Complexity miniproject report

Co-evolution of financial regulation and financial systems

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University of Warwick, Complexity Centre, June 2012

Abstract

Nowadays most countries have different financial regulations and banks can move aspects of their business from one country to another to benefit. Regulators can respond by changing their regulatory regimes. We use agent-based modelling to find if the evolution of a mix of regulatory regimes might lead to a more robust system than some globally agreed regulatory regime. The financial contagion is found to be the key to understanding the relationship between regulatory regimes and the system robustness. We focus on one particular channel of contagion: the overlapping claims that different sectors of the banking system have on one another. Mix of regulatory regimes is shown to lead to a more robust system. The degree of regulation diversity is found to be negatively related to the completeness of the structure of the interregional claims: regions in complete claims structures have similar regulatory regimes and are more stable.

1. Introduction

Despite the fact that banking sector has always been one of the most heavily regulated ones in any economy, recent global financial crisis as well as less devastating regional banking crises, which occur from time to time in different parts of the world, clearly show that our banking system is far from being as robust as one would want it to be.

To design an optimal regulation proved to be quite a challenge. First let us look at why banking sector has to be regulated. There are two main reasons: first, a bank failure causes systemic damage to the economy and, second, bank management has limited liability. Indeed, whereas negative effects of a regular factory bankruptcy are relatively small in magnitude and do not last for long (the other factories in the industry have to increase output to meet the demand, someone else has to take on the factory if it is profitable or the employees have to look for another job, etc) a bank failure might start a chain reaction of long lasting negative effects. For example, after a bank failure people do not trust banks any longer, they withdraw their funds from other banks some of which become insolvent because of this unexpected increase in demand for liquidity. Next, those banks that managed to survive this so called bank panic find that they do not have much funds to invest, therefore industries cannot grow as they cannot obtain credits. Finally, the whole economy does not grow or even shrinks. So in contrast to the local effects of a regular factory failure, a bank failure makes long lasting serious damage to the real economy which is usually referred to as the systemic effect. Moreover, even though management does not want to ruin their business because of the fact that they would not be held responsible for all the damage they would cause by their bankruptcy (limited liability) they are less interested in keeping the bank solvent than the society.

In order to insure stable operation of the banking system the regulator does two things: it insures proper risk management, i.e. it does not allow banks to take on too much risk, and provides information for proper risk estimation. In order to insure proper risk management a regulator might impose certain ratio requirements, restrict certain activities, enforce certain risk analysis, perform regular checks,... etc. For instance, a ratio requirement might read "for short term corporate credits, the amount of reserves should be greater than 10% of the total value of credits issued". Banks might be restricted from dealing with real estate or obliged to use stochastic stress tests to manage their interest rate risks. Also the regulator usually shares some information with banks so that they can properly estimate their risks. For instance, a regulator might publish annual reports about the macroeconomic situation in the region, provide banks with interest and inflation rate forecasts... etc. There might be more sophisticated means of information sharing: a regulator might give banks hints by requiring more reserves for the types of assets which are known to be riskier by the regulator but not the banks. So in a sense the regulatory regime itself could give banks some information about the risks involved or, in economical terms, the regulator can signal by choosing a regulatory regime.

In mathematical terms, the regulatory regime $\underline{r}$ chosen by a regulator affects the banking system of the region in the following two ways:

- first, it affects the probability of bank default in the region. The stricter the regulation, the lower the default probability: $p_d = p_d(r, \dots)$
- and, second, it affects bank profits in the region. The stricter the regulation, the lower the profit: $\pi = \pi(r, \dots)$

There is a trade off between the default probability and the effectiveness of the banking system: if we make the regulation stricter, we restrict banks from more activities, we oblige them to store more reserves which makes it more difficult for them to serve businesses, they issue less credits and serve less customers and, as the result, the whole economy operates not in its full capacity. Roughly speaking, all the speculation about banking regulation design is about how to decrease the default probability and at the same time not to cut profits too much as it makes banking system less effective. Given the regulation design, i.e. the functional forms $p_d = p_d(r, \dots)$ and $\pi = \pi(r, \dots)$, the regulator chooses an optimal regulatory regime $\underline{\hat{r}}$ for its region based on some internal policy it has. For example, the internal policy of a regulator might be to keep the default probability less or equal to 0.5% but usually it is certainly more complicated.

The other factors, denoted as dots in the formula above, that the default probability depends on might include not only the intrinsic characteristics of the region in question but also the characteristics of the adjacent regions as well as the structure of the network involved. There is much empirical evidence that banking crises exhibit contagion properties that is when one region suffers a banking crisis, the probability of default in the other regions increases, especially in the adjacent regions. That means we have to admit that the default probability of one region depends on the default probability of other regions. In other words, when choosing its regulatory regime each regulator has to take into account the actions that the regulators in the other regions make. In this case a natural question to ask is whether it is better in terms of the whole system robustness to make every single region to follow the same globally agreed regulatory regime or a mix of regulation builds a more robust system. To address and expand on this question is the main goal of this miniproject. We will first identify the key elements needed and then build an agent-based simulation model to answer the following main questions:

- Under what conditions can a diverse set of regulatory regimes enhance system stability?
- Under what conditions does regulatory arbitrage undermine system stability?

The rest of the report is organised as follows. In section 2, we review some theory on financial contagion which served as an inspiration for this miniproject. In section 3, we present the co-evolution model and analyse analytically two "toy" cases which will later be a source of intuition for further results obtained by simulation. Section 4 explains the simulation study specification and presents its results. Finally, in section 5, we conclude by discussing the main results obtained, their applicability and possible extensions of the basic framework.

2. Theoretical models of financial contagion

As long as the goal of this miniproject is to examine the relationship between the system robustness and the regulatory regimes in its regions, we need first to focus on how the stability of a given region depends on the stability of other regions or, in other words, on the mechanism of financial contagion.

Some early works, rethought after the Russian default in 1998, are based on changes in investor “psychology”, “attitude”, and “behaviour”. This stream of research dates back to early studies of crowd psychology and classical models of disease spread. Some models even compare the behaviour of stock market investors with the foraging behaviour of ants.

Modern theories are usually less descriptive and trying to emphasise a particular mechanism of financial distress propagation. Some theories look at the financial contagion among financial markets. This stream of research tries to explain contagion through a correlated information or a correlated liquidity shock channel. In the case of correlated information, price changes in one market are perceived as signals for the values of assets in other markets by the investors, causing their prices to change as well (e.g. see King and Wadhwani (1990)). The theory based on correlated liquidity shocks suggests that liquidity shocks (and therefore the crisis periods) are positively correlated because after a liquidity shock (e.g. for some reason everybody withdraws their money from banks causing a distress) in one region, investors in other regions experience an unexpected loss as their assets from the stressed region fall in value, they now have to raise more liquidity which causes liquidity shocks in their regions. This behaviour effectively transmits the initial shock. Other works, such as Alen and Gale (2000) and Boissay (2006), view financial contagion as a result of linkages among financial institutions. The former provides a general equilibrium model to explain how a small liquidity preference shock in one region can spread by contagion throughout the economy and shows that the possibility of contagion depends strongly on the structure of the network involved. The later looks at the financial contagion on the firm level, the mechanism the author proposes is based on trade credits which are credits individual firms grant each other without bank mediation.

From the mathematical point of view, these approaches have a lot in common as they emphasise the importance of links between the agents (be it regions, individual banks, or firms) and the overlapping of interregional claims.

Let us look a bit closer at the explanation proposed by Alen and Gale (2000). They consider the economy which consists of 4 regions with a large number of identical banks and identical consumers each of whom is endowed with one unit of a homogeneous consumption good. There are three dates $t = 0, 1, 2$. At date 1 consumers learn whether they are early consumers, who value only consumption at date 1, or late consumers, who value only consumption at date 2. The type of consumer is assigned randomly at date 0 with certain probability. The prior distribution of consumer types in each region can be of two types: "high", when there are many late consumers, and "low", when there are few late consumers. Banks do not observe the state of the region but they know what the states could be. At date 0 consumers put their units to a bank which invests them on their behalf. Any consumer can withdraw her unit either at date 1 or 2 depending on her type. Banks have two assets to invest in: a short-term asset, which pays a return of 1 unit at date 1, and a long-term asset, which pays $R > 1$ at date 2 or $r < 1$ at date 1. The long-term asset pays higher return if held to maturity but is costly when being liquidated in the middle period. Banks know what the average demand for liquidity would be but they cannot predict the exact figure. The number of early and late consumers fluctuates randomly (and so does the demand for liquidity) in each region, but the aggregate demand for liquidity remains relatively constant. Under these conditions, banks could benefit from interregional insurance if regions with liquidity surpluses provide liquidity for regions with liquidity shortages. One of possible implementations of such insurance is an interbank market of deposits. Suppose region A has more early consumers than average while region B has less early consumers than average. Banks in both regions can exchange some deposits at date 0 and later at date 1 the banks of region A can meet their obligations by liquidating some deposits in the banks of region B and at date 2 the banks from region B liquidate theit deposits in the banks of region A. This insurance mechanism works pretty well as long as total liquidity in the interbank market can meet total demand. However if we imagine that both regions A and B happened to have more early consumers than average, then most probably banks of both regions would fail to meet their obligations at date 1. Alen and Gale (2000) consider 4 regions and different structures of the interbank market, they show that the system exhibits the highest robustness only when all the banks exchange their deposits.

3. The Model

We assume that the economy consists of regions, each of which has its regulator, and banks. That means we won't explicitly take international corporations, individual firms, pension funds, or other bodies into account. This assumption holds as long as it is the banking regulation which affects the financial system most and is the most dynamic. It makes sense to divide the world into a number of regions each of which has a distinct set of characteristics defining its financial market. The regions in question do not necessarily correspond to different countries because a country might have several regions different in terms of the financial market properties; for example, a bank in New-York is quite different from a bank in Boston, both in terms of businesses they serve, the regulatory regimes they are subject to, and risks they face. Let us say that each region *i* at time *t* is described by a vector $\overrightarrow{A_i^t} = (S_i^t, N_i^t, EC_i^t, R_i^t)$, where

- $S_i^t \in \mathbb{N}$ refers to the total size of the banking sector in the region.
- $N_i^t \in \mathbb{N}$ is the current number of banks in the region.
- $EC_i^t \in [0, \infty)$ stands for the *Entry Cost* which is the sum of money needed to establish a bank in a region, this cost can be interpreted as the cost of the banking licence.

- $R_i^t \in [0,1]$ is a variable which contains information about the regulatory regime currently used.

We shall assume that the goal of a bank, just like that of any corporation, is to maximise its enterprise value which can be viewed as a discounted sum of its profits. There are two distinct ways a bank can spread its business to other countries: branches or subsidiaries. A foreign branch is a type of foreign bank that is obligated to follow the regulations of both the home and host countries. Because a foreign branch banks' loan limits are based on the parent bank's capital, a foreign branch can provide more loans than a subsidiary bank. A subsidiary is incorporated in the host country but is considered to be owned and managed by a foreign parent bank. The subsidiary bank only needs to operate under the host country's regulations. According to some recent literature[1], the majority of banks choose to go abroad by subsidiaries. Mostly because it exposes a parent bank to less risk and because most countries have liberalised its regulation so that it is not too costly to open a new bank. Therefore, we can state in the model that banks go abroad by subsidiaries.

Next, the *n-th* bank profit at time *t* in area *i* is given by

$$\pi_n^t\left(\overrightarrow{A_i^t}\right) = -EC_i^t + \frac{S_i^t}{N_i^t}(1 - R_i^t) \quad (1)$$

This is one of the simplest ways to define bank profits in a completely competitive banking market, as one can see the market is divided evenly by the banks present in the region. Let us move on discussing how the parent bank chooses which area to go. For the sake of simplicity we assume that each parent bank has full information i.e. the n-th parent bank can calculate $\pi_n^t(\overrightarrow{A_i^t})$ and p_i^t- the default probability - for all values of *i* and having obtained all this information it makes a choice which region to go. Clearly, higher potential profits increase the probability to invade a region, while higher risks decrease it. For simplicity, we assume that when building a subsidiary a parent bank tries to maximise its expected profit given by

$$E(\pi_n^t(\overrightarrow{A_i^t})) = (1 - p_i^t) * \pi_n^t(\overrightarrow{A_i^t}) - p_i^t * EC_i^t = -EC_i^t + \frac{S_i^t}{N_i^t+1}(1 - R_i^t)(1 - p_i^t) \quad (2)$$

Timing of the simulation

At each time step we do the following:

1. Each parent bank makes a move:
    a. it builds a new subsidiary
    b. closes an existing subsidiary because it became not profitable
    c. does noting
2. Financial contagion simulation is run; as an outcome:
    a. Some subsidiaries become bankrupt
    b. Nothing happens

[1] See for example Cerutti E., G. Dell'Ariccia, M. Soledad Martinez Peria[2007]

3. Each regulator updates its regulatory regime

Regulation update rule

A regulator wants to minimise the amount of bank failures. Clearly, it is not its only goal: if it were the case, the optimum would be not to have banks at all. As we know, banking system benefits the society by channelling funds from those who want to invest to those who have investment opportunities and so doing it facilitates economic growth. A regulator takes that into account and therefore faces a trade-off between the economic growth and the stability of the banking system.

For simplicity, we assume that each regulator has certain target value of the default probability which it tries to maintain. It makes its regulatory regime stricter (i.e. it increases variable R_i^t) if it sees that the default probability is greater than the target value and makes it looser (i.e. it decreases variable R_i^t) otherwise:

$$R_i^{t+1} = \begin{cases} R_i^t + (1 - R_i^t) * Exp\left({p_i^t - \widetilde{p_\iota}}/{\widetilde{p_\iota}} \right), if\ if\ p_i^t \geq \widetilde{p_\iota} \\ R_i^t - R_i^t * Exp\left({\widetilde{p_\iota} - p_i^t}/{\widetilde{p_\iota}} \right), if\ p_i^t < \widetilde{p_\iota} \end{cases} \tag{3}$$

We use the functional form of the update rule as stated above; it makes sure the regulatory regime remains in the allowed interval [0,1] and does not get stuck in the extreme values. Also it takes into account the fact that the regulator responds more to bigger gaps.

Financial contagion

We state that regions are connected to form a network. Using the ideas from Alen and Gale (2000) and the other papers reviewed in section 2 we say that each region *i* has certain probability of shock p_i^s. This probability depends on the regulatory regime and on real characteristics such as technologies used, geographical location, political system etc. For example, in a region where most businesses depend on agriculture bad harvest might cause a shock: businesses have no revenues, they cannot payback their credits, as the result, banks are short of liquidity which may cause bankruptcy. We assume that the probability of a shock is a function of the regulatory regime only and use the following specification:

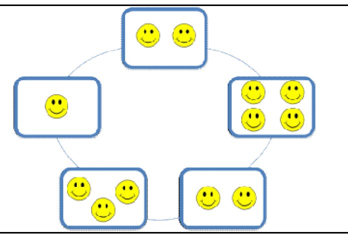
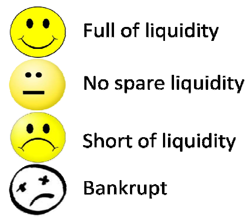
$$p_i^s = p_i^s(R_i^t) = \tilde{p}^s(0.1 + 0.9 * (1 - R_i^t)) \tag{4}$$

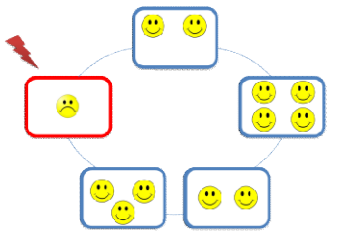
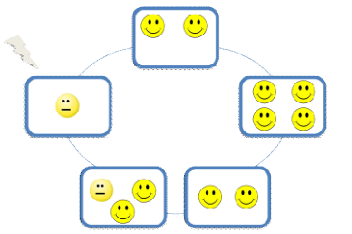
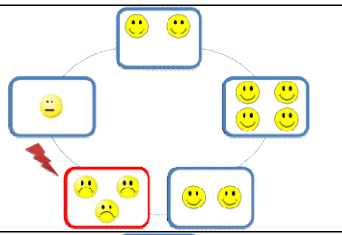
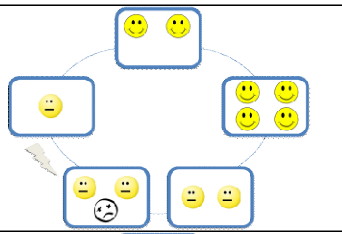
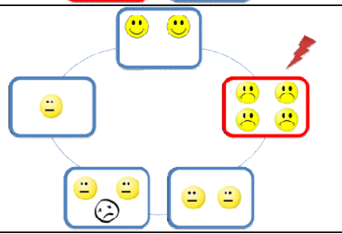
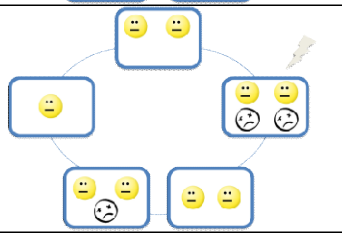
The regulator can change the probability of shock from $0.1\tilde{p}^s$ to $\tilde{p}^s$. This models the idea that the regulator can decrease the probability of shock but cannot eliminate shocks completely. There is an interbank market which serves as an insurance: banks from connected regions can help each other if needed. Suppose that each bank can be in 4 states:

B = "Bankrupt"
S = "Short of liquidity" or "Shocked"
N = "No spare liquidity" or "Neutral"
F = "Full of liquidity" or "Fine"

In our model financial contagion consists of several rounds. At the beginning of each round a region is chosen at random and with the probability of shock corresponding to this region a shock occurs. A shock sets all the banks in the region to state S. A bank cannot stay in this state for long. It either switches to state N if helped by a peer or to state B if not. A bank in state S can be helped by a bank in state F of another region which is connected to the shocked region. the bank that has helped some other bank switches from state F to state N. See an illustrative example of financial simulation propagation in the table below.

Table 1
Illustrative example of financial contagion propagation

Initialisation and notations			Let's look at an illustrative example. We begin with a network of regions. All banks are full of liquidity.

Round	Shock	Response	Comments
1			The first shock occurs and sets one bank to state *S*. In this case, a bank of the region below has helped. Now both affected banks are in state N.
2			Next shock occurs. There are 3 shocked banks and only 2 peers to help so 1 shocked bank becomes bankrupt.
3			The last shock affects 4 banks. There are 2 peers to help so 2 banks become bankrupt

This simple mechanism models the ideas discussed in sections 2, namely the overlapping of the interregional claims. Indeed, when a crisis happens in one region adjacent regions suffer as well as their claims on the troubled region fall in value and so they switch from F to N. But the fact that overlapping exists helps the troubled region out so it switches from S to N rather than to B. Regions that has once suffered problems from other regions problems liquidates its claim on other regions and becomes "neutral". The model could also be interpreted in terms of interbank deposit or loan market.

Now let us analyse analytically two "toy" cases:

Case 1: Isolated region

Let us consider an isolated region i.e. a region which degree in the network is zero. For this region the probability of default equals the probability of shock:

$$p_i^t = p_i^s(R_i^t) \tag{5}$$

Banks will be entering this region until expected profit becomes zero or negative:

$$E(\pi_n^t(\overrightarrow{A_i^t})) = -EC_i^t + \frac{S_i^t}{N_i^t+1}(1-R_i^t)(1-p_i^t) \leq 0 \tag{6}$$

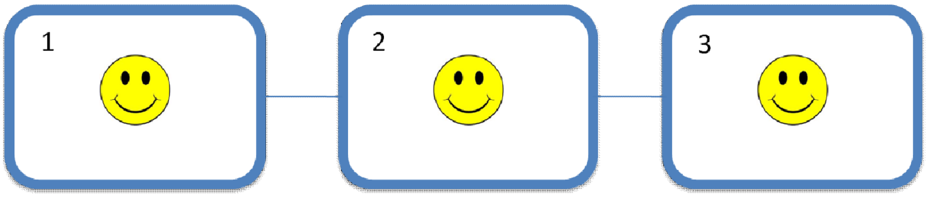
Using this simple idea one can easily derive the number of banks in this region in equilibrium:

$$N_i^t \approx \frac{S_i^t(1-R_i^t)(1-p_i^t)}{EC_i^t} - 1 \tag{7}$$

As we can see, the regulator in an isolated region fully controls the default probability. The number of banks depends on the default probability and therefore is also under the regulator's control.

Case 2: Simple chain

Figure 1: The simple chain network



Let us now consider 3 regions which form a simple chain. Suppose each region has only one bank. Given the number of rounds in the contagion simulation, one can easily calculate the default probability for each region in this case.

Table 2
Default probabilities in the simple chain network

Total number of shocks	Default probabilities
1	$p_1^t = p_2^t = p_3^t = 0$
2	$p_1^t = p_1^s$ $p_2^t = 0$ $p_3^t = p_3^s$
3	$p_1^t = 2p_1^s$ $p_2^t = 2p_2^s(p_1^s p_2^s + p_1^s p_3^s + p_2^s p_3^s) < 2p_2^s$ $p_3^t = 2p_3^s$

From this simple case one can draw the following conclusions which hold in the general case as well.

- First, among two identical regions, the region with higher degree has lower default probability.
- Second, the default probability of a region depends not only on its own regulatory regime but also on the regulatory regimes of the adjacent regions.

As long as the default probability in region 2 is lower than in other regions, parent banks will invade this region, so in equilibrium we might expect that, other things being equal, regions with higher degree have more banks and from (7) lower default probabilities.

4. Simulation study

The model outlined in the previous section is essentially a model of the co-evolution of banking regulation and banking systems because we allow banks to choose where to operate and we allow regulators to change their regulatory regimes. Let us now move on describing the simulation that we made.

There are two groups of agents, or populations, evolving together: banks and regulators. We decided to begin with a simulation in which only banks are allowed to evolve while the regulatory regimes remain constant. Also we set regions to be identical in terms of the regulatory regime, probability of shock, size, and entrance costs. So the only parameter in which regions might differ is their degree in the network. We make simulations for Erdős–Rényi (ER) random networks with different parameter p_{ER} (the probability of an edge occurrence). We want to look at how the overall system robustness depends on the completeness of the network and how the default probability of a region depends on its degree in the network.

Table 3

Simulation 1: banks' evolution only

Parameter	Value used	Definition
N	100	Number of parent banks
M	100	Number of regions
p_{ER}	0, 0.01, 0.02, ... 0.2	The probability of an edge in the random network
$\tilde{p}^s$	0.3	The probability of shock
CSteps	100	Number of contagion rounds
T	1000	Total number of time steps
S	100	Region size
EC	1	Entry costs
R	0	Regulatory regime

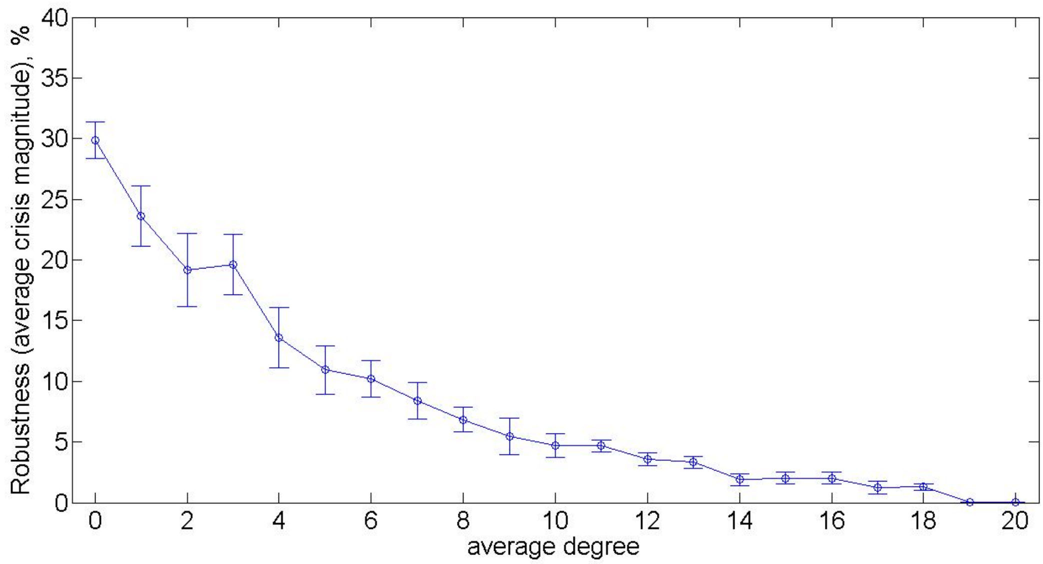
As pointed out in the previous section, parent banks have full information. That means they know the model design, the current state, the parameters, and the default probabilities. In order to estimate the default probabilities, at each time step we run contagion simulation 1000 times and record the sample default probabilities which are then passed to parent banks.

There are two possible equilibriums in this system. In the first equilibrium, the number of banks being built equals the number of banks being destroyed by the financial contagion. In the second equilibrium, the total number of banks achieves its saturation and the banks which fall due to the financial contagion are being rebuilt relatively quickly. As one could expect, the system ends in the first equilibrium if the simulation is started with only a few banks present in the network in the initial state. If there are few banks in the network most regions turn out to be isolated and the default probability in this case equals the probability of shock which is relatively high. So in this situation banks die out on their own and there is no contagion. Clearly, this equilibrium is not the one we are interested in. The other equilibrium can be reached if the system is initialised with a relatively large number of banks. In this case the connections between the regions significantly reduce the default probability and on average the number of banks going bankrupt at a time step becomes less than the number of banks that can be rebuilt[2].

[2] Due to the simulation design the maximum number of banks built at a time step is equal to the number of parent banks N.

Graph 1

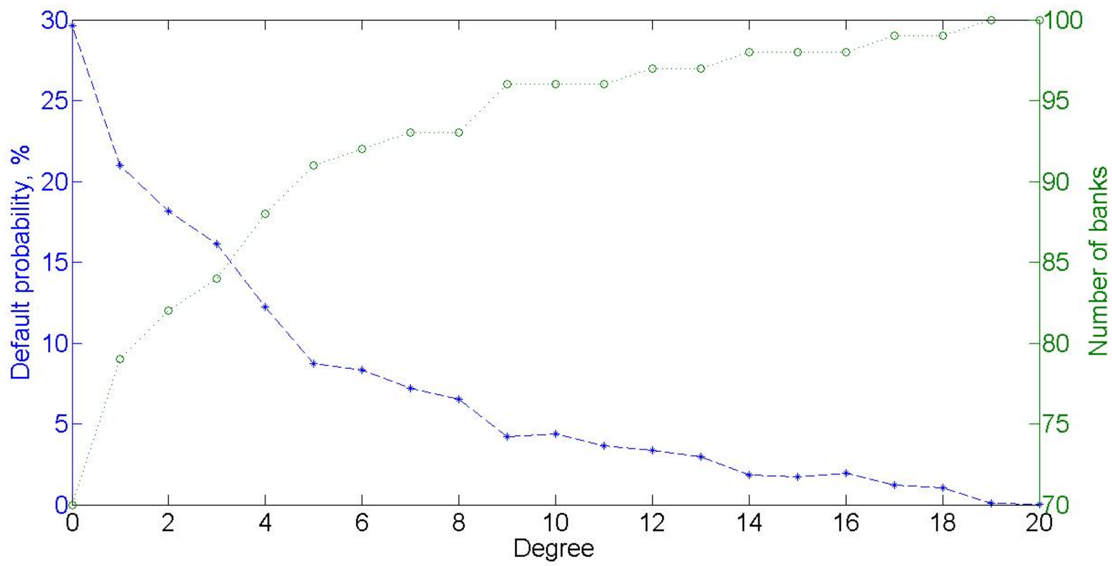
The robustness of the system with respect to the average degree of the network



Shown in graph 1 is the robustness of the system with respect to the average degree of the network. We measure robustness as the number of banks going bankrupt during the contagion run relative to the total number of banks in the system. As one can see, the total robustness increases as we add edges to the network. This result is in agreement with Alen and Gale (2000) and might seem intuitively predictable. Indeed when a shock hits a region, the distress is being distributed among the adjacent (connected) regions and the more connections are there in the network, the more potential banks to shift the distress on exist, and therefore the less likely actual defaults are. However on the other hand, networks with more edges have more banks in equilibrium and so each shock is more destructive there.

Graph 2

The default probability (left axis) and the bank number (right axis) in equilibrium with respect to the degree



Shown in graph 2 is the default probability (left axis) and the bank number (right axis) in equilibrium with respect to the degree of a region. Well-connected regions enjoy lower default probabilities and larger bank numbers. The relationship between the bank number and the default probability follows well formula (7). As one can see the difference in the default probability is quite high: 0.3 for isolated regions and less than 0.03 for regions with more than 15 connections. If regions were allowed to change their regulatory regimes poorly-connected regions would toughen their regimes, clearly that would make the whole system better off.

In the next simulation we allow the regulatory regimes to change and set the target value of the default rate 0.05.

Table 4

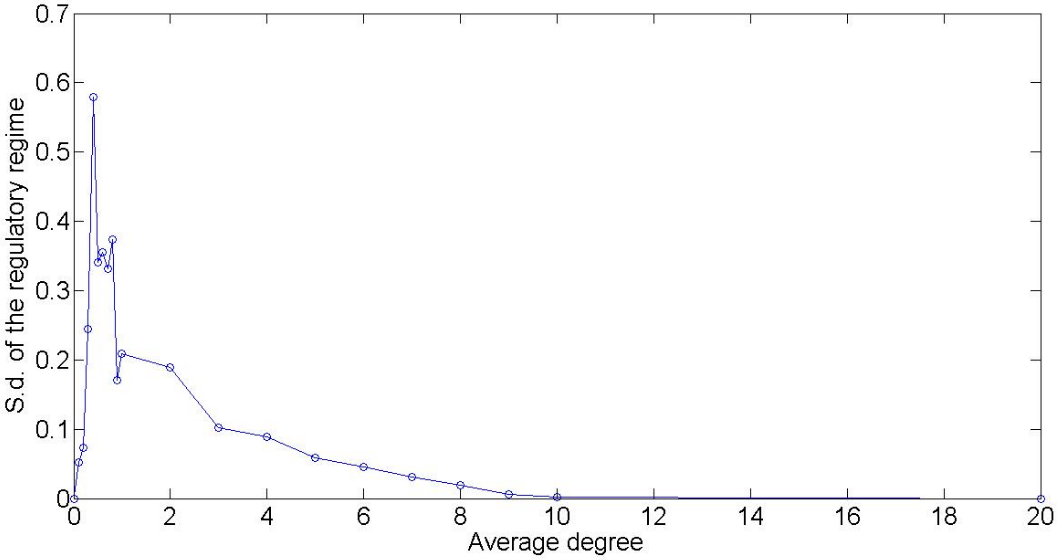
Simulation 2: co-evolution of the banking system and regulatory regimes

Parameter	Value used	Definition
N	100	Number of parent banks
M	100	Number of regions
p_{ER}	0, 0.001, 0.002, ...,0.01, 0.02, ... 0.2	The probability of an edge in the random network
$\tilde{p}^s$	0.3	The probability of shock
CSteps	100	Number of contagion rounds
T	1000	Total number of time steps
S	100	Region size
EC	1	Entry costs
$\tilde{p}$	0.05	Regulators' target level of the default probability

In this particular case the choice of parameters insures that each region has banks in equilibrium. Isolated regions have to have the toughest regulatory regime, approximately 0.9, in order to keep the default probability as low as $\tilde{p}$=0.05. The region size is large enough to make in profitable for banks to enter isolated regions even when they enforce tough regulatory regimes; using (7) the average number of banks in isolated regions is around 85. If the region size were sufficiently small, isolated regions would not be able to maintain the target default probability because under the regulatory regime required for such target banks would decide not to come in these regions.

Simulation shows that total robustness of the system levels down to $\tilde{p}$=0.05 for all values of network parameter p_{ER}. This result is predictable: as long as each region adjusts its regulatory regime so that the default probability is equal to the target level, the total robustness of the system increases. It is interesting to look at how diverse the optimal mix of regulatory regimes is depending on the completeness of the network. Shown in graph 3 is the standard deviation of the regulatory regimes in equilibrium with respect to the average degree of the network. As one can see for a completely disconnected network the standard deviation is zero, i.e. all regions choose the same regime, which makes perfect sense because in this case regions are perfectly identical. As we add edges to the network the degree of regulation diversity first grows, then reaches its saturation, and finally falls to zero again for connected networks. The intuition for this result is quite obvious. When we have a sparse network with a few edges, there are a lot of isolated regions and also a lot of pairs, pairs are significantly more robust than isolated regions so the regulatory regime that pairs choose is way looses than that of the isolated regions. As we increase further the average degree, there are many regions with degree n and n+1 where n is about the average degree. As we can see from graph 2 the difference in default probabilities between such regions decreases with n (the curve is convex) so one can expect that such regions would choose closer regulatory regimes as n increases. Clearly in the case of a well-connected network regions choose the same regime - zero - so the standard deviation vanishes for a sufficiently large number of edges in the network.

Graph 3
The standard deviation of the regulatory regimes in equilibrium with respect to the average degree of the network



We have shown that the structure of the network is a crucial parameter that seriously affects the robustness of the banking system. So far the structure of the network has been exogenously fixed in our simulations. However, most probably it also evolves in time as regions may establish connection between each other to enlarge the interregional interbank market that we mentioned in section 2. Indeed, from the economical point of view, two regions might benefit from establishing a connection which means that the banks of these regions exchange some deposits which would be profitable as long as the probabilities of shock of both regions are the same. So any simulation in which the network is allowed to grow would have in equilibrium a more robust system with less diverse mix of regulatory regimes.

5. Conclusion

This miniproject examines the relationship between the stability of the global banking system and the international structure of banking regulation by using agent-based modelling, some economic theory, and the co-evolution approach. We focus on the overlapping claims that different regions have on one another, show that this may be a channel for the financial contagion, and build a model of co-evolution of banking regulation and banking system that takes this into account. In the model banking crises result from a chain of uncorrelated stochastic liquidity shocks. The probability with which liquidity shocks occur in any given region is viewed as generic characteristic of the region which depends on the regulatory regime and some 'real' characteristics such as the technologies and businesses of the region, its geographical position, political system ... etc. Because of the overlapping claims that different regions or sectors of banking system have on one another when one regions suffers from a liquidity shock, the other regions suffer a loss because their claims on the troubled region fall in value. If this spill over effect is large enough it can cause a contagion i.e. propagation of a financial crisis which started in one region to other regions. We have explained that because of the contagion properties that financial crises exhibit when choosing its regulatory regime each regulator has to take into account the decisions made by the other regulators. The main goal was to figure out whether it is better in terms of the whole system robustness to make every single region to follow the same globally agreed regulatory regime or a mix of regulation builds a more robust system.

Our simulation shows that if all regions use the same regulatory regime, other things being equal, the completeness of the overlapping claims structure, i.e. the network formed by the regions, determines the robustness of the banking system: more complete structures turn out more robust. Moreover, individual regions that have more connections to other regions enjoy lower default probabilities and larger bank numbers. We have shown that if all regions use the same regulatory regime, poorly-connected regions have incentives to toughen their regulation and by so doing they would decrease their default probabilities and increase the overall robustness of the global banking system. Therefore we have shown that under the conditions implied in the model a mix of regulatory regimes builds a more robust banking system. It turns out that regulation should be adjusted to each individual region as long as regions are different. However, we show that for well connected regions the regimes chosen are very close so common agreed regulation is possible. This result justifies the process of banking regulation integration which has been in progress for the last 30 year: 20 major economies, the countries of G20, are implementing the same banking regulation Basil III. Also according to the logic of the model, the process of banking system integration should continue because establishing new connections between the regions can be beneficial both for the regions in question and for the whole system. Ultimately, when the system is well connected the regulation would no longer be that meaningful, it could be the same throughout the world and very basic as long as the system is robust due to the interregional connections.

Possible extensions of the presented framework most probably should relax the assumption that both banks and regulators have full information as this assumption is key in this work and is one of the most arguable in the literature. Hardly could one estimate properly default probabilities. Incomplete information approach would make room for signalling games and other channels for financial contagion such as correlated information or herding behaviour of investors.

6. References

Allen, F and D. Gale[2000]: "Financial Contagion", Journal of Political Economy, Vol. 108, No. 1.

Banerjee, A. [1992]: "A simple model of herd behavior", Quarterly Journal of Economics, Vol. 107 (3), p. 797–817

Boissay, F[2006]: "Credit chains and the propagation of financial distress" European Central Bank working paper series, No. 573

Cerutti E., G. Dell'Ariccia, M. Soledad Martinez Peria[2007] : "How banks go abroad: Branches or subsidiaries?", Journal of Banking & Finance, Vol. 31, p. 1669–1692

Claessens S, K. Forbes[2001]: "International Financial Contagion: An Overview", Kluwer Academic Publishers, p. 3-17

Duffie D, A. Li, T. Lubke[2012]: " Policy Perspectives on OTC Derivatives Market Infrastructure", Federal Reserve Bank of New York Staff Reports, No. 424

Gai P., S. Kapadia [2010]: " Contagion in financial networks", Bank of England, Working Paper No. 383

Kaminsky, Graciela L., and Carmen M. Reinhart[2000]: "On crises, contagion, and confusion", Journal of International Economics, Vol. 51, p. 145-168

King, Mervyn A., S. Wadhwani[1990]: "Transmission of volatility between stock markets", Review of Financial Studies, Vol. 3, p. 5-33

Lagunoff, Roger D., S. L. Schreft [2001]: "A model of financial fragility", Journal of Economic Theory, Vol. 99, p. 220-264

Mackay, C. [1841]: "Extraordinary Popular Delusions and the Madness of Crowds" London: Bentley

"Basel III: A global regulatory framework for more resilient banks and banking systems", 2010, Bank for International Settlements Communications CH-4002 Basel, Switzerland, ISBN: 92-9131-859-0