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Agent Based Interbank Network Dynamics with Individual Bank Interaction Rules

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Abstract. Recent banking crisis consequences have driven regulators to focus on most systemic and most important institutions. Partly because of this decision, most papers concentrate their banking system stability analysis on scenarios merely studying a small and specific group of institutions. However it may not be correct to only base an analysis of fully interconnected system stability on few agents, even though they represent the core of bank network. Here, it is assumed that interbank networks can be assimilated to a complex system and so their characteristic behavior cannot be reduced to only one level of description. This paper proposes to provide an approach to represent interbank systems by agent-based model which permits to study impact of individual decision policies on system stability.

Keywords: Agent-based Model, Financial Contagion, Interbank Market, Network Model, Systemic Risk.

1. Introduction

The succession of financial crisis in last decades has refocused the debate on banking regulation approach. Furthermore, recent crisis has highlighted the importance of "systemic risks" and especially, the leading role of institutions interconnectedness. Today, it is commonly accepted among regulators and financial actors that banking system is exposed to dangers of financial instability and contagion. This is why latest regulation issues have mainly grappled with these problems, and concern primarily bank capital, liquidity and coverage against systemic risks. On the other hand, several studies raise controversial issues related to Basel III [1], and in particular, on the possibility that Basel III rules may compromise the economic functions performed by bank s[2]. As they are today, these rules are specifically concentrated on institutions described as ''too-big-too-fail'' whose failures may be prone to tear down the entire financial system.

Much research about financial network structure [3] has highlighted the fact that there exists a clustering phenomenon inside banking system [4] which cannot be neglected. Because interbank system comprises both identified systemic big institutions and a large number of smaller ones the balance sheet of which is very difficult to collect, none of usual macroeconomic and micro economic approaches[2], [9], [10] can provide an adapted representation of such system. To cope with this difficulty, it is assumed in present paper that interbank networks can be represented by two classes: the *core* of banking network composed by most important institutions, and the *periphery* whose agents cannot individually lead to system-wide failure, but such that a set of them can create enough perturbation to weaken the network. All agents in the network are given individual behavioural rules allowing them to decide their own policy choice. Main difference is that core dynamics elements are followed from initial real balance sheets, whereas periphery elements are only initially represented by a distribution build up from observation of a subset of known banks in this class. Opening the possibility to include different scales in system control could be an interesting way to work on future banking regulation. What is meant here is that banking regulation objective is to maintain system stability from rules controlling potential perturbation, which basically implies that rules are targeting all perturbation sources. In regard to last years, suspicion is growing that actual banking regulation does not cover efficiency enough niche perturbations. Present paper is an attempt to treat the underlying issue of previous comments: how to model banking system to get an efficient and coherent analytical framework focusing on relation between micro behaviour and macro stability.

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The next sections propose a methodology to represent real system in credible agent-based model with reasonable number of agents, and give a numerical application of this methodology in the case of European interbank system. The third section describes structure and interactions of computational agent-based model applied to European interbank market.

2. Interbank Network Structure

Unlike most papers on banking system where banks are not differentiated (ie where agents are of equal importance) [7], a more realistic analysis of real interbank network system [8] leads to split this environment into two parts:

- The network *core*, composed of group A of N_A real banks representing most important and systemic institutions. Group A may typically gather a large fraction (up to 40%) of interbank network flows.
- The network *periphery*, constituted by the remaining other banks which will be further split in group B' formed by $N_{B'} >> N_A$ medium-sized banks, and group C' with $N_{C'} >> N_A$ small banks respectively representing the two groups usually existing in such system. In real terms for a banking network, the total amount $N' = N_A + N_{B'} + N_{C'}$ is quite large (at least few thousands up to tens of thousands). So it is necessary to reduce real system periphery to more affordable representation model keeping reliably its main features. This is also imposed by the difficulty to have access to all data sheets of periphery banks.

The idea is to take advantage of inequalities $N_{B'}, N_{C'} >> N_A$ for replacing real medium and small banks of network periphery by fictitious ones and, if possible, much smaller in number. This is motivated by the fact that banks belonging to network core (group A) are by their size individually able to tear down the entire banking system, so describing them nominally and individually is essential for model dynamics. On the contrary, as shown previously[6], medium and small banks do not individually constitute a threat for network stability, though a set of medium-sized banks can generate network perturbations possibly leading in turn to system failure. For this reason bank dynamics in groups B' and C' do not need to be individually followed[8] So they can be replaced by smaller sets N_B and N_C of initially distributed fictitious ones which should satisfy the conditions that

$$N_B + N_C >> N_A \tag{C$_1$}$$

and

$$\Phi - \Phi_A = \Phi_{B'} + \Phi_{C'} = \Phi_B + \Phi_C \tag{C$_2$}$$

with Φ_J the liquidity fluxes injected in the system by group J banks (J=A,B,B',C,C'), and Φ the total liquidity flux injected in the network. Their number should also be such that in fictitious groups B and C there are enough elements between which individual typical transactions are such that

$$\delta\Phi_{B,C} << \Phi_A \tag{C$_3$}$$

to allow initial randomly distributed distribution of their fictitious representation over real corresponding ranges of liquidity fluxes $\Delta\mathcal{J}_B$, $\Delta\mathcal{J}_C$ in groups B' and C' constructed from a selected small set of $n_{B'} << N_{B'}$ and $n_{C'} << N_{C'}$ actual banks which are prone to belong to groups B' and C', and an extrapolation of their balance sheet has been done for getting variation intervals $\Delta\mathcal{J}_B$, $\Delta\mathcal{J}_C$ within which aggregate values of securities item, aggregate values of loans item, and so on, are possibly located. Conditions ($C_{1,2,3}$) are fixing the range where N_B, N_C can be defined from real network data. Condition (C_2) is imposed to respect the global flux balance between real network core and periphery. Incidentally if one cannot capitalize on banks name of groups B and C, one cannot capitalize on their balance sheet either. This is another reason for which it is believable that a key of macro-prudential policies lies elsewhere.

Finally the total mean of monthly liquidity $\mathcal{L}_{tot}$ which circulates in the whole system is evaluated. In the application to European banking system, the value $\mathcal{L}_{tot} \approx 4{,}675\ M€$ is found, which matches to the order of magnitude of monthly currency in circulation in Euro Area[1]

[1] Series key : BSI.M.U2.Y.V.L10.X.4.U2.2300.Z01.E; European Central Bank; Dataset name: Balance Sheet Items; Frequency: Monthly; Reference Area: Euro area

3. Model

3.1. Agents' Data

As seen above, the interbank network model is composed by $N = N_A+N_B+N_C$ real and fictitious banks all represented by the following simplified balance sheet:

Table 1: Simplified Balance Sheet

Assets	Liabilities
Loans	Deposit
Securities	Borrowings
Cash	Equity

Three kinds of securities $S(t)$: free risk $S_{fr}(t)$, hybrid $S_h(t)$ and risky $S_r(t)$, are considered. All of them present different market risk exposures and so they are remunerated in accordance with.

Loans $I(t)$ contains interbank loans $I_i(t)$ but also customer loans $I_c(t)$. Interbank loans are dynamically represented throughout simulation, whereas customer loans are supposed to be a random variable remunerated to a rate close to rate for housing loans. Borrowings $B(t)$ are only borrowings contracted on interbank market and deposit represents households saving. The equity $V(t)$ is only increased by provision for risk, ie 8% of nominal value for granted loan or 8% of total value of bought securities.

Finally, cash $M(t)$ is inherited cash from previous period plus intraperiod cash flows and represents available liquidity.

In order to differentiate individual behaviour, agents are categorized in three different strategies : free risk, hybrid, and risky. These strategies reflect the agent's appreciation of liquidity with regard to gain. Agents belonging to "free risk" strategy prefer to maximize their liquidity instead of their gain, "hybrid" agents attempt to maximize their gain for a fixed value of liquidity, and "risky" agents prefer to maximize their gain instead of their liquidity. Strategies mainly intervene in investment choices.

3.2. Interactions

First, at the beginning of each period the variation of deposit is computed for each agent so that:

$$D_t^k = \pi D_{t-1}^k + (1-\pi)\left[(1-\sigma_d)\frac{D_t}{N_t} + \sigma_d \epsilon_t^k D_t\right] \tag{1}$$

where

π is the self-regressive component of deposits, σ_d is the random component of aggregate deposits, N_t is the number of banks at period t, D_t is the aggregate value of deposits at period t and ε_t the portion of random deposits remaining in bank k.

Then the cash of period t is evaluated:

$$\begin{aligned} M(t) = M(t-1) + \ & S_{fr}(t)R_{fr}(t) + S_h(t)R_h(t) + S_r(t)R_r(t) \\ & -D(t-1)R_d(t) + \Delta D + \sum I(t)\, R_i(t) - \sum B(t)\ R_i(t) \end{aligned} \tag{2}$$

where

$R_{fr}(t)$, $R_h(t)$, $R_r(t)$, $R_i(t)$ and $R_d(t)$ are respectively the yield for free risk securities, the yield for hybrid securities, the yield for risky securities, the loan rate, and the deposit rate, ΔD is the variation of deposit between t and t+1.

According to the value of M(t), each agent is declared liquid or illiquid. When $M(t) < 0$, the agent cannot meet its commitments and has to refinance itself. When $M(t) > 0$, the agent has the ability to invest. In both cases, the agent manages to ensure its solvability and its futures liquidities. For this to happen, each liquid agent is allocated a lending capacity:

$$o_t^k = (1-\sigma_0)\frac{\Omega_o}{N_t} + v_t^k \sigma_0 \Omega_o \tag{3}$$

where

σ_0 is the random component of aggregate portfolio demand, Ω_0 is the aggregate value of portfolio demand and v_t^k is the portion of random portfolio demand that remains in bank k.

To decide the position of agents in refinancing process a last variable "trajectory" dependent parameter is considered, consisting in a weighted factor P(t) over last three available liquidities, expected available liquidities at t and next three ones in such a way that:

$$\mathrm{P(t)} = \sum_{\mathrm{i}=-3}^{3} \mathrm{a_i M(t-i)} \tag{4}$$

with weights $\sum_1^3 \mathrm{a_i} = \sum_{-3}^{-1} \mathrm{a_i} = 0.25$; $\mathrm{a_0} = 0.5$.

Finally all agents belonging to one of the two cases presented below will enter refinancing process as liquidity seekers:

$$\mathrm{M(t)} < 0$$

$$\mathrm{P(t)} < 0 \; and \; M\mathrm{(t)} > 0$$

In case 2, the agent may have two positions in refinancing process: liquidity seeker and investor. Agents which are liquidity seekers have two possibilities of refinancing: to borrow or to sell securities. To choose between these two options the agent will decide according to the decision rule below:

$$\mathcal{D} = \mathrm{Max}\ \{\mathcal{P}_1, \mathcal{P}_2\} \tag{5}$$

with $\mathcal{P}_1 = (\Sigma\ \Delta S)^{-1}$, $\mathcal{P}_2 = (\Sigma\ \Delta B)^{-1}$, and where $\Sigma\ \Delta S$ and $\Sigma\ \Delta B$ are respectively the sum of all securities items variation and the sum of all borrowing items variation since the beginning of simulation. From $\mathcal{D}$ an agent having sold more securities than it has borrowed will choose to contract a loan to refinance itself, whereas an agent having borrowed more than it has sold securities will choose to sell its securities. Investor agents will proceed in opposite way: an agent having bought more securities than it has lent will choose to loan whereas an agent having lent more than it has bought securities will choose to buy.

Thus to formulate their liquidity demand seekers have to evaluate how much they want to borrow or to sell:

$$\mathrm{X(t)} = \min(\mathrm{P(t)}, 0) + \min(\mathrm{M(t)}, 0) \tag{6}$$

In order to maximize their chances to conclude transaction, agents survey the average of available liquidity of system. By this way, if X(t) >> $M_{Syst}(t)/N(t)$, with N(t) the number of active agents in network at period t, the agent will prefer to contract several transactions instead of only one. Once all liquidity seekers have formulated their demand, agents having available liquidity will select first all demands respecting the criterion defined in (5) and then they choose the best transaction according to their strategy. When illiquid agents could not refund themselves on interbank market, they have two options:

- They have enough securities to borrow at REPO rate from Central Bank
- They have not enough securities for buying liquidity and they are thrown out of the system

An illiquid bank whose securities are pledged makes it a priority to redeem its securities. If it needs to borrow again before redeeming its securities already pledged, it is thrown out of the network. Finally when liquid banks still have available liquidity at the end of period, it is supposed that they can buy new securities on primary market, or choose to save this cash for the next period.

4. Application to European Interbank Network

The model has been applied to European interbank network with following data for banks in groups B and C [11] and dispersion $\sigma_T \approx 35\%$. Group A banks [12] parameters are documented from their actual balance sheets. Calculations have been performed for a set of random initial values inside intervals $\Delta\mathcal{J}_B$, $\Delta\mathcal{J}_C$ constructed from Table 2 and for different individual bank strategies, and averaged.

Table 2: Initial Average Mean Values of Simplified Balance Sheets for Group B and C Banks

Average (M€)	Group B	Group C
Borrowings	15 836	889.6
Loans	25 391.8	889.6
Deposits	77 098.5	3 437.9
Equity	5667	833.5

The worked out model comprises 22 identified banks in group A, 100 medium size banks in group B and 478 small banks in group C. Reported results concerning A) without different policies, Figures 1A,2A, and B) with different policies, Fig. 1B, 2B, are showing the very different consequences of individual policies on global network dynamics especially as concerns exchange liquidity flows and the number of banks thrown out of the system (Fig. 2A, 2B) which both directly reflect the weakness of evolving network. The very important role of intermediate illiquid state clearly appears in the sense that there is no real risk for a banking system to have a large percentage of such banks as long as this is just a transitory state corresponding to natural exchanges between banks. Conversely, large steady illiquid bank group weakens the network on the longer run by giving banks of this group more opportunity to fail and be ejected out of the network. Results are confirmed by other studied scenarios.

Case A

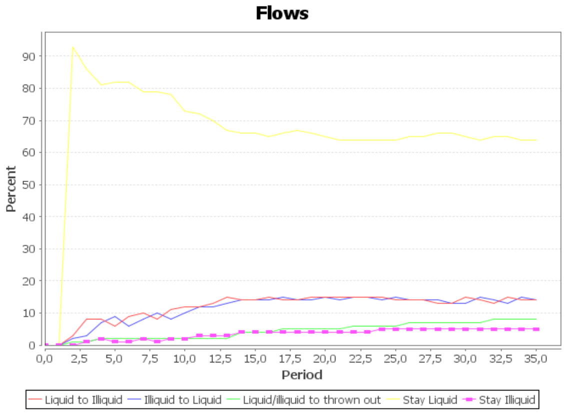

Fig. 1A : Liquidity Flows in Network Between Fig. 1A: Liquidity Flows in Network Between Different Liquid, Illiquid and Thrown out States

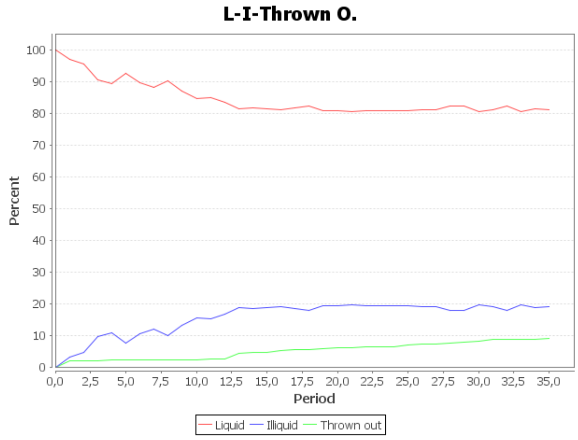

Fig. 2A : Distribution of Banks in the Three Liquid, Illiquid and Thrown out States

Case B

Fig. 1B : Liquidity Flows in Network Between Different Liquid, Illiquid and Thrown out States

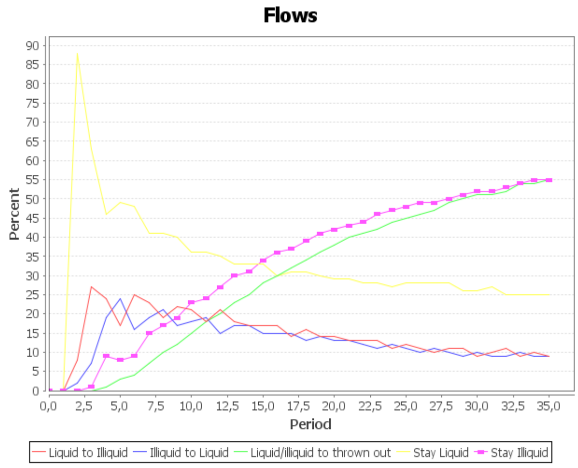

Fig. 2B : Distribution of Banks in the Three Liquid, Illiquid and Thrown out States

5. Conclusion

Recent observations of interbank network system has been showing strong enough connectedness between banks for questioning justification of Bale III prudential rules only based on big systemic institutions. A model has been worked out to provide faithful and manageable representative model of such system which combines both macro and micro effects not clearly handled in previous approaches. It is shown from analysis of interbank network based on data collected from European one that resulting system dynamics is very sensitive to individual bank decision policies. This leads to the conclusion that macro stability of interbank system cannot be fixed on the only consideration of its large and well identified systemic banks, due to the large effect of liquidity flux exchanges between the other banks of the network.

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[12] Subsets $n_{B'}$ and $n_{C'}$ are respectively from *Group B'*: La Banque Postale, LCL, CIC, Banco Pastor, Credit du Nord, UBI Banca Group; from *Group C*': SMC, Tarneaud, Courtois, Volksbank, Espirito Santo, LCF E. Rothschild

[12] Société Générale, BNP Paribas, BPCE, HSBC, RBS, Barclays, UBS, Morgan Stanley, Santander, Crédit Agricole Group, Commerzbank, Citigroup, Goldman Sachs, JP Morgan, BBVA, VTB, ING, Dexia, Unicredit, BOA, Crédit Suisse, Deutsche Bank