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Simulation of financial contagion effect using the NetLogo software at the level of the banking network

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Abstract. *The complexity of current financial systems around the world makes it difficult to create indicators that accurately assess the systemic risk of any institution. One of the most important issues that has been highlighted in recent years has been the interconnection of banks in the financial network. This led to an increase in the likelihood of contagion, a scenario in which small shocks, which initially impacted only a part of the institutions in the system, spread across the network. Thus, this paper studies the effects of financial contagion that can be transmitted in a banking network, simulating the spread of this effect with the help of the NetLogo IT solution. In recent years, banking accidents have led to a significant disruption of the financial system around the world. Even the COVID-19 pandemic can represent a systemic shock in the banking network and not only and an ascending evolution of the pandemic will be able to create a financial contagion effect at the level of banking institutions.*

Keywords: financial contagion, NetLogo, banking network.

JEL Classification: G4, G10, G17, G21.

1. Introduction

The economy, defined as a set of economic activities, can be described as a network, having as links companies (banking, non-banking), public entities, non-governmental organizations. Any change in this complex network can generate shocks that are not very visible at the macroeconomic level, but can greatly affect both this level and the microeconomic level.

Attracted by the banking field and the fact that the role of a bank is to mobilize the financial resources of economic market actors (citizens – individuals or legal entities) and direct them to viable, economic areas for the development of their systems and their support, I consider that This research is well chosen in the current context of all microeconomic, climate, environmental, legal and, in particular, social and political changes.

Banking is becoming more and more complex, and that should make us think: do we know everything we need to know about banks and their business? Is it enough to be guided by the bank's staff to make a decision? Could knowing the mechanism of the functioning of this institution provide us with more than just useless information? Do we have enough methods to prevent potential systemic shocks with contagion that can cause economic crises?

In recent years, banking accidents have led to a significant disruption of the financial system around the world. Even the economic crisis of 2008 has shown that we need to better understand financial networks and systemic risk.

The complexity of current financial systems around the world makes it difficult to create indicators that accurately assess the systemic risk of any institution. One of the most important issues that has been highlighted in recent years has been the interconnection of banks in the financial network. This led to an increase in the likelihood of contagion, a scenario in which small shocks, which initially impacted only a part of the institutions in the system, spread across the network.

2. Theoretical framework and previous research

The concept of contagion was first used in 1797, by David Ricardo, a British political economist who attributed this concept to the feeling of panic that led to the suspension of convertibility, the unfounded fears of the timid part of the community.

In 1895, the French sociologist Le Bon wrote that the ideas, emotions, and opinions that fuel the crowd are as powerful as germs. The term contagion was used quite rarely before 1995, after which it appeared occasionally in articles presenting the impact of the Mexican crisis on other Latin American countries.

Taken from medicine as a concept, contagion means the manifestation or transmission of viruses throughout the body, and then, by switching from virus to disease, its transmission to other people.

Only after the crisis in Thailand took place, when the currency was devalued and affected other Asian countries, affecting financial markets globally. These events aroused the interest of researchers so that in the early 2000s began to appear academic papers in order to try to study to measure, understand, predict and prevent international financial contagion.

The study of contagion in financial systems is very current in the context of the global credit crunch and the damage caused by financial institutions. Contagion refers to the spread of defaults through a system of financial institutions, each of which in turn causes increasing pressure on the other components of the system.

The term systemic risk refers to the threat posed by contagion to the financial system as a whole, due to the non-fulfillment of obligations by one (or more) component institutions.

It is considered that financial systems, defined as a collection of banks and financial institutions in a developed country, can be modeled as a random network of nodes or nodes with stylized balance sheets, linked by direct links or margins representing “interbank lending”.

The Swedish Central Bank, being the first central bank in the world to set up a financial stability department and to publish its first financial stability report in 1998, defined financial stability as “the safe and efficient operation of the entire payment system” and considered that the most important pillars that ensure balance are:

- A regulatory framework composed of regulations and decrees, complemented by concrete risk assessment actions and inspections on irregularities of individual institutions.
- Another important pillar is the central bank's timely monitoring of systemic risk.
- Crisis management measures is another important issue. All pillars require the division and cooperation of central banks and supervisory departments.

A first goal is to develop a conceptual, mathematical framework that can determine systemic susceptibility in a rich class of infinite random network models, with sufficient flexibility to include the most important structural features of real financial networks.

The starting point will be the model proposed by Gai and Kapadia (hereinafter referred to as GK) and the analytical methods developed for this model. The basic assumptions introduced in the GK model are:

1) The network is a large (actually infinite) graph randomly oriented with a prescribed degree distribution.
2) Each node is labeled with a stylized bank balance sheet that identifies its external assets and liabilities, its internal assets and liabilities (total interbank) and γ, net worth or equity (total assets minus total liabilities); Initially, the system is in equilibrium, each node has a positive net value.
3) Each targeted edge is labeled with a deterministic weight that represents the positive exposure of one bank to another. These weights are deterministically dependent on the marginal rate and are compatible with interbank assets and liabilities (IB) at each node.

4) A random shock is applied to the system balances that are triggered by default or the insolvency of a fixed fraction of nodes.
5) The residual value available to the creditors of a default bank is zero and therefore the shock has the potential to trigger a cascade of other banking failures.

The literature examines, first of all, how different financial network structures respond to the breakdown of a single bank in order to identify the structures that are more fragile. In the following, information will be presented from the literature of the contagion field. In addition, I will analyze whether network theory can be used to understand how interbank markets can freeze, as they did in the months after August 2007.

The aspect of the literature analyzed measures the role of social networks in investment decisions and in corporate governance, among other areas. Another approach examines how network theory can be used to investigate the investment banking sector.

Multiple connections between banks can reduce the risk of contagion. While the risk of contagion may be higher in the highly interconnected banking system, research shows that shocks can have complex effects. The more complete the set of links between banks, the lower the risk of contagion in the system.

The contagion literature has two approaches: examining direct links and indirect balance sheet links. Looking for contagious effects through direct links, early research by Allen and Gale (2000) studied how the banking system responds to contagion when banks are connected under different network structures.

Allen Franklin and Douglas Gale (2000), in their work "Financial Contagion", state that this concept of contagion is defined by small shocks that affect several institutions or sectors and are then spread throughout the financial sector of the contagion economy.

Gai and Kapadia (2007) develop a model of contagion in financial networks and use similar techniques as the epidemiological literature on the spread of diseases in networks to assess the fragility of the financial system, depending on banks' capital buffers, degree of connectivity, and market liquidity for failed banking assets. As with Allen and Gale, they find that greater connectivity reduces the likelihood of widespread default.

However, shocks can have a significantly greater impact on the financial system when they occur. In addition, the network's resilience to high shocks depends on shocks that attract certain fragile points associated with structural vulnerabilities.

3. Forms of financial contagion in banking

Based on rigorous analysis and how national and global economic systems have behaved in terms of systemic shocks and how economic crises have spread, I will present four concepts of contagion, which Paul Masson (1998) proposes:

- "Monsoon" type contagion: it is given by the instability it creates worldwide, in the context of the explosive development of society and economic-financial globalization.

This form of contagion is transmitted in a complex network of as many countries as possible.

- "Spillover" contagion: it is highlighted when the crisis settles in the economy of a country and then spreads in a complex network of as many countries as possible.
- "Residual" type contagion: for each country there is one or more departments of specialists that deal with the forecast of the economic situation and give a residual value to the analysis and testing methodologies observed in the correlation matrix between a country's economy and other countries or even the global economy. The changes that exceed this level of prognosis that specialists give and affect a complex network of countries, taking into account the residual valuation, give the name of this type of contagion.
- Contagion related to "volatility": it is usually found on the capital market when the amplitude of volatility is transmitted from one capital market to another, highlighting the investment risk.

4. Study case

The research in this paper starts from the bases of the contagion model proposed by Gai and Kapadia regarding financial networks. The model highlights the spillover contagion, the one in which one starts from an event generated by a bank and which is subsequently tested as a contagious effect in the entire banking network.

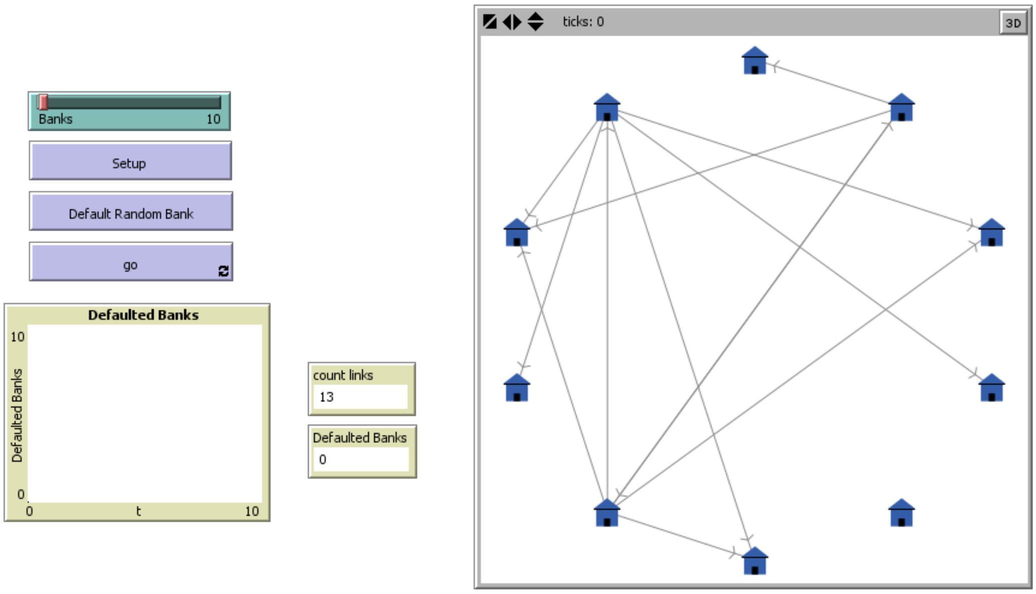
In addition to adapting and processing the model to the situation in Romania, it will also have its own contribution, related to step 3 described below. To demonstrate the dynamics of contagion in this banking network and to observe the regulation and self-regulation of banking institutions in a turbulent environment, I will use the modeling environment offered by the NetLogo 6.0.4 program.

Step 1: Build the model

The model consists of a set of banks that are interconnected through a network of bank and interbank loans. The following figure shows a simple banking network with a set of 10 banks with randomly drawn interconnections, proposed by Gai and Kapadia. The arrows that enter a bank are links, connections and represent the assets owed to the bank by other banks. Arrows coming out of the bank are liabilities due to other banks.

More clearly, according to graph theory, each bank is represented by a node of the graph connected to each other by interbank exposures with other banks.

Figure 1. *Representation of a simple banking network*



Source: http://people.brandeis.edu/~blebaron/classes/agentfin/GaiKapadia.html

Step 2: Description of the model

In modeling contagion based on system dynamics, it is considered that all banks in the network are initially solvent and that the network is disturbed at a time t = 1 by a default state established in a bank.

The basic dynamics of this model is quite easy to understand. When a bank is in default, it spreads a shock to other banks, involving all its obligations. These will become unnecessary and the bank will then be vulnerable itself depending on the state of its balance sheet. The solvency condition is given by the following condition:

$$(1-\delta)C_i^{IB} + c * A_i^M - P_i^{IB} - D_i > 0$$

Where

C_i^{IB} – represents loans that the bank has received from other banks in the interbank market or foreign assets, such as mortgage loans;

A_i^M – is a form of illiquid asset on the balance sheet;

P_i^{IB} – represents the liabilities of the balance sheet containing the obligations towards other banks on the interbank market;

D_i – represents the bank's deposits;

δ – represents the percentage of banks that are in a state of default in the analyzed banking network;

c – represents the resale price of the external asset.

The GK10 model assumes the following input variables to simulate the analyzed model:

$$C_i^{IB} = 0{,}2$$

$A_i^M = 0{,}8$

$P_i^{IB} = \sum_j \alpha_j \text{ , } \alpha_j = \frac{0{,}2}{N_{out}}$

$$D_i = 1 - P_i^{IB} = 1 - \sum_j \alpha_j$$

N_{out} – represents the number of output variables. If there are no input factors, then it means that $C_i^{IB} = 0$ și $A_i^M = 1$.

If there are no output variables, then it is considered that $D_i = 1$.

Step 3: Testing in a dynamic environment, simulating the effect of random spread of a contagion

For this, I will use the Netlogo 6.0.4 library called “Viruses on a network”. This model demonstrates the spread of a virus through a network. Although the model is somewhat abstract, an extrapolation of the interpretation of this model is that each node represents a bank and I will model the progress of a systemic risk through this network to see if it will turn into a financial contagion. Each node can be in one of three states: sensitive, infected or resistant.

According to information from the Netlogo library, in the academic literature, such a model is sometimes called a SIR model for epidemics. The basic model called SIR (Sains, Infectes, Retablis) involves the following:
S – means individuals who are healthy or very unlikely to be infected;
I – means individuals who are infected;
R – means agents that recover and can no longer become infected, assuming in this model that a cured agent is permanently immunized.

Being a dynamic model, the size of each of these populations is obviously variable over time, which can be modeled by a function of the independent variable denoted by t (time). Then, each parameter depends on time: $S(t), I(t)$ *and* $R(t)$. If during the spread of the contagion, the size of the total population is considered constant, then the model can be written mathematically as follows:

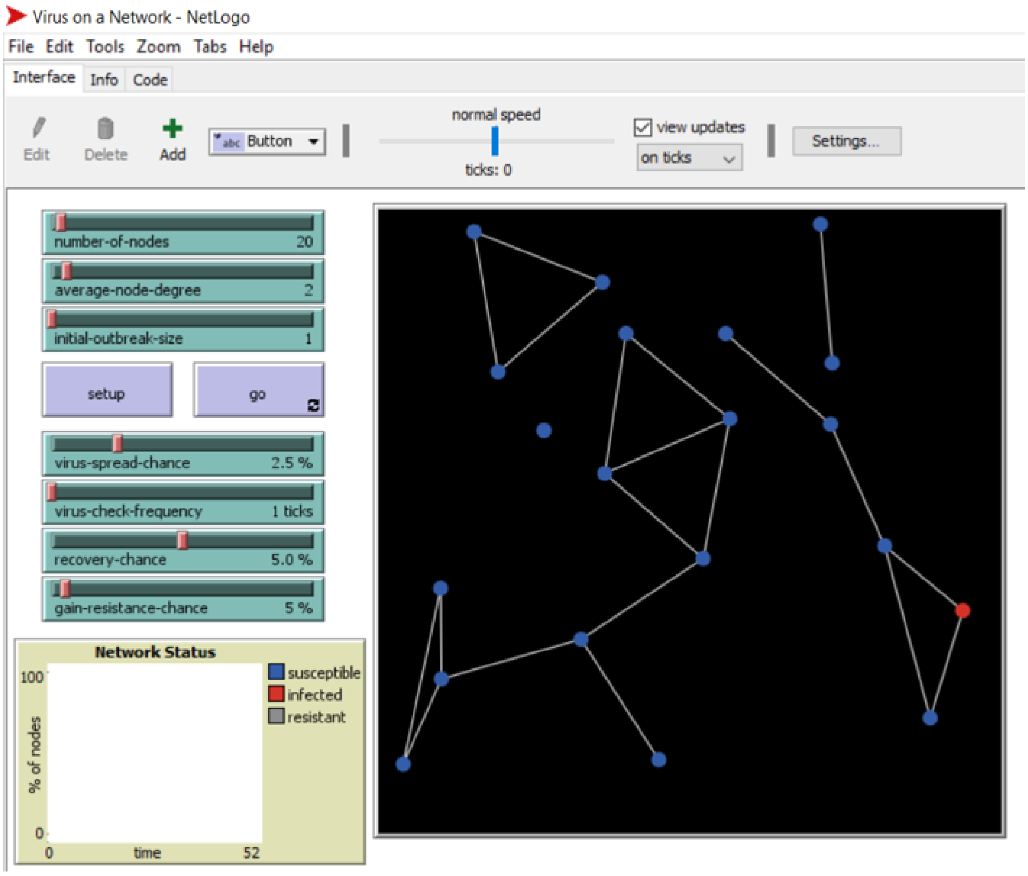
$$S(t) + I(t) + R(t) = P$$

P – represents the total population.

The model will take into account the following scenarios and assumptions:

Scenario 1: I will assume a small degree of connection between banking networks, the average degree of a node will be 2. This scenario I will call the ***optimistic dynamic scenario.***

Figure 2. *Input scenario 1*



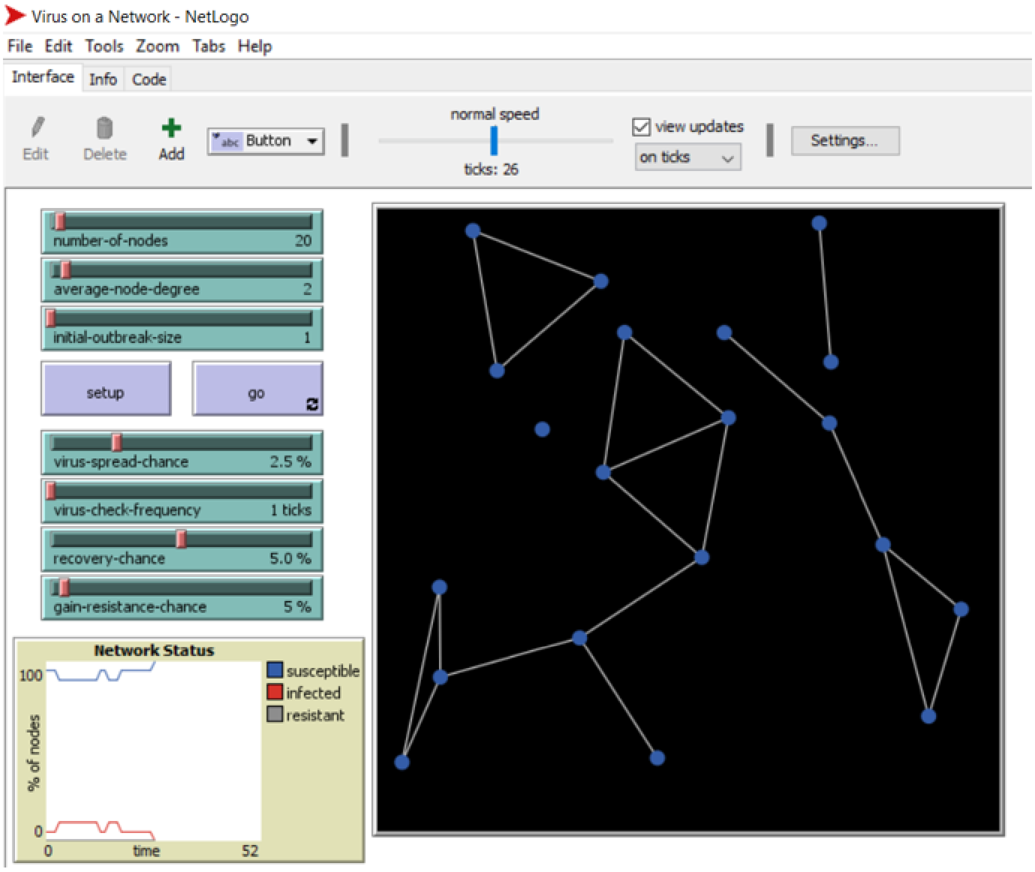
Source: Author processing in Netlogo.

Hypothesis 1:

- The number of initial nodes that will form the network will consist of 20 banking units.
- The number of affected banking units will initially be set to 1.
- The degree of change in the spread of the virus will be set to the probability of 2.5%.
- The frequency of checking the virus will be done at 1 ticks, approximately in real environment by 1 day.
- The rate of adaptability to change will be 5%.
- Resistance to change will be 5%.

As expected, the banking network will not be affected for several reasons. The main reason is related to the structure of the network. It can be seen from the figure above that not all nodes are interconnected, i.e. some financial institutions are not connected to others, so it would not be able to spread the contagion effect to all units. Over time, the infected bank has healed through measures taken by specialists and through the ownership of the cyber system as a complex adaptive system of adaptability, property seen as a way of regulation and self-regulation in this dynamic system.

Figure 3. *Output scenario 1*

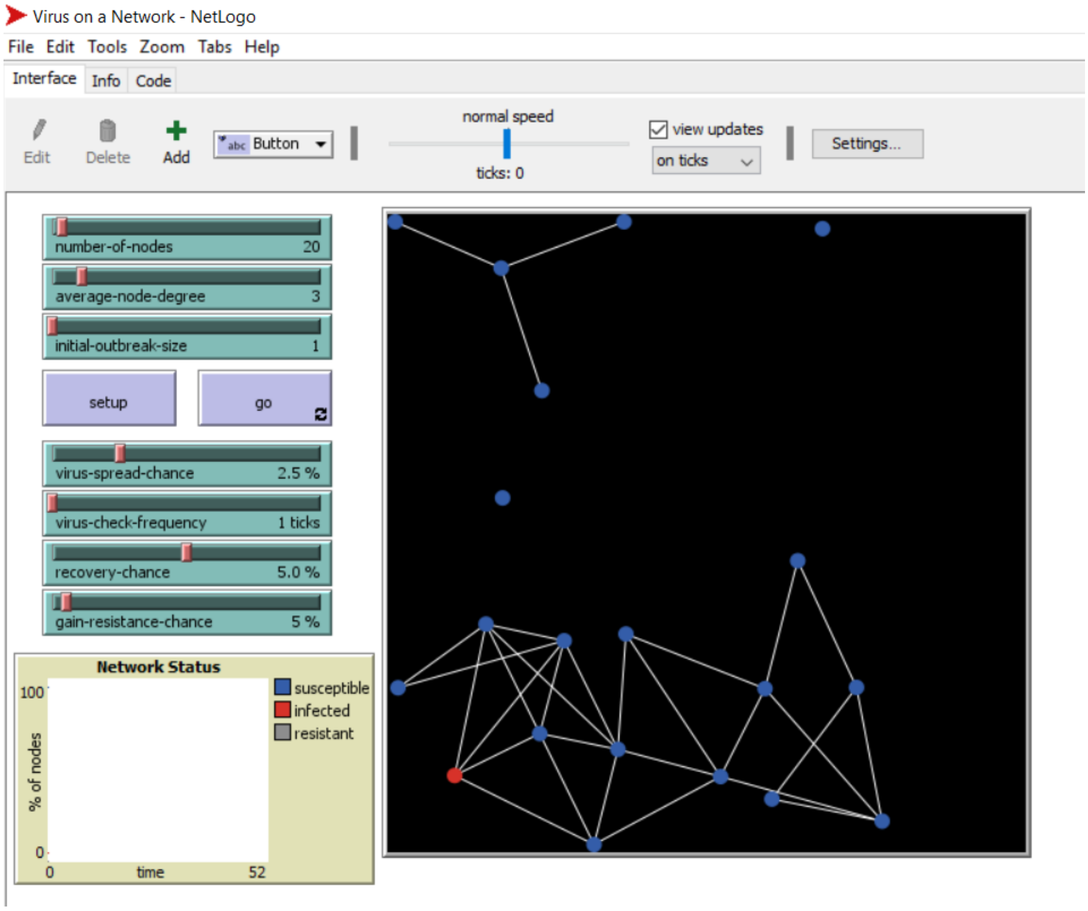


Source: Author processing in Netlogo.

In the figure above you can see how the sensitivity rate of the network, marked in blue in the "Network Status" dial, evolves directly with the infection rate, marked in red in the same dial. Assuming that the frequency of checking for the existence of the virus is equivalent to 1 ticks = 1 day, the dynamic system was simulated in the period of 26 days after which the contagious node healed, according to the figure above.

Scenario 2.1: I will assume a small degree of connection between banking networks, but insignificantly higher than scenario 1, the average degree of a node will be 3. This scenario I will call the ***dynamic test scenario***. The input data of this scenario can be seen in the figure below.

Figure 4. *Input scenario 2*



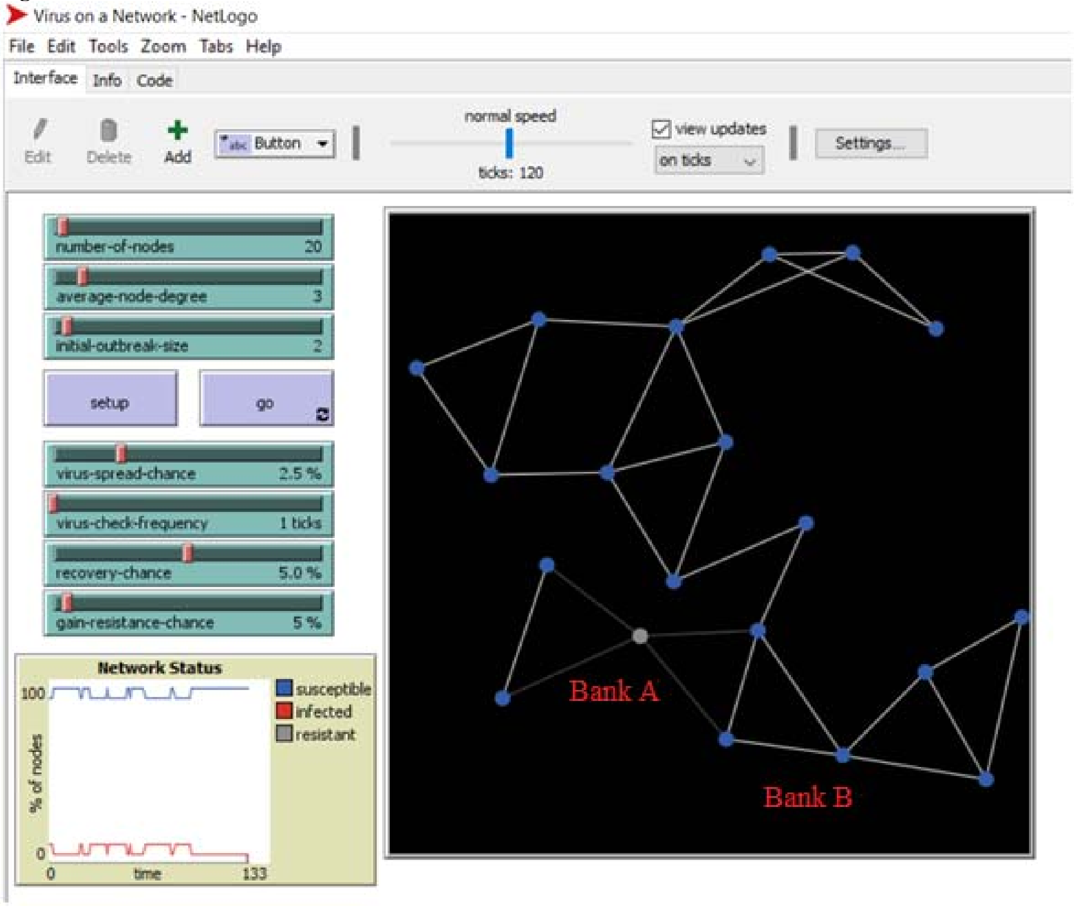
Source: Author processing in Netlogo.

In this case, we can see that not a complex network of all network nodes is formed, even then not all banks are interconnected.

Even if the result was expected to be similar to that of the first scenario, another interesting aspect can be observed that reinforces the importance of studying the contagious effects of an economic network. Although the first scenario has changed very little, there is still an increase in infected agents.

Scenario 2.2: I will assume a small degree of connection between banking networks, but insignificantly higher than scenario 1, the average degree of a node will be 3. In addition, I will infect two banks in the network. I will call this scenario ***the dynamic test scenario, the beta version.***

Figure 4. *Scenario simulation result 2.2*



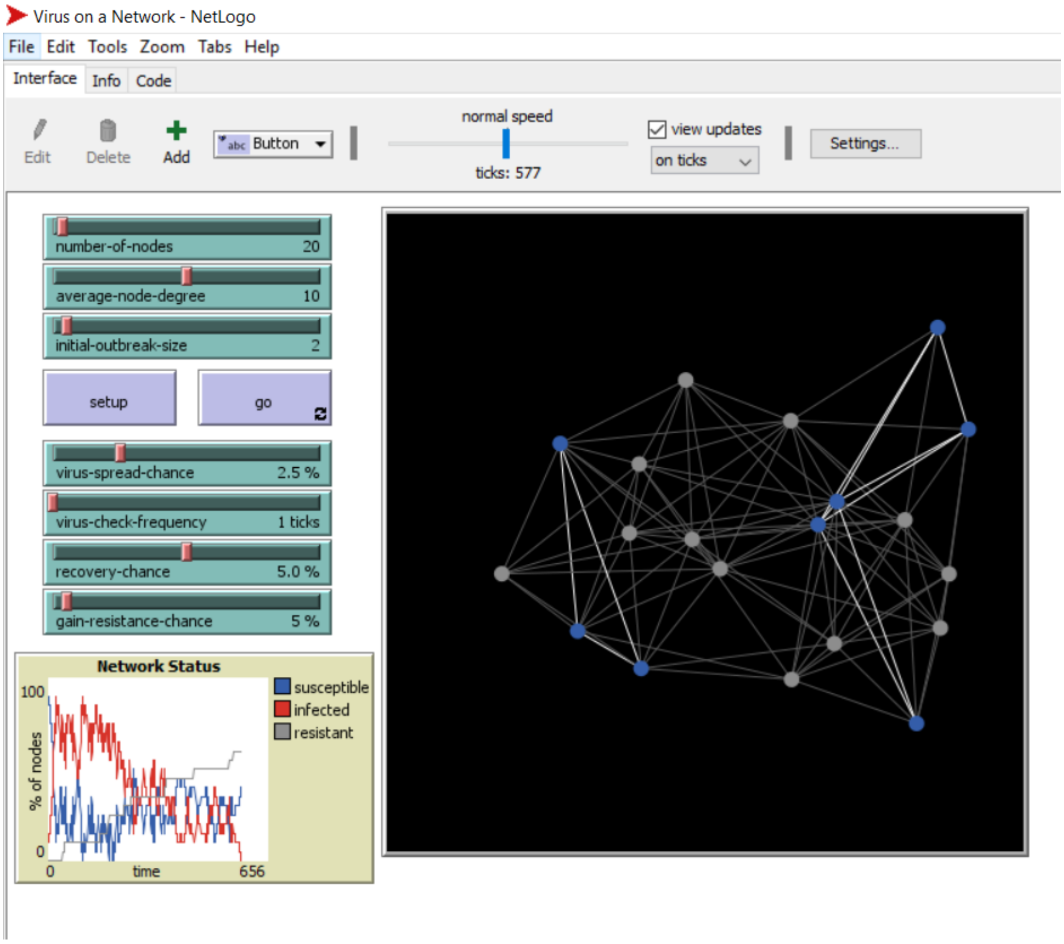
Source: Author processing in Netlogo.

In the figure above, we notice a very interesting aspect. Although Bank A and Bank B were the triggers of systemic risk in the above network, Bank A has become resistant over time to this contagion. This can also be explained in reality because some institutions may identify certain methods of assessing the risks encountered during its life cycle.

Historicity is another property of the complex adaptive system and is evident in the simulation of the model proposed above. We can learn from past experiences and adapt to new conditions and the new environment so that we can find relevant tools in quantifying contagious, systemic events.

Scenario 2.3: I will assume a small degree of connection between banking networks, the average degree of a node will be 10. In addition, I will keep two banks in the network that will be systemic risk triggers. I will call this scenario ***the dynamic test scenario, the gamma version.***

Figure 5. *Scenario simulation result 2.3*

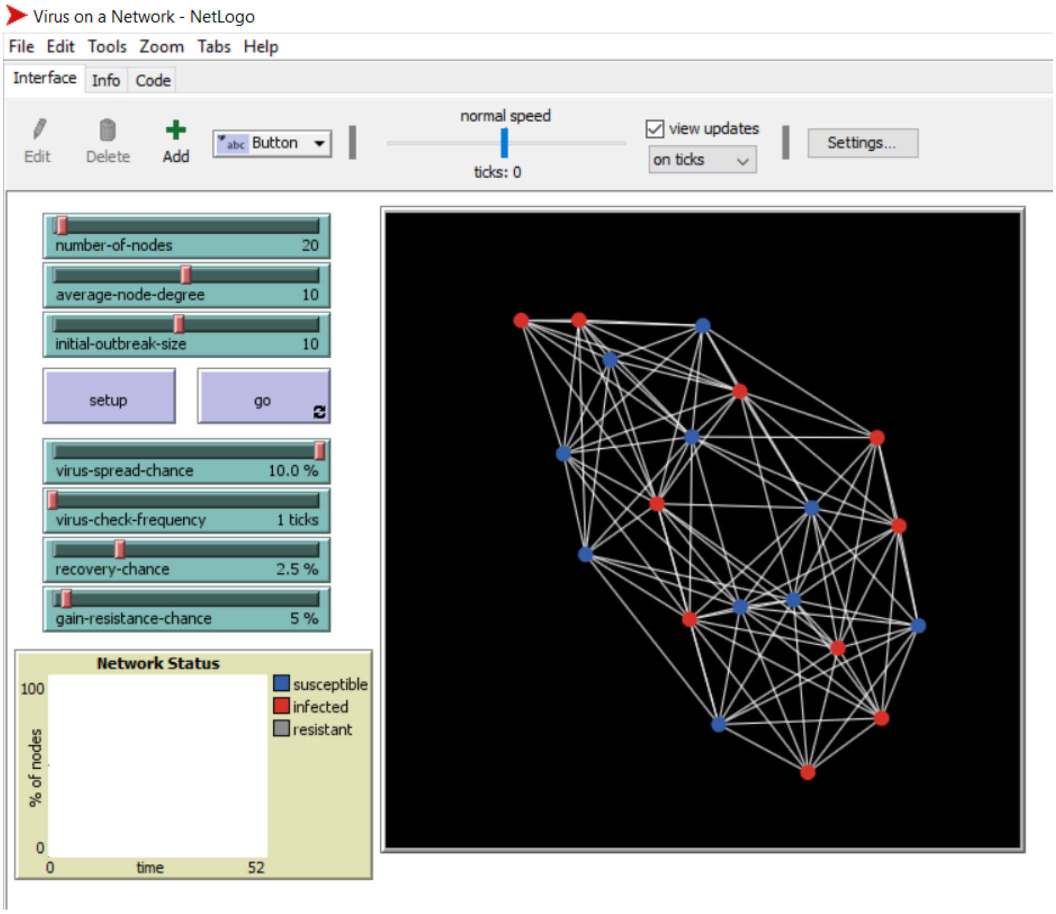


Source: Author processing in Netlogo.

Although there has been an interesting evolution in the way systemic risk has spread in the network, it can be seen that most banks have gained immunity over the shock propagated in the network.

Scenario 3: I will assume a high degree of connection between banking networks, the average degree of a node will be 10. In addition, I will change the banks in the network that will be systemic risk triggers and I will set them with the number 10, half of them. I will call this scenario the pessimistic dynamic scenario. The input data for this scenario can be found in the figure below.

Figure 6. *Scenario simulation input data 3*

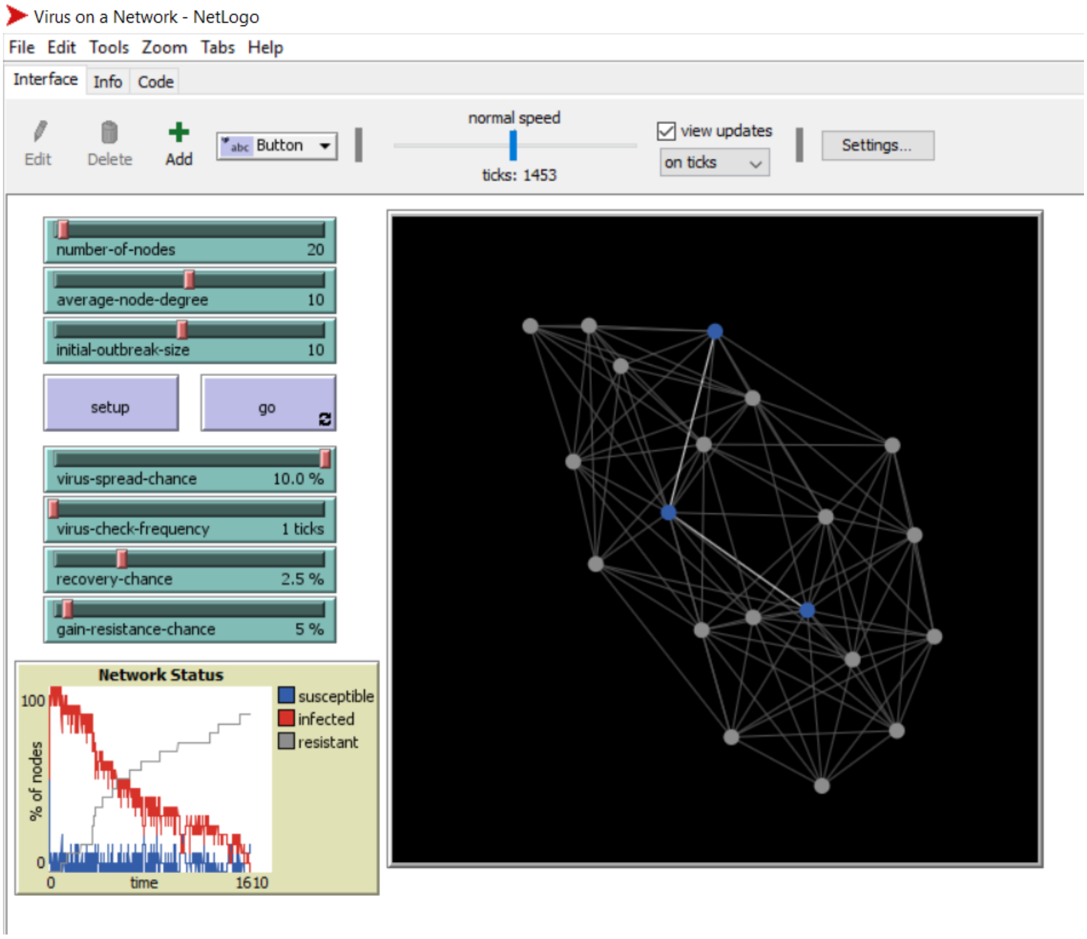


Source: Author processing in Netlogo.

In this scenario, the parameters virus-spread-change = 10% and recovery-change = 2.5% were also modified, as can be seen in the figure above.

The following figure shows the results of the simulated pessimistic dynamic model. Of the 20 banking units, 17 became immune from the contagion and 3 remained susceptible to a new possible systemic risk effect. However, the crisis in the network was removed after about 4 years, according to the simulation.

Figure 7. *Output data simulation scenario 3*



Source: Author processing in Netlogo.

Based on the 3 optimistic, test and pessimistic scenarios I can conclude the following ideas:

- It is stated that small changes in the network can lead to a significant impact, if not the onset of a crisis, to increase the time required to remove the contagious event. In scenario 2.3, a period of approximately 2 years was required to deal with the events propagated in the network.
- Scenario 1, the optimistic one, reinforces the idea of how the nodes in the network are connected, in reality the economic systems (banks). The lower the degree of connectivity, the lower the impact, viewed at the microeconomic level. If they increase the average degree of a node, which means that they increase the number of connections between the nodes of the network with this node, it increases both the risk of propagation of systemic events in the network and the creation of a contagion at the level of banking networks. But, at the same time, due to the spread of risk to other economic units, there is also the possibility that that affected institution will recover faster.
- Although the pessimistic scenario shows that over time banks eliminate the events that led to the contagion from the network and become immune, we must not lose sight of

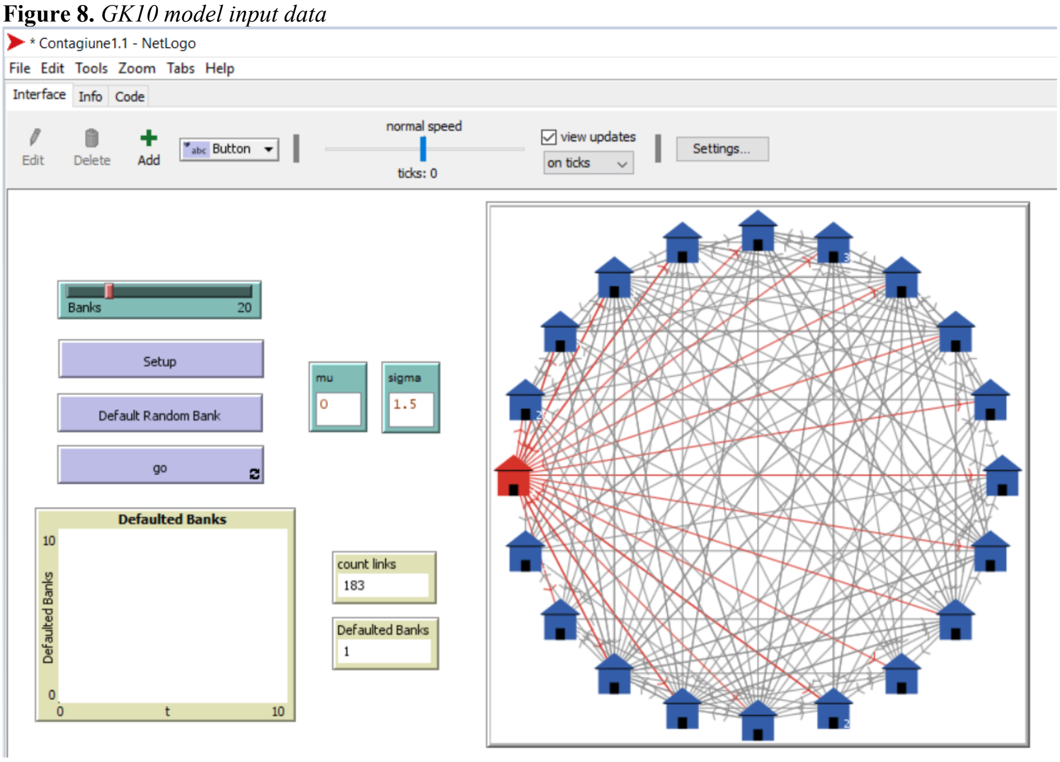
the fact that it took a period of about 4 years to identify the right measures to treat these situations. In addition, in reality, banks are interconnected with each other, but they also interact with other economic systems such as businesses, the money market or other cyber systems seen as complex adaptive systems.

- Like any market economy system, the commercial bank pursues the same goal, namely to maximize profits. Sometimes, this objective can have a negative effect in an economic system, when the bank no longer has the role of relegation and stability regarding certain macroeconomic imbalances. I remember the turbulent episode of 2008 when Lehman Brothers bank collapsed, a collapse due to poor management of the balance between the bank's liabilities and assets. Emerging and developed economies are most prone to such episodes of turbulence and can lead to a crisis with a major impact on a national or perhaps global economic system.

Step 4: Simulation of the GK10 Model

In the first scenario, the GK10 model considers that one of the banks, chosen at random, is in a state of default. The figure below shows the input data of the model.

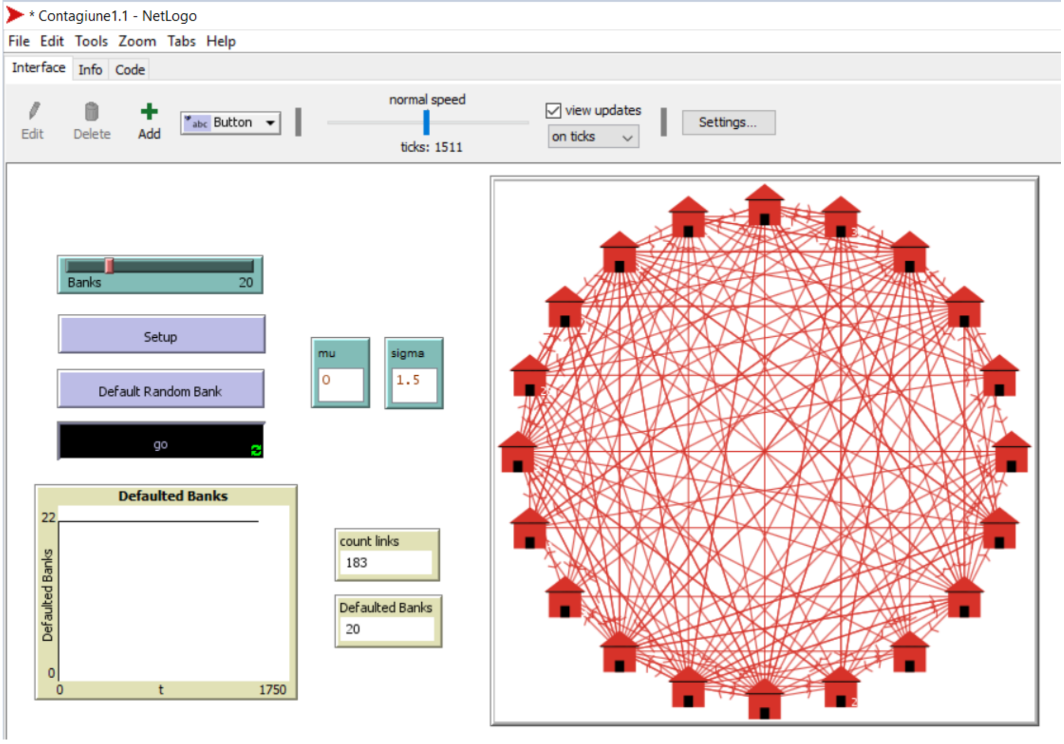
Figure 8. *GK10 model input data*



Source: Author processing according to source code available at: http://people.brandeis.edu/~blebaron/classes/agentfin/GaiKapadia.html

Following the simulation of this model, it resulted that all banks went into default, the contagion effect being propagated in a systemic chain.

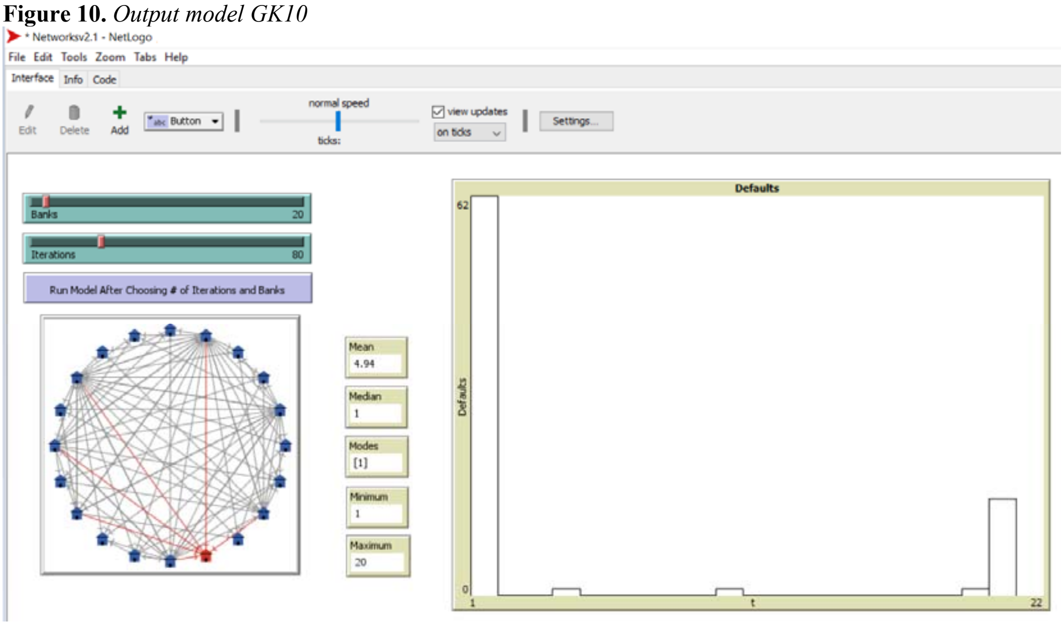
Figure 9. *Output model GK10*



Source: Author processing according to source code available at: http://people.brandeis.edu/~blebaron/classes/agentfin/GaiKapadia.html

For the second scenario, the GK10 model proposes the simulation of several default executions. To keep the degree of comparisons in the model, we also chose a number of 20 banks. This model brings the novelty of rendering statistical information on the default number. The results can be seen in the figure below.

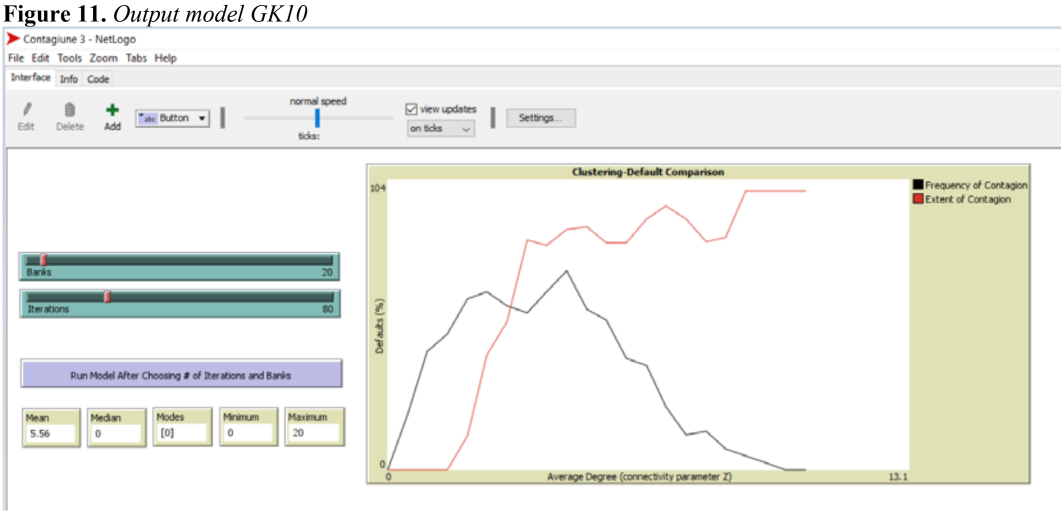
Figure 10. *Output model GK10*



Source: Author processing according to source code available at: http://people.brandeis.edu/~blebaron/classes/agentfin/GaiKapadia.html

The simulation in the figure above is done in 80 iterations, for 20 banks. You can see the histogram and statistics on the default number. The proposed model concludes with testing a final set of runs in NetLogo on how the connectivity that forms between banks varies.

Figure 11. *Output model GK10*



Source: Author processing according to source code available at: http://people.brandeis.edu/~blebaron/classes/agentfin/GaiKapadia.html

The black line in the figure above represents the frequency with which a contagious event propagates from a bank in the network. As connectivity increases, so does the likelihood of a banking contagion in the banking network.

However, over time, due to coevolution and adaptability, and not only due to these properties, but also to the others that characterize a bank as a complex adaptive system, an increase in connectivity also leads to a decrease in banking failures. This can be justified by the fact that the banking sensitivity towards other systems is spread over a certain period of time on several banks. If only one bank will not survive in this environment, the banking system will be less affected.

The red line shows the spread of a financial crisis conditioned by its onset. It increases as the connectivity between banks increases.

The GK10 highlights several aspects, among which I will list the following:

- In an uncertain environment and in contrast to the explosive development of society and the emergence of multitudes of data and information, the correct identification of the systemically significant critical element of a financial system remains a difficult issue.
- The degree of connectivity between banks and how they are connected has a significant impact on the dynamics of the model.
- When systemic risks are measured only by the degree of severity, but not by the probability of occurrence, the degree of connectivity turns into a simple monotonous relationship.

5. Conclusions

Existing financial crises over time have highlighted the importance of systemic risk, defined as macro-level risk that can affect the stability of the entire financial system. Bank failures have in recent years led to a disruption of the financial system and a significant spread of financial threats to the national or global economy. Due to the lack of visibility on the structure of the financial system, as well as the lack of a systemic risk monitoring methodology, the process of anticipating default status in a bank's loan portfolio by regulators has been hampered.

The complexity of contemporary financial systems is another challenge in defining appropriate systemic risk indicators that could help an objective assessment of the systemic importance of financial institutions and an objective framework for assessing the effectiveness of macro-prudential policies.

It must be understood that the role of a bank is to mobilize the financial resources of economic market actors (citizens - individuals or legal entities) and to direct them to viable, economic areas for the development of their systems and their support. Thus, the bank is a very important player in an economy, be it national or global.

Based on the model proposed by Gai and Kapadia, we conducted a case study in this paper to evaluate the contagion effect from the perspective of several hypotheses.

In an uncertain environment surrounded by a lot of information, the evaluation of systemic events and the measurement of the severity of a network is a sensitive topic and must be approached with great care. The connectivity of banks and the interdependencies created with the actors of the economic environment define the dynamics of the banking system in a country.

The analysis of contagion effects remains an important and topical issue for the financial-banking system. Thus, also for the following researches, I set out to analyze the contagion effect both from the perspective proposed by Gai and Kapadia, and from the perspective of Allen and Gale. The model proposed by Allen and Gale explains how a regional liquidity shock can lead to bankruptcy not only in that region, but, under certain conditions, extends to other regions. This is possible because the regions are interconnected through the relationships between banks in several regions.

Note

(1) The Netlogo 6.0.4 modeling program can be downloaded, free of charge at this time, from the following available address: https://ccl.northwestern.edu/netlogo/6.0.4/.

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