system of interconnected banks. The simulation imitates a wave of contagion of the banking system, which is generated as a random graph. In order to analyze the behavior of the system in general, we perform a multiple generation of random graphs and consider the obtained mean values. We analyze the influence of a set of input economic parameters with regards of the properties of the banking system as a "critical infrastructure". We used different subordination models of the graph structure, with regards of contemporary financial theories and taking into account recent documents of the European financial commissions. The results of the simulations permit to do important recommendations concerning the methods for protecting and optimizing the banking system.

ACM Classification Keywords: I.6.5: Model Development, I.6.6: Simulation Output Analysis. G.2.2 Graph Theory, G.2.3 Applications

INTRODUCTION

The recent global experience highlights the need to monitor systemic risks arising from both the macroeconomic developments in the economy and from the global financial markets. This requires new concepts, methodologies and models for financial system transformation and network crisis management. We applied mathematical modeling in order to understand the behavior of the banking system as a network infrastructure.

The mathematical formalism in this work is based on graphs. The nodes are banks and the edges imitate the interbank connections. We did four main successive steps in our approach. The first was to elaborate algorithms running on the graph in order to adjust the model from the point of view of its economic parameters and to simulate the behavior of banks system when it is submitted to an external economic shock. The second step was to include in the system additional processes in order to better imitate some particularities of the financial market in situation of crises. The third step was to adjust the structure of the underlying graph as self-organized dynamical system. On this bases, we propose possible ways to protect the system, namely to limit the propagation of the shock. We performed computer simulations of the proposed measures of protection. The rest of this paper is organized following these main steps.

Underlying economical calculus: We build a random graph with a chosen number N of nodes (banks) which have lent to one another with probability of p . The probability p expresses an important economic parameter - the connectivity of the banking system. So, p_{ij} is the probability that bank i has lent to bank j . The existence of an interbank borrowing from bank i to bank j is expressed by means of an edge between these two banks (the graph is oriented). The generation of the graph is performed using a simple random selection of Z edges from the full set of $N*(N-1)$ edges of the corresponding complete graph. $Z = N*(N-1)*p$, where p varies from 0 to 100%.

We construct the graph of a hypothetical banking system by using the following **inputs**:

N – number of banks;

p – probability of connection;

E – total external assets of the banking system;

E/A – percentage of system's external assets to system's total assets;

c/a – percentage of bank's capital to total bank's assets.

Each node is generated with its initial balance¹, following a step-by step repartition of the actives and passives of the entire system. In big, the parameters of the balances - capital, assets and deposits are calculated depending on the number of connections that each node has obtained after the generation of the graph. More precisely, the banks balance sheets are calculated by starting with the external assets of the banking system as a whole (E). Having the formula for the total assets $A = E + I$, where I is the total interbank assets in the system and having E and E/A as an input, we find A and I : $A = E / (E/A)$ and $I = A - E$. Knowing the total size of the interbank exposures, the **weight w of each edge** is found by dividing I to the total number of edges: $w = I / Z$.

From there we find the individual bank's interbank assets and borrowings by multiplying w to the number of outgoing and incoming connections to each node (bank) in the graph. We denote the individual bank assets by a . So: $a_i = e_i + i_i$, where e are the external assets i.e. loans and other investments to non-bank counterparties, and i denotes the interbank assets, i.e. exposures to other banks in the system. On the other side of the balance sheet we have the liabilities, denoted by l , so $l_i = c_i + d_i + b_i$, where c_i is the capital of bank i , d_i are the deposits (from non-bank customers) of bank i , and b_i denotes the borrowings (from other banks) of bank i . As every balance sheet, $a_i = l_i$. The algorithm which calculates these bank-balance parameters has one iterative loop for distributing the "rests of the total money" after this first distribution.

The interbank assets i of one bank are the borrowings b of another – these linkages are used as a **shock transmitting channel**.

THE MODEL OF THE SHOCK

We simulate a propagation of damages over the nodes of the graph. The edges are channels of transmission. We concenter that the initial shock S arises in the economic environment, and, being external for the system, it affects the external assets e of a bank. The size of the shock S is a chosen percentage of the external assets of the initially shocked bank. In the proposed simulation, when a bank receives a damage s_i , its capital c_i is the first to absorb the losses (figure 1).

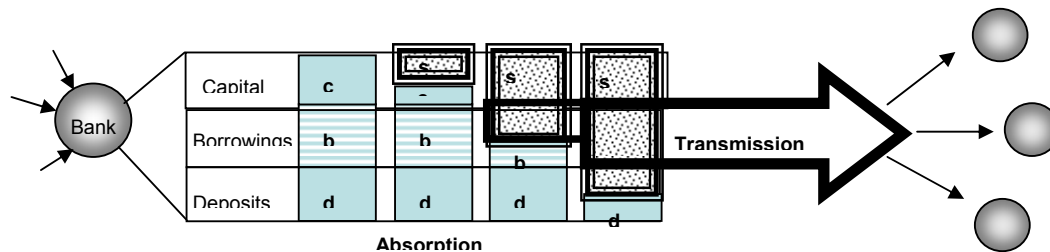


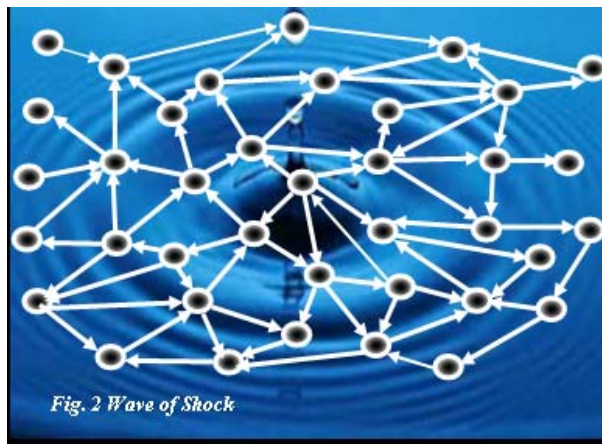
Figure 1. Shock absorption and transmission.

If the damage is greater than the bank's capital, then the bank is in failure. The borrowings b_i are the next to absorb the losses, thus the shock is transmitted to the net. The damage is then transmitted to the network, harming the neighbor bank-nodes. So, in the process of propagation we distinguish two states of a bank – "touched bank", when the bank settles down its capital, but resists the shock and "bank – transmitter", when the bank has lost its capital and the damage has touched its borrowings from other banks. If the losses exceed the borrowings b_i , then the clients' deposits d_i are damaged. We called that third possible state of a node a "dead bank". The economic theory does not take into account the damages received by the deposits (the non-bank clients) and our analyses is not centered on the harmed deposits.

As illustrated on figure 1, the initial shock absorber of the damage S is the capital c , the transition of the damage to the system is via the borrowings b and the final shock absorber of the damage are the deposits d .

¹ The precise procedure is described in Mirchev, Slavova, Elefteridis 2010.

The damage, transmitted to each of the bank-borrowers depends on the weight w of the connecting edge. In the model, the edges have the same weight and we distribute the unabsorbed damage equally on each outgoing edge. The attained banks receive the damage in the same way – they decrease their capital, further they lose their borrowings and become transmitters of the contagion wave. The process of propagation goes on until there are not more touched banks (the shock is absorbed by the system).



One may do an analogy with the propagation of a wave in a fluid as it is illustrated on fig. 2. Each node has two functions: 1. the bank is an *absorber* of damages by means of its capital and 2. the bank is a *transmitter* of the shock after the threshold of its capital is reached. The number of edges included in the process has also a double function. The distribution of the damage over the outgoing edges diminishes the fractions of damage and increases the number of touched banks (*diversification*). There is one more phenomenon which deserves our attention: the nodes stock the incoming damages via its entering edges. A given bank can initially resist the damage by absorbing it, but after some time can 'brake down' as the propagation of damages has reached it several times via different paths (note also that the graph has cycles). We called this phenomenon a *gradual exhausting*. It causes a postponed rising of the number of failed banks.

The output that we register is the number of failed banks (bank defaults).

The simulation of the system's behavior is done by means of measuring the output when varying the values of the input parameters.

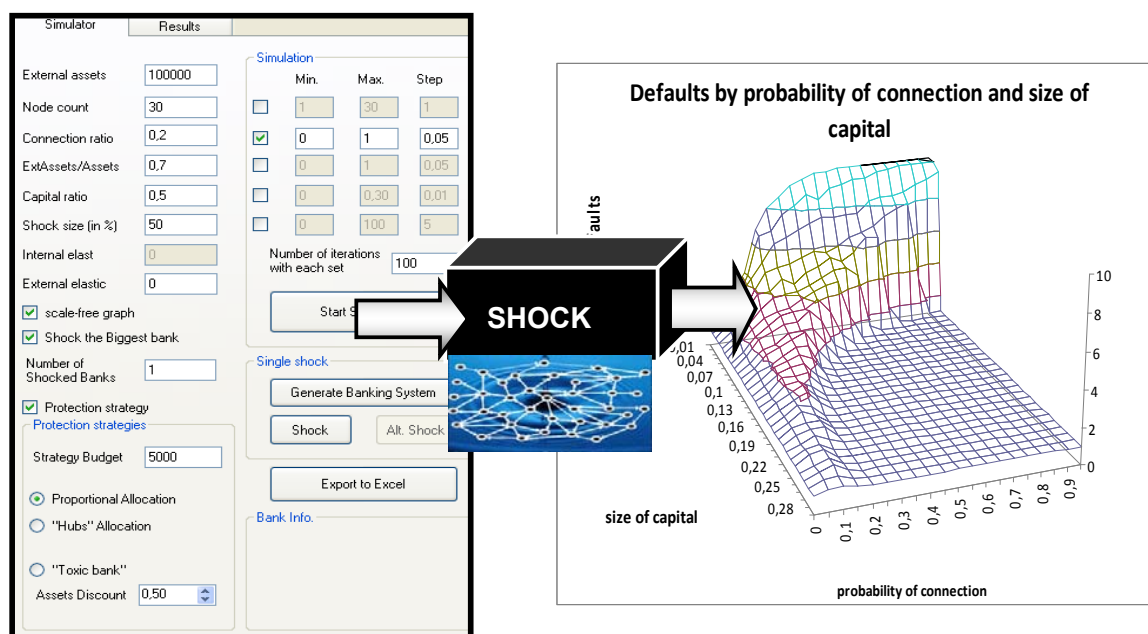


Figure 3. Simulation architecture

The influence of each input parameter is examined separately, by increasing gradually its value in small successive steps, when the other parameters stayed fixed (Figure 3.). For each value of the examined parameter,

we performed multiple generations of random graphs (we performed 100 generation per step), we run the simulation of the shock and we calculated on the bases of the received 100 outputs the *average* of the number of failed banks. The programs are realized in Visual C#. The outputs, transferred in MS Excel tables, are used as source for the graphics and the further analyses of the system's behavior.

We conceived, implemented and tested several algorithms, realizing the described above process, called "Wave". The accuracy tests were performed by checking the total bank balances of the entire system before and after the wave of shock (see table 1). Each point of the graphic-examples given further is obtained after 100 runs of "Wave" on random graphs. That has required a special attention to the complexity of the used algorithms and especially of the one which calculates the propagation of the shock.

ANALYSES OF THE RESULTS

The described algorithms and simulation method were used for the initial evaluation of the systems behavior. The interface and the outputs of the simulation are given on figure 4 and figure 6 respectively.

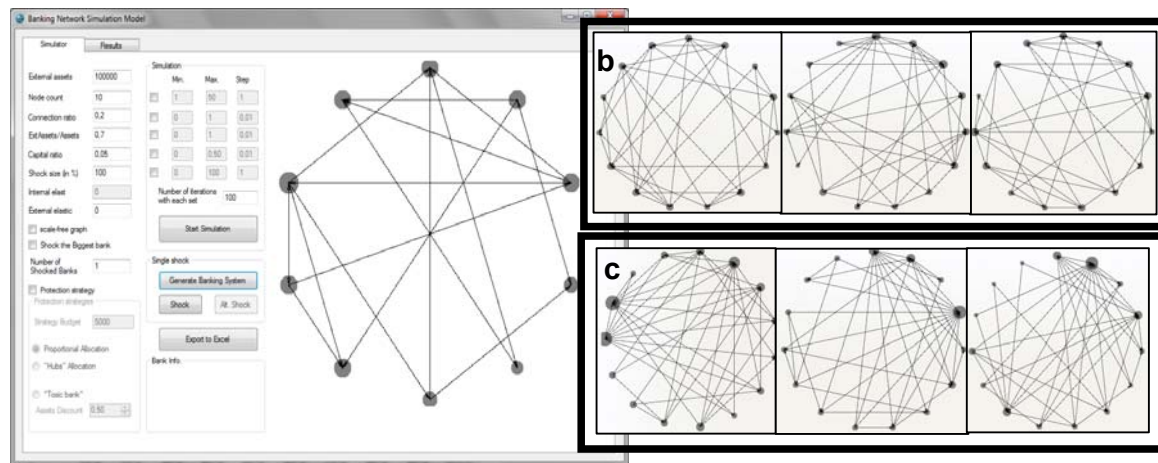


Figure 4. – Simulation model interface – written on Microsoft Visual C# Express; b) Examples of three random graphs with 15 nodes and connection ratio $p=20\%$; c) Examples of three scale-free graphs, connection ratio $p=20\%$.

From the point of view of the analogy with a fluid system that we made, the connection ratio p is a parameter with a crucial importance. In order to check the processes that we have supposed existing in such system, we give the example of analyses of the influence of the connection ratio from a more formal point of view. The results of simulation are shown on figure 5. The simulation is made for values of p between 0% and 100% - from a disintegrated system to a completely connected system. When the system is disintegrated, only the initially shocked bank defaults. With the rise of connectivity, the number of failed banks increases till a certain point of deterioration. In the interval where the connectivity is very poor, the graphics rises quickly as the damages are distributed in big fractions and the contaminated banks immediately fail harming the deposits. In this case, to suppress the wave of shock, the system utilizes also its second shock absorber.

With the further rise of connectivity, the portions of damage transmitted to the “neighbors” decreases and the number of banks which succeed to cushion the shock rises. That corresponds to the flattened part of the graphics on fig. 5. The effect of gradual exhausting is clearly observable on the graphics, expressed by the second rise of the curve. In fact, with the rise of connectivity, the damages distributed to each of the neighbors decrease and the deposits are less utilized as shock absorbers. The pathways of the contagion wave become longer and start crossing the same nodes several times. So, after a number of “attacks”, all these banks “give up” and fail “en bloque”.

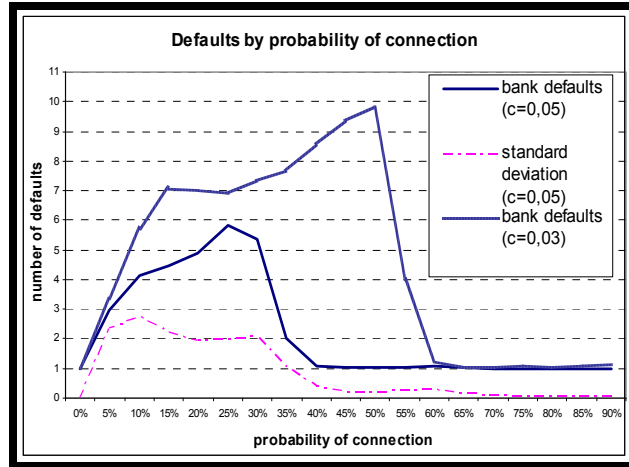


Fig.5. Number of defaults depending on the graph connectivity

After some degree of connectivity, the distribution of the shock becomes big enough to produce fractions which are absorbed immediately from the touched banks. That corresponds to the saturation point of the graphics. The positioning of the point of saturation depends on the capital – the first shock absorber. A system with less capital (on the graphics $c=0,03$) needs more connections to absorb the shock. That is illustrates also on figure 6.d.

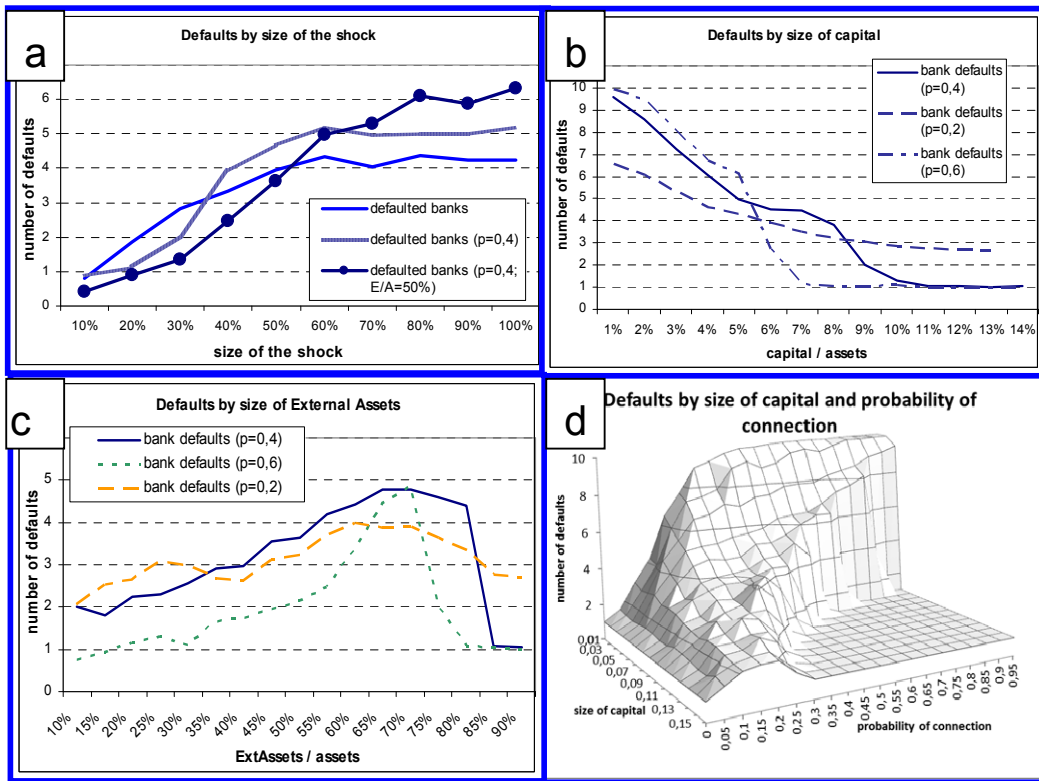


Figure 6. Outputs of the Simulation. Graphics - failed banks depending on a) the size of the shock; b) the size of the system’s capital ; c) the external assets; d) the connection ratio and the capital

The economic interpretation of the influence of the input parameters is deeply discussed in Mirchev, Slavova Elefteridis 2010. Here we provide an example - the analyses of the influence of the size of the shock (fig. 6.a).

While increasing the size of the shock (fig 5.a), the extent of contagion also increases to a certain point where the shock is distributed to enough banks and can be absorbed. This mechanism depends on the level of bank interconnectedness. In more connected banking system the contagion effect is greater. Nevertheless, the contagion pattern is different: while the shock is relatively small, the more connected network is absorbing the shock better as it is distributing small fractions of the shock to many neighbors. After certain point the effect of contagion prevails over the effect of diversification and the contagion sequence rolls over. After a certain point of saturation the increase in the size of the shock is not provoking additional failures because the shock is distributed to sufficiently many nodes in the system.

The simulation model developed using graphs and algorithms for economic parameters calculation and the propagation wave of the shock in the banking system show an adequate behavior in the sense that the simulation results are easily explicable in terms of parameters and financial and economic dependencies. The model reveals that the stability of the system depends not only on the individual bank's stability, but also on the intensity and the size of interbank connections i.e. how integrated the banking market is.

The system's behavior will be different if its resistance decreases during the wave propagation because of the fact that the absorbers are weaken. And, if the shock touches more nodes, the wave propagation will be changed. In fact, that is a more realistic model of the financial system.

FINANCIAL MARKET REALITIES - WEAKEN ABSORBERS AND MASSIVE SHOCK

Further, instead of the initially modeled perfect market liquidity, we introduced the liquidity effect described by the elasticity of the assets' price to the assets sales and the **mark-to-market accounting** effect to the banks' balance sheet accounts. That financial phenomenon is like a progressive decrease the resistance of the shock absorbers, as it decreases the power of their capital. The assets price is decreasing with the same proportion as the assets sold on the market compared to the total assets in the system. We introduced coefficient '*elasticity*', affecting the magnitude of the liquidity effect. Value 0 means no liquidity effect or perfectly inelastic asset price (perfect liquidity), and 1 means full liquidity effect or unitary elasticity of the asset price.

$$\% \text{ of change in assets price} = 1 - \text{elasticity} * (a_{\text{sold}} / A)$$

Banks' assets are re-evaluated on each simulation cycle with the current assets market price. When a bank defaults it sells all its remaining assets and exerts pressure on the assets prices.

In parallel with that the balance sheets of all other remaining banks are revaluated and the amount of assets is decreased in accordance with the new prices. The effect of the mark-to-market accounting principle is that is weakening all the banks. A kind of additional shock cumulates over the balance sheet. As it was supposed, the contagion profile with mark-to-market accounting resembles to a contagion profile of less capitalized banking system (fig 7.).

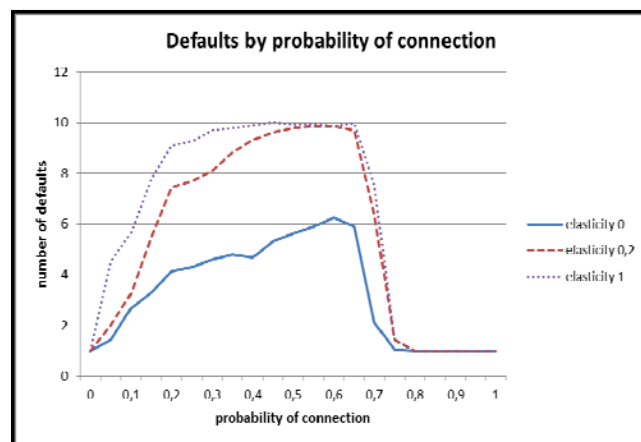


Figure 7. Defaults by connection ratio and liquidity effect

As the plots of the simulation conform (figure 8.), the system loses resistance. With the same level of initial shock the banking system needs more capital to withstand the contagion. The detailed economic analysis of the liquidity effect is given in Mirchev et al 2010.

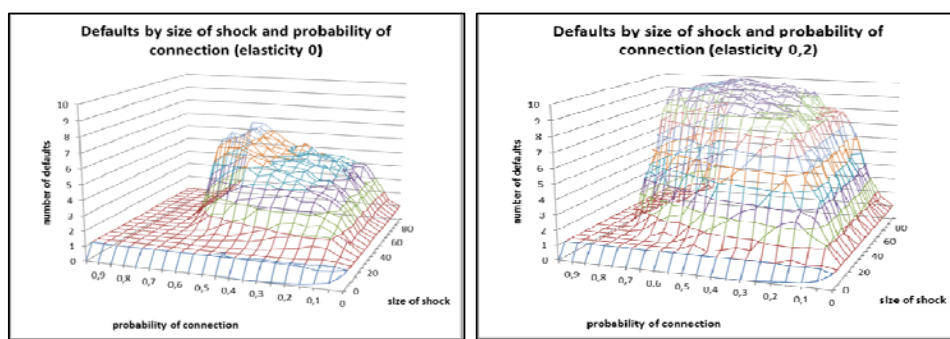


Figure 8. Influence of the liquidity effect – less resistant system.

Most of the external shocks would affect several or all banks simultaneously. We introduced the ability to shock several banks at the beginning of the simulation. The contagion profile shows how vulnerable and fragile a banking system is (fig. 9.). When increasing the number of initially shocked banks the contagion effect is stronger (wider contagion area).

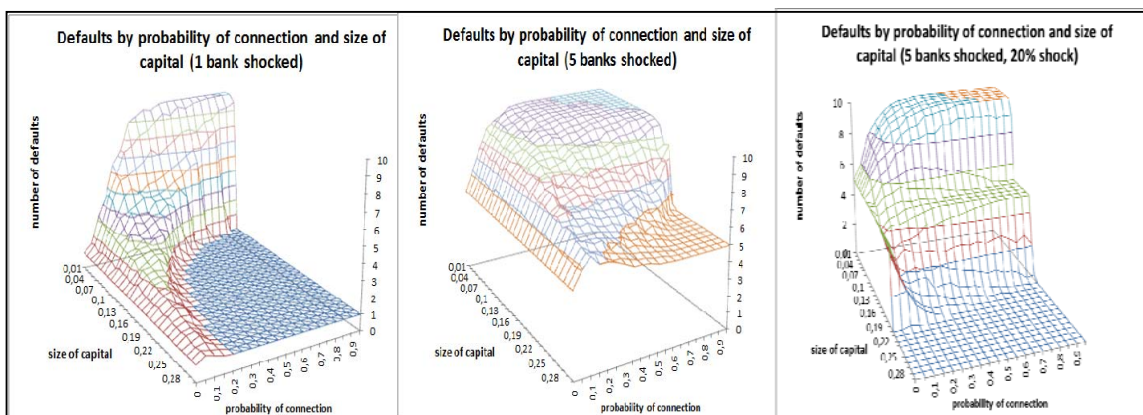


Figure 9. Influence of the Massive chock a) one bank b) 5 banks; c) 5 banks 20% of shock

We conducted similar simulations, but this time maintaining relatively identical size of the shock in the different scenarios i.e. increasing the number of initially shocked banks while decreasing the shock size for each bank (figure 9.c). A slight increase in the contagion area is observable, it is due to the fact that the initial shock is spread to more banks and thus the number of “powerful” contagion channels increases. We can see a slight increase in the contagion area (fig. 9.c.) due to the fact that the initial shock is spread to more banks and thus we have more contagion channels. By further increasing the number of initially shocked banks, the relative size of the shock for each bank is getting smaller and we see a new three staged contagion profile. First, when the banks have lower capital shock absorbers, the contagion effect works and we have high number of defaults. At some point by increasing the banks’ capital the effect of diversification starts prevailing and the number of defaults is limited only to the initially shocked banks. By further increasing the capital level, having in mind that with high number of initially shocked banks the size of the shock is relatively small, the banks are getting able to withstand the shock and the system scores no defaults.

The influence of the liquidity effect when the shock touches several banks can be previewed as gradually weakening the system in addition of the massive shock. That is the worse situation, as the two factors harm the system's resistance (see figure 10). Several simulations of different scenarios are performed using the possibility to vary the input values and the results are analyzed from the economic point of view in details in Mirchev, Slavova Elefteridis, 2010.

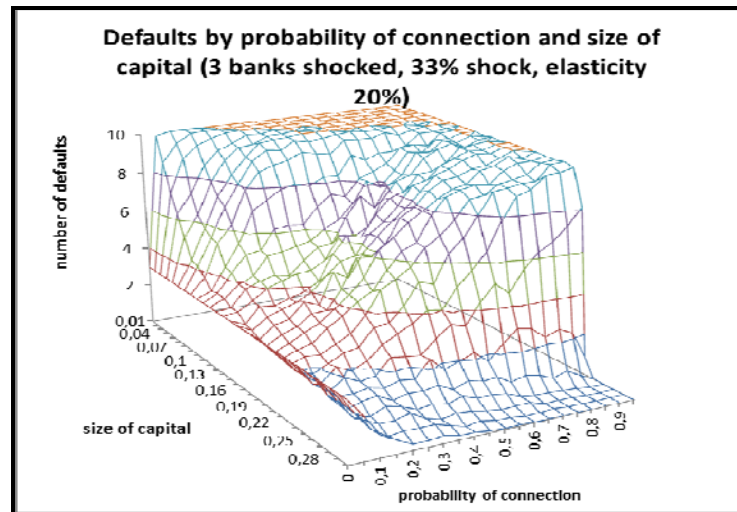


Figure 10. Realistic situation – massive shock + liquidity effect

The simulations gave the possibility to figure out possible strategies to protect the banking system. That was done with regards of the existing modern tendencies in the economic theories and taking into account the recent documents of the European Union. At EU level for *critical infrastructures* have been adopted stock exchanges and settlement systems. Considering the importance of the banking market (which dominates over other sectors of the financial market in the EU), we suggest its consideration as a separate critical infrastructure (social networking infrastructure). It is the economic infrastructure connecting the market participants in the economy and facilitating the processes of financial resources transformation. That assumption has necessitated modifying the underlying graph.

NEW TOPOLOGY AND PROTECTION STRATEGIES

Until recently, the banking system was considered as a set of financial institutions competing in a specific market – the banking market. In this respect, their role was not considered different from any other market player on the financial and non-financial markets. When a bank fails, the law provides protection to the creditors and in most cases to those entrusted their money to the banks - the depositors. But the crisis has shown us that the disturbance occurred in the financial market is rapidly transmitted to the rest of the economy. All the entities, relying on the banks services for conducting their businesses, are also affected adversely. The social function of the banks comes into focus - their role as financial intermediaries in the economy.

A model for analyzing and strengthening the stability of the banking market, considered as critical infrastructure would include the following steps:

1. Mapping the real topography (banks inter-connectivity) of the banking network.
2. Identification of the hubs in the system – the supervisory efforts could be focused to these nodes depending on their importance.
3. Assessing the extent of the threat / possible damage, which a hub brings to the system. The risk depends on the hub's size and connectivity with other hubs and nodes in the network. This evaluation is performed through simulations or analysis through the development of a "fault-tree" for spreading the initial shock.
4. Budget analysis – determines the optimum allocation of resources. Possible tool is the "network-wide investment" - after assessing the possible negative effects of each hub in the system, the investments

are allocated in such a way that minimizes the overall negative effect. Priority is given to the most important hubs, which have the greatest impact on the network stability.

Many communication and social networks have power-law link distributions, containing a few nodes which have a very high degree and many with low degree. The high connectivity nodes play the important role of hubs in communication and networking, a fact which can be exploited when designing efficient protecting algorithms. The presence of self-organized criticality in social networks is often evidenced by a power-law scaling of event size distributions, which can be measured by linear regression on logarithmic axes. The power-law scaling can also be induced by the stochastic nature of the social phenomena.

Financial markets are largely integrated, but the institutions responsible for their supervision and safeguarding the financial stability remain divided along the national lines. Studies on the stability of financial systems (Allen 2000, Nier 2008) used the assumption that the participants are equal, and the distribution of links is a random. Studies on social networks (as are the banking/financial markets) show that their structure is more complex (Lewis, 2009) and have the characteristics of scale-free networks and small-world networks.

Scale-free networks (fig. 10.b) are networks whose degree distribution follows a **power law** - probability of a node to make connection to other depends on the number of connections, which it owns. The radius of the network - the number of edges between the two most distant nodes, is relatively small. They are clustered - some nodes called "hubs" have much more connections than others. Hubs in the banking system are the systematically important banks.

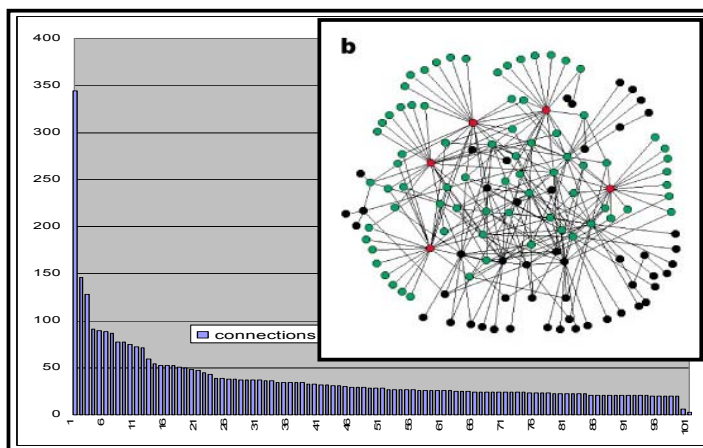


Fig 10. A scale-free graph (b) and the distribution of its connections

We implemented the Barabási–Albert algorithm for generating random scale-free network using a preferential attachment mechanism (nodes with higher degree have stronger ability to grab a connection). Examples of generated scale-free graphs are given on figure 4.c. The plot of the distribution of the number of connections of our generated graph is given on figure 10.a.

The simulation showed that the scale-free banking system is prone to stronger contagion effect and the number of defaults rises sharply due to the presence of hubs (figure 11). It is important to note that for the scale-free system, while increasing the interconnectedness of the system, the defaults are dropping rapidly in comparison with the random network. .

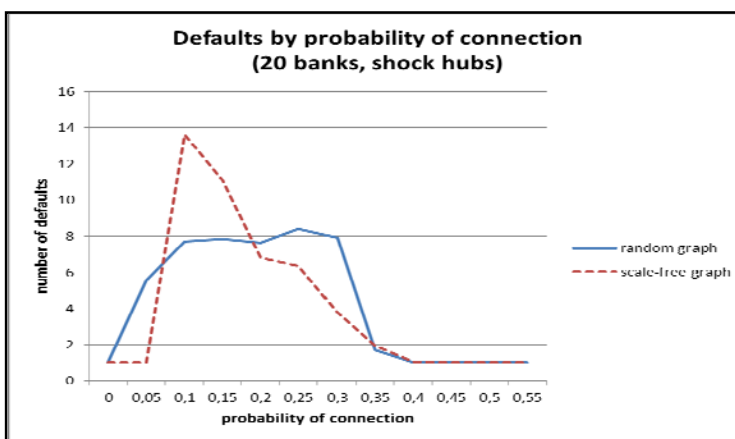


Figure 11. Behavior of the scale-free network (---) and the random (___)

The assumption that the system has a scale-free underlying graph allowed the construction of a fundamentally new type of model for simulating the measures ensuring stability and efficiency of the banking market

For applying such model there could be implemented and refined few basic principles (Lewis, 2006) with the following interpretation:

Principle 1: You need a network to fight a network. This principle applied to the banking system may have the following two meanings:

(1) Systemic instability in the banking market has a network nature, so the means to oppose it should have a network character (a network of national supervisors - ESFS).

(2) Due to the size of European and international banking market only network approach would be effective. It is not economically feasible to protect every link in the system. European Commission studies show that the national Deposit Guarantee Schemes in the EU would not withstand the shock if several hubs (large, systemically important banks) fail.

Principle 2: Protect the hubs, not the connections. This principle is directly related to the preceding because the banking market is built on a network basis. Hubs are critical points, therefore they must be protected. Considering the scarcity of resources and the fact that such a network could be enormous in size, it is not possible to protect each node of the system, so efforts should be focused on the critical points.

Principle 3: Invest 80/20. The capital in the banking system is not equally allocated. One could say that the majority of the assets in the banking system are held by a small number of banks. This suggests that the 80/20 rule could be applied, i.e. 80% of resources should be invested in 20% of the units (which are critical to the system).

Principle 4: Asymmetric thinking. Innovation in the financial sector often is used as a way to avoid certain regulations. In this regard, regulatory approaches must evolve, and adapt to the market situation, and anticipate and manage the development of the system.

Principle 5: Dual purpose solutions. The scarcity of government resources raises the question for stakeholders' involvement in the process of seeking solutions for improving the stability of the banking system. Example, the establishment of joint entities for electronic or cash payments, creation of shock absorber funds and other initiatives with purely private capital, would increase the stability of the system, but would also help to improve its efficiency. Thus resources optimization could be achieved.

Taking into account these principles, we introduced in the simulation model **three protection strategies**:

The first consists of proportional allocation of bail-out funds to the banks. This strategy resembles to a theoretical government bail-out program where the banks' capital is increased. The result of its simulation is on figure 12.b.

The second one is a derivate of the first, but the bail-out funds are allocated only the biggest banks (the hubs). The result of its simulation is on figure 12.c.

The third strategy is called "toxic bank" and resembles to a theoretical government bail-out program, where there is a special institution buying the troubled assets from the banks while applying certain discount ratio. For better comparison we are using identical budget amount for all strategies. The result of its simulation is on figure 12.d.

We can see that the different strategies affect the contagion profile in a different aspect. The "proportional allocation" strategy reduces significantly the number of defaulted banks when the shock to the initial bank is moderate. The "hubs allocation" strategy gives overall lower number of defaulted banks. Nevertheless, this strategy is more effective when we have a full-scale shock. The "toxic bank" strategy turns out to be the most effective. It gives the lowest number of defaulted banks, independently of the shock size, because this strategy is the most flexible – the funds are allocated on a case-by-case basis covering only the troubled banks. Depending on the regulators or government's policy and the budget limits, a different discount ratio could be applied while buying toxic assets from the banks. Irrespective to their effectiveness and characteristics, all the strategies are bound with the same budget limits and when the shock gets enough big they cannot save system entirely. If the

funds limit is not sufficient to cope with the shock scale, these strategies can only postpone the system breakdown and give enough time for the economists and politicians to engage in more serious reforms.

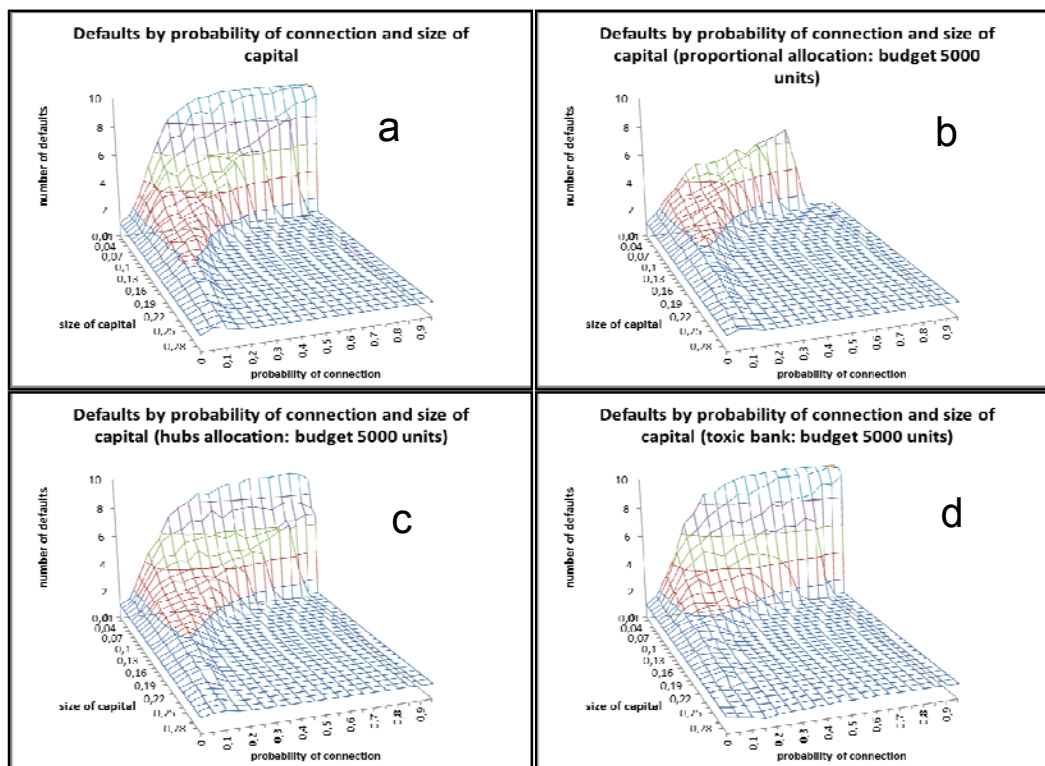


Figure 12. The non-protected system (a) and the system, protected with different strategies (b-d)

Looking at the overall contagion profiles of the different strategies, we can notice that the “proportional allocation” strategy is more effective when the system is significantly undercapitalized. This is due to the fact that the strategy increases directly the capital base of the banks in the system. The “toxic bank” strategy is more effective with moderately capitalized banks because it reduces the toxic portfolios without affecting their capital.

CONCLUSIONS

The results obtained show that the implementation of the network approach to the banking system offers interesting opportunities for reorganizing its structure and predicting its response in crisis situations. This would contribute to the financial system transformation recommended in 2009 by the European Commission¹, and for the establishment of a new system for European financial regulation and strengthening the cooperation and coordination between national supervisors.

The adoption of the banking system as a high-level economic infrastructure (separate critical infrastructure) allows the development of fundamentally new type of methods for ensuring stability and efficiency.

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Authors' Information



Velina Slavova, professor, New Bulgarian University, Department of Computer Science, vslavova@nbu.bg (She coordinated the work and gave instructions. Also gave some algorithmic ideas and explained the results from a formal point of view. Hates programming, but finally implemented "Wave" just to see how to improve its complexity)



Lyubomir Mirchev, Ph. D. student, University of Nice – Sophia Antipolis, France, University of National and World Economy – Sofia, working at the National Bank of Bulgaria; mirchev@gredeg.cnrs.fr (The main figure. That's his idea, a part of his Ph. D Thesis in finance. Important: he is not bad in programming. He invented the protecting strategies.)



Hristian Elefteridis, B. Sc. Student, New Bulgarian University, Department of Computer Science, hristian4o@nbu.bg (He realized almost all the programs within his diploma work and understood everything in finance. He is too familiar with all these new technologies...)