

Impact of Liquidity Crunch on Interbank Network

I. Lucas, N. Schomberg, F-A. Couturier

Abstract—Most empirical studies have analyzed how liquidity risks faced by individual institutions turn into systemic risk. Recent banking crisis has highlighted the importance of grasping and controlling the systemic risk, and the acceptance by Central Banks to ease their monetary policies for saving default or illiquid banks. This last point shows that banks would pay less attention to liquidity risk which, in turn, can become a new important channel of loss. The financial regulation focuses on the most important and “systemic” banks in the global network. However, to quantify the expected loss associated with liquidity risk, it is worth to analyze sensitivity to this channel for the various elements of the global bank network. A small bank is not considered as potentially systemic; however the interaction of small banks all together can become a systemic element. This paper analyzes the impact of medium and small banks interaction on a set of banks which is considered as the core of the network. The proposed method uses the structure of agent-based model in a two-class environment. In first class, the data from actual balance sheets of 22 large and systemic banks (such as BNP Paribas or Barclays) are collected. In second one, to model a network as closely as possible to actual interbank market, 578 fictitious banks smaller than the ones belonging to first class have been split into two groups of small and medium ones. All banks are active on the European interbank network and have deposit and market activity. A simulation of 12 three month periods representing a midterm time interval three years is projected. In each period, there is a set of behavioral descriptions: repayment of matured loans, liquidation of deposits, income from securities, collection of new deposits, new demands of credit, and securities sale. The last two actions are part of refunding process developed in this paper. To strengthen reliability of proposed model, random parameters dynamics are managed with stochastic equations as rates the variations of which are generated by Vasicek model. The Central Bank is considered as the lender of last resort which allows banks to borrow at REPO rate and some ejection conditions of banks from the system are introduced.

Liquidity crunch due to exogenous crisis is simulated in the first class and the loss impact on other bank classes is analyzed through aggregate values representing the aggregate of loans and/or the aggregate of borrowing between classes. It is mainly shown that the three groups of European interbank network do not have the same response, and that intermediate banks are the most sensitive to liquidity risk.

Keywords—Systemic Risk, Financial Contagion, Liquidity Risk, Interbank Market, Network Model.

I. INTRODUCTION

IN a world with perfect information, banks would have no trouble in getting funded because they would be able to determine banks health. Since 2007 sub-prime crisis and banking and financial crisis in the fall of 2008, Europe has suffered a recession; the reliance between European banks has been deteriorating and the interbank market has been idling (Fig. 1).

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Fig. 1 Deposits of the Eurosystem of MFI residents in the euro area
Sources: European Central Bank; Euro area (changing composition), Outstanding amounts at the end of the period (stocks), Eurosystem reporting sector - Deposit liabilities, Total maturity, All currencies combined - Euro area (changing composition) counterpart, MFIs sector, denominated in Euro, data Neither seasonally nor working day adjusted (Balance Sheet Items)

Financial crises have highlighted the huge cost of bank system failure for the whole economy (Fig. 2).

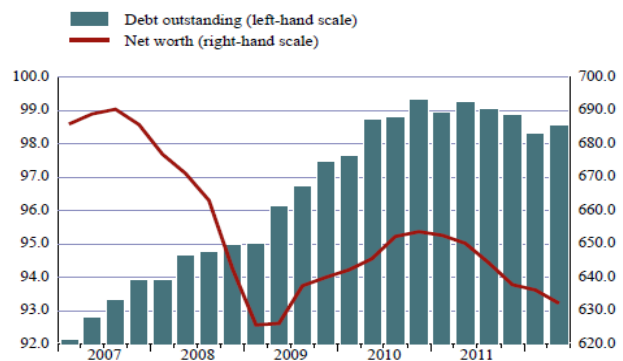


Fig. 2 Households debt and net worth
Source: European Central Bank and EUROSTAT

This is why financial stability has become an important concern for governments and central banks. The analysis of threats to financial stability must be based on the study of systemic risks: how risks encountered by individual banks can affect a whole financial system. Recent banking crisis has highlighted two major points. First the possibility of grasping and controlling the default appears as a very important concern and second, for saving default banks the Central Banks have been in turn ready to ease their monetary policies. This last element assumes that banks would pay less attention to liquidity risk. The liquidity risk already existed before 2007 crisis but the fragility of financial system state and the quantitative easing could encourage a lax behavior of banks with regard to liquidity risk [12]. In the light of the difficult

post-crisis years, it is worth to understand and to quantify the expected loss incurred because of liquidity risk contagion. Moreover, the study of loss mechanism related to liquidity risk is important because default risk and insolvency can result in liquidity crisis.

Most empirical studies have dealt on how a sudden failure of an individual institution turns into systemic risk ([16], [10], [18], [17], [13], [5], [11]). Only most contemporary authors treat the importance of contagion phenomenon ([5], [11]), and only few authors study liquidity risk contagion ([6]). Present study is not based on how contagion is happening nor how different network structures affect the global level of systemic risk ([15], [2], [4]). In a way similar to Cont and Moussa [5] who studied the loss contagion mechanism related to default risk in Brazilian interbank network, present paper attempts to highlight the fact that different parts of European interbank network do not have the same liquidity risk sensitivity.

From liquidity definition of Borio and Drehmann [7] "funding liquidity risk as the ability to settle obligations with immediacy", a network is built up the structure of which is based on an agent-based model. Previous studies on simulated network structure have examined the contribution of connectivity and concentration to the increase in loss share among counterparties in case of default ([1], [14]), and have highlighted the point that systemic risk is concentrated on a few nodes in financial network. This important observation suggests that bank network is of small world type ([3]) rather than pure random one ([8]), and fully justifies the proposed split of banks in the network regarding shock transmission and network robustness. So along this line, a network of 600 banks has been constructed to simulate a liquidity crisis from the failure of few banks. To this aim the network environment has been split into two classes: the first one is composed by 22 actual large banks. The second class is a blend of fictitious 578 banks smaller than the ones belonging to first class, and further split into two groups of medium and small banks to figure out more appropriately their various interactions. Finally network evolution follows a set of behavioral descriptions mostly inspired by the mathematical scheme of Estrada and Osorio [9]. From the results it is possible to analyze the expected loss associated with liquidity risk contagion and incurred by the 22 actual largest banks through different aggregate values such as the loan aggregate or the borrowing aggregate value from the second class to the first one.

Three liquidity crisis scenarios have been simulated: asset variation, confidence crisis and forced illiquidity in specific banks. Only the last one is presented here and the two other scenarios have been separately published ([19], [20]). Unlike first two scenarios which create illiquidity into the whole network by asset variation or deposit reduction, the scenario described in this paper condenses illiquidity in specific group of banks, the real ones fit in model. The regional liquidity crunch analysis's objective is to provide study of illiquidity contagion phenomenon.

II. THE INTERBANK NETWORK STRUCTURE

For the realization of network model the European bank environment has been split into three groups. Group A contains the 22 most important and systemic banks (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) whereas groups B and C represent the other smaller banks of the system. It is assumed that large banks prefer to deal with other large banks instead of small ones. Group A fits with class A, whereas groups B and C are composing class B. All banks in the network are connected with different weights in order to allow a large (or small) bank to loan and/or to borrow a larger amount of money from a large bank than from a small one. In present version 600 banks have been selected as representing the 600 most connected banks of the European network.

A bank k is represented by a five-uplet $(A_t^k, L_t^k, V_t^k, B_t^k, D_t^k)$ where each variable is an item of balance sheet:

- A_t^k is the stock of securities
- L_t^k is the interbank loan
- V_t^k is the equity
- B_t^k is the interbank borrowing
- D_t^k is the deposit

It is further assumed that deposits come from the retail activity.

The connections between banks exist in the model through loans and borrowings. The loans of each considered bank are saved into banks memory. In the same way, the aggregate value of loans (and the aggregate value of borrowings) between each class can be evaluated. Although the default risk is not treated, the possibility is inserted into the model for a bank not to be paid in order to spread the illiquidity through the network. So doing, it is checked at each period beginning if a counterpart is dead and in this case the amount of loan, plus the interest to the available liquidity of concerned banks, is reduced.

III. SYSTEM PARAMETERS

A. Deterministic Rates

The model includes three rates:

- ρ the loan rate, used as follows to calculate loans (1) and borrowings (2) interest for bank k at period t from values of period $t-1$:

$$L_{t-2}^k + [(1 + \rho_t)^2 - 1]L_{t-2}^k \quad (1)$$

$$B_{k,t-2} + [(1 + \rho_t)] * B_{k,t-2} \quad (2)$$

- r_{at} the deposit rate, used as follows to calculate the interest due to deposits for bank k at period t from values of period $t-1$:

$$(1 - \beta)D_{t-1}^k + r_{dt}D_{t-1}^k \quad (3)$$

with β , the reserve requirement ratio,

- ρ_a the securities yield, used to compute the income from securities for bank k at period t from values of period t-1:

$$\rho_a A_{t-1}^k \quad (4)$$

The variation of these three rates is generated at each period according to Vasicek model:

$$dr_t = a(b - r_t)dt + \sigma dW_t \quad (5)$$

where b is the long term mean level, a the speed of reversion and σ the volatility. Coefficients b and σ are computed on the longer frame over the last three years where the Euribor rate maturity 12 months is the more stable.

B. The Aggregate Values

In the model there are two parameters which represent an aggregate value:

- D_t^k the aggregate deposits, used in the calculus of the collection of new deposits for each bank k :

$$D_t^k = \pi D_{t-1}^k + (1 - \pi) \left[(1 - \sigma_d) \frac{D_t}{N_t} + \sigma_d \epsilon_t^k D_t \right] \quad (6)$$

- Ω the aggregate demand for credit, used to compute σ_t^k , the portfolio of loans bank k is able to extend :

$$\sigma_t^k = (1 - \sigma_0) \frac{\Omega}{N_t} + v_t^k \sigma_0 \Omega \quad (7)$$

where π is the part of redeposited from earlier deposits in the same bank, ϵ_t^k the portion of random deposits remaining to bank k, v_t^k the portion of random portfolio demand that remains in bank k, N_t the number of banks in the network at period t, σ_d the random part of aggregate deposits and σ_0 a random part of the aggregate demand for credit explained in next section.

The first parameter is indexed to deposit rate variation whereas the second one is indexed to loan rate variation. Indeed it is assumed that if deposit rate increases there will be more deposit, and if loan rate decreases the demand for credit would increase.

C. Random Components

In the model there are two parameters which represent a random component:

- σ_d the random component of aggregate deposit (see (6))
- σ_0 the random component of aggregate portfolio demand (see (7))

The first parameter is indexed to deposit rate variation whereas the second is indexed to loan rate variation. Indeed it is assumed that if deposit rate increases banks would attract more deposit, and if loan rate increases they would be tempted to grant more loans.

It is further assumed that the two parameters are equal value for all banks of system.

IV. INTERACTION RULES

System simulation has been made over three years or 12 trimester periods. For each period the main really existing cash flows are simulated for evaluating the available banks liquidity at period end. This includes:

- repayment of matured loans (function growing of cash, see (1))
- payment of matured borrowings (function decreasing of cash, see (2))
- liquidation of deposits made in the previous period (function decreasing of cash, see (3))
- income from securities (function growing of cash, see (4))
- collection of new deposit (function growing of cash, see (5))

Then the liquid and the illiquid banks are determined by computing their available liquidity,

$$M_t^k + \beta D_t^k = D_t^k - A_{t-1}^k - L_{t-1} - r_{dt} D_{t-1}^k + (1 + \rho_t)^2 L_{t-2}^k + \rho_a A_{t-1}^k + V_{t-1}^k - (1 + \rho_t)^2 B_{k,t-2} \quad (8)$$

with,

$$M_t^k = M_{t-1}^k + (1 + \rho_t)^2 L_{t-2}^k + \rho_a A_{t-1}^k - r_{dt} D_{t-1}^k - (1 - \beta) D_{t-1}^k + (1 - \beta) D_t^k - (1 + \rho_t)^2 B_{k,t-2} \quad (9)$$

and where M_{t-1}^k is the cash inherited from previous period:

$$M_{t-1}^k = (1 - \beta) D_{t-1}^k - L_{t-1}^k - A_{t-1}^k + V_{t-1}^k + B_{t-1,k} \quad (10)$$

The loan portfolio each bank is able to extend is computed and this value is assigned for refunding illiquid banks. It is assumed that group A-banks are refunded first. Once the new demands of credit are granted, the second channel of refinancing begins. Illiquid banks sell their securities redeemed by liquid banks. When liquid banks do not buy all the securities sold by illiquid banks, the latter have two options:

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

When liquid banks have available liquidity after buying all the securities sold by illiquid banks (so all illiquid banks are refunded thanks to interbank market), it is supposed that liquid banks policy is to increase their equity based on their available liquidity. 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.

V.RESULTS

As seen above, two kind of aggregate values are computed:

- AL_i Aggregate values of loans from group $i \in \{A|B|C\}$ to group A
- AB_i Aggregate values of borrowings from group $i \in \{A|B|C\}$ to group A
- AS_i Aggregate value of securities held by the group $i \in \{A|B|C\}$

So a vector of system state V is obtained at each period end. This vector comprises five variables:

$$for i \in \{A|B|C\} : V = (AL_i, AB_i, AS_i, NBI_i, NBT_i)$$

where NBI_i is the number of illiquid banks in group i and NBT_i the number of thrown banks out of group i .

V is used here for observing system state during one period for the whole network and specifically for analyzing the reaction of groups in different scenarios. Three cases have been analyzed: an asset variation, an exogenous crisis where the available liquidity of group A-banks is strongly reduced, and a confidence crisis where the two aggregate values of the model are reduced. Only asset variation will be discussed here and compared to system normal mode run, the two other cases being presented in a separate paper. For each case the average of 1000 simulations is computed.

A. The Reference Mode

The model presents a trend to “mop up” liquidity deficit. This is because weakest banks (with inefficient refunding capacity) are thrown out so the network is constantly filtered. Moreover, in present study only interbank operations and a simplified trade of securities are considered so the evaluation of available liquidity (or liquidity deficit) is subjected to fewer constraints. This gives the global illiquidity as a function of time displayed on Fig. 3.

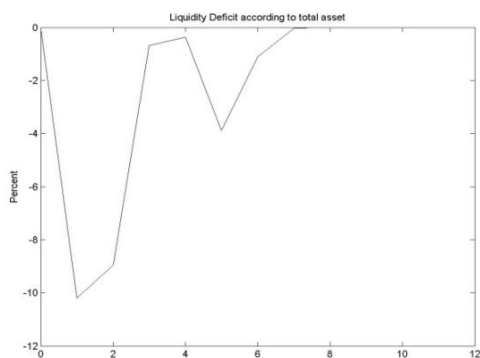


Fig. 3 Percentage of illiquidity in the network vs. time

As shown on Fig. 4 (a), group B-banks are the most sensitive to illiquidity (they are banks with the most important liquidity deficit except group A-banks). Indeed, these banks are a fictitious panel build to represent banks less important than the ones belonging to group A. They receive less deposit and they have a smaller portfolio than in group A. However,

against group C-banks which have the smallest portfolio in the whole network and receive even lesser deposits than group B-banks, their own refunding capacity is the worst. Whereas class A-bank is strong and large enough and group C-bank is small enough to resist to a shock, group B-banks are in the middle which escapes the law of the strongest and the law of the smallest. Group A-bank has the priority to get loans and has securities enough to borrow from central bank at REPO rate in case of confidence crisis for example, and group C-banks need less refunding than other classes, because less active, and they must have a too small portfolio to feel a market crisis. Moreover, it is assumed that banks with smallest liquidity deficit and belonging to group A get loans in first; so this behavior supports the fragility of group B-banks.

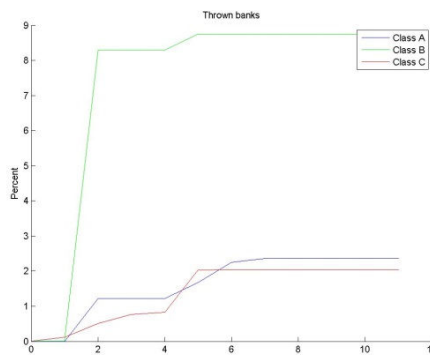


Fig. 4 (a) Percentage of thrown banks in different groups vs. time

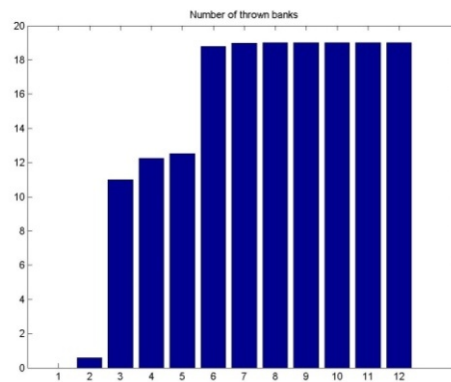


Fig. 4 (b) Number of thrown banks in different groups vs. time

B. Regional Liquidity Crunch

In this case it is supposed that all group A-banks have their available liquidity (or liquidity deficit) decreased (or increased) by the effect of an exogenous cause to the system, represented by the coefficient C_e . Then a percentage of their available liquidity (or liquidity deficit) is deduced (or added). Even though only banks of first class are initially forced to be illiquid, Figs. 5 (a)-(c) shows that same results observed in other scenarios are also recorded: medium-sized banks are the most impacted and systemic features of banks belonging to

group A is highlighted.

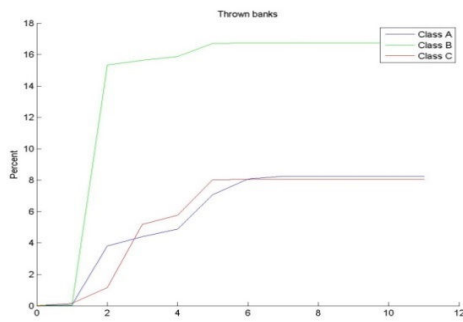


Fig. 5 (a) Percent of thrown banks vs. time for $C_e = .3$

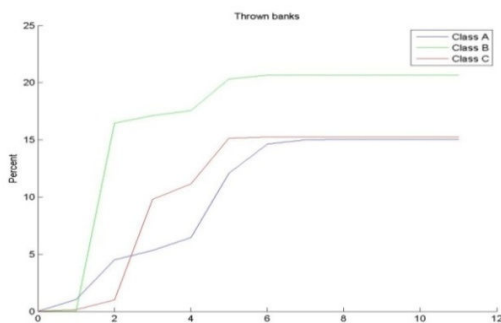


Fig. 5 (b) Percent of thrown banks vs. time for $C_e = .6$

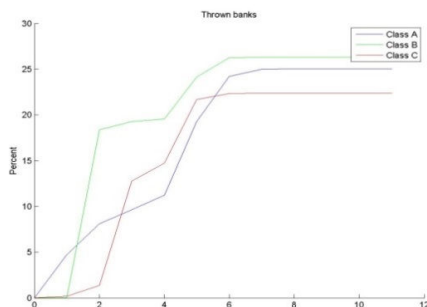


Fig. 5 (c) Percent of thrown banks vs. time for $C_e = .9$

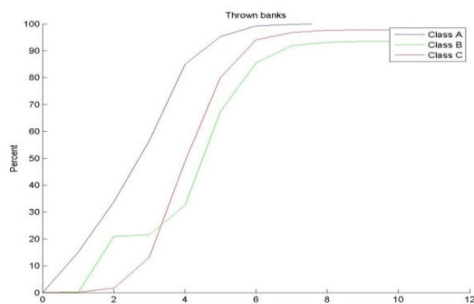


Fig. 5 (d) Percent of thrown banks vs. time for $C_e = 1.2$

In other words interbank market dependence on group-A banks during refunding process is very important. Indeed, banks belonging to group A have highest liquidity potential and even in the case where they need to refund themselves, they benefit from their image to borrow at low rate or to easily find counterparties. Thus, by paralyzing banks of group A so they cannot play their funders role in interbank market, the whole network is affected by a liquidity dry-up. By introduction of solvability constraints for borrowing from Central Banks (represented in the model by conditions of ejection) and the liquidity crunch created in group A, the result presented here gets sense of trend leading towards European interbank market situation without liquidity infusion from European Central Bank.

The fact that systemic risk can be originated by a handful of institutions has already been treated in literature ([16], [10], [18], [17], [13], [5], [11]) but only some contemporary authors treat the importance of contagion phenomenon ([5], [11]). Here, the implemented software for making analysis does not only permit to observe contagion phenomenon but also permits to identify loss impact related to one specific bank failure thanks to real banks integration in the model. Furthermore, with regard to guidelines of G 20's Financial Stability Board (FSB) agreement on a globally unique and standardized legal entity identifier (LEI) ([21]), this model's feature seems to be particularly interesting and pioneering.

Overall, the total number of thrown banks increases as a function of percentage increase added (or deduced) to available liquidity (or liquidity deficit) of group A-banks. This result highlights the importance of making independent the rest of network from these banks which are at the heart of interbank market.

VI. CONCLUSION

A network model has been set up to evaluate the liquidity risk of European banking system. It gathers the main features of exchanges between banks and splits them into classes corresponding to their networking importance. The 22rst most important ones are identified from their real dynamics, whereas the other ones are represented by a typical but fictitious distribution of 578 elements themselves split into two groups to better figure out the various flux exchanges between all network. Exchange rules have been fixed and system evolution has been numerically analyzed, which shows its relative sensitivity to different situations. Of the three considered cases: an asset variation, a confidence crisis, and an exogenous crisis, which have been compared to a reference normal case, only the last one is reported here, the other ones being deferred to a separate publication. In all reported simulations, group B of medium size banks appears to have the largest sensitivity to variation of the coefficients representing the three studied cases in the model. This is confirming the importance of bank network correctness representation, and in particular, the weakness of a very large but purely random bank distribution miscalculating some reactions. The interesting point is the possibility to extract an overall robustness coefficient characterizing global system

vulnerability to different, including unexpected, situations.

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REFERENCES

- [1] F. Allen, D. Gale: Financial Contagion. *J. Political Economy*, Vol.108, pp.1-33, 2000.
- [2] S. Battiston, D. DelliGatti, M. Gallegati, B. Greenwald, J.E. Stiglitz : Default Cascades: When Does Risk Diversification Increase Stability?, Report ETH-RC-11-006, ETH Risk Center, Zurich, 2011.
- [3] M. Buchanan: Nexus: Small Worlds and the Groundbreaking Science of Networks. W.W. Norton, New York, 2002.
- [4] G. De Masi, G. Iori, G. Caldarelli : Interbank Network, Data and Modeling, GSDP-ABM Workshop, Paris, Sept 9, 2011; G. De Masi , G. Iori , G. Caldarelli : The Italian Interbank Network: Statistical Properties and a Simple Model, Noise and Stochastics in Complex Systems and Finance, Vol.6601, p.1, 2007.
- [5] E. Bastos e Santos, R. Cont : The Brazilian Interbank Network Structure and Systemic Risks, Working Paper 219, Banco Central do Brasil, Oct. 2010; R. Cont, A. Moussa : Too Interconnected to Fail: Contagion and Systemic Risk in Financial Networks, Financial Engineering Report 2009-04, Columbia Univ., 2009.
- [6] D.W. Diamond, Ph.H. Dybvig : Bank Runs, Deposit Insurance and Liquidity, *J. Political Economy*, Vol. 91(3), pp. 401-419, 1983; and : Banking Theory, Deposit Insurance and Bank Regulation, *J. Business*, Vol.59(1), pp.55-68, 1986.
- [7] C. Borio, M. Drehmann : Towards an Operational Framework for Financial Stability: 'Fuzzy' Measurement and its Consequences, XII-th Annual Conf. of Banco Central de Chile on "Financial Stability, Monetary Policy and Central Bank Activity", Santiago, Nov. 6-7, 2008
- [8] P. Erdos, A. Renyi : The Evolution of Random Graphs, *Magyar Tud. Akad. Mat. Kutato Int. Kozl.*, Vol.5, pp.17-61, 1960.
- [9] D. Estrada, D.R Osorio : A Market Risk Approach to Liquidity Risk and Financial Contagion, Banco de la Republica de Colombia, Borradores de Economia 002453, 20, 2006; R. Cifuentes, G. Ferrucci, Hyun Song Shin: Liquidity Risk and Contagion, *J. European Economic Association*, Vol.3(2-3), pp.556-566, 2005.
- [10] C.H. Furfine : Interbank Exposures : Quantifying the Risk of Contagion, *J. Money, Credit and Banking*, Vol.35(1), pp.111-128, 2003.
- [11] J. Bessis: Risk Management in Banking, J. Wiley, New York, 2010; Gai et al., 2010.
- [12] M.-S. Gauvin: La Relation Liquidité : Prix d'Actifs comme Complément au Principe de Sélectivité du Renouement par un Prêteur en Dernier Ressort, Mémoire de Master 2, USTV, UFR Sci. Econ. Et Gestion, 05/07/2010.
- [13] P.E. Mistrulli: Assessing Financial Contagion in the Interbank Market: Maximum Entropy vs. Observed Interbank Lending Patterns, *J. Banking and Finance*, Vol.35(5), pp.1114-1127, 2011.
- [14] Müller, 2006; B. Shargel, H. Sayama, I.R. Epstein, Y. Bar-Yam : Optimization of Robustness and Connectivity in Complex Networks, *Phys. Rev. Lett.*, Vol.90(6), 068701, 2003.
- [15] E. Nier, J. Yang, T. Yorulmazer, A. Alentorn: Network Models and Financial Stability, *J. Economic Dynamics and Control*, Vol.31, pp.2033-2060, 2007; X. Freixas, B.M. Parigi, J.-Ch. Rochet : Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank, *J. Money, Credit and Banking*, Vol.32(3), Part 2: What Should Central Banks Do?, pp. 611-638, 2008.
- [16] A. Lehar: Measuring Systemic Risk: a Risk Management Approach, *J. Banking and Finance*, Vol.29(10), pp.2577-2603, 2006.
- [17] L. Ratnovski: Bank Liquidity Regulation and the Lender of Last Resort, *J. Financial Intermediation*, Vol.18(4), pp. 541-588, 2008.
- [18] P. Gai, S. Kapadia: Contagion in Financial Networks, Working Paper 383, Bank of England, March 2010.
- [19] I. Lucas, N. Schomberg, F-A. Couturier: Confidence Crisis Contagion in Interbank Networks, Proc. Intern. Conf. on Computing in Economics and Finance for the Society for Computational Economics, July 10-12 2013, Vancouver.
- [20] I. Lucas, N. Schomberg, F-A. Couturier: Liquidity Risk Contagion in Interbank Networks, Proc. Intern. Conf. on Financial Systems Engineering and Management, July 4-5 2013, Singapore.
- [21] A. Groody: A second report on the Global Identification of Counterparties and Other Financial Market Participants, Financial InterGroup Holding Ltd, 169 E 69th St Frnt New York, NY, 10021 USA, December 20 2012.