Network Approach to Interbank Market: A Survey

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Abstract

The recent crisis calls for a better understanding in the interbank market. This paper surveys the recent literature, which studies the system stability under different interbank network formations. I include some stylized and important theoretical papers, which provide the economic meaning of the interbank markets, uncertainty source, and moral hazard problem under the simple network structure. I also consider the complex and dynamic network formations, where banks are strategic and not identical in terms of size and credit condition. Paper ends with a discussion of the future directions for research, which include a better understanding in calibrating the theoretical models using a more real world based network formations and a better mapping of the generic properties of the network.

I. Introduction

The recent financial crisis has generated substantial amount of new researches in understanding the stability of interbank market. The purpose of this paper is to survey the literature on both theoretical and applied network approach to the resilience of financial systems. Network theory allows researchers to investigate into the fundamental issues under complex market structures. The financial sector as a whole, such as interbank market can be illustrated as a network graph. Each node represents one individual bank. Link represents an interbank lending relationship between two nodes. Weight quantifies the exposure between two parties. Edge direction illustrate an in or out interlink from one bank's liability or asset to another bank's asset or liability. Network models allow us to study the network structure by charactering the different properties of nodes and links.

Theoretical approach to the financial market stability focus on the limited network formations. The main network structures which have been taken into account are: completely connected network, cycle network and disconnected network. The most well known papers to model the contagion through the interbank system are Allen and Gale(2000) and Frexias et al(2000). Agents types followed by following Diamond and Dybvig(1983), while the major difference is Allen and Gale(2000) deals with time-coordination problem, while Frexias et al(2000) deals with space-coordination problem. Allen and Gale(2000) reveals the fact that network formation matters under the economic environment when banks face uncertainty agents' type. Frexias et al(2000) documents the existing trade-off between efficiency and stability. The autarkic formation is the safest one but banks will be less efficient in investing fewer money in the risky assets compared to other interbank formations. The diversified network formation is always stable when the nodes number is big enough, which indicates the intuitive explanation that the diversified network allows the insolvent banks to share their losses with its interlinked banks, thus, the system is more resilient to default. Brusco and Castiglionesi(2007) introduces moral hazard problem into Allen and Gale(2000) framework. They showed that by taking moral hazard into an account, the Allen and Gale(2000)'s result has been reversed. A more connected interbank deposit

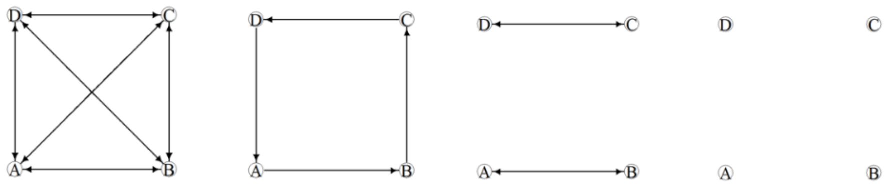

Figure 1: Network Formations in Theortical Approach

market is more venerable than the less connected interbank market. Fundamental questions have been investigated and answered by using numerical network approach. Robust-yet-fragile property has been found in the financial system(Gai and Kapadia, 2010). Caccioli et. al(2011) answered the question on whether it is 'too-connected-to-fail' or it is 'too-big-to-fall'. By considering a network with power law distribution on both degree and balance sheet size, they concluded that 'size' is more important in reducing the contagion probability. In this survey, we study the relevant literature in explaining the interbank stability and efficiently. Bank heterogeneity, moral hazard, capitalization and liquidity requirements haven been taken into an account when studying the network formation.

The survey aims to provide an introduction of network theory approach to the financial system. I begin with reviewing the most used network models and their application in financial market in Section II. The literature on theoretical approach under simply network formations is treated in Section III, while Section IV considers the complex network formations with numerical approach. Section V provides suggestion for future research direction. R code for network graph visualization has been provided in Appendix.

II. Network Models and Interbank Market

The interbank market provides risk-sharing to the banks within the system. The incentive for a bank to participate in the interbank market is to share its idiosyncratic shock among the banks which are linked with him. When a negative shock hits the bank's balance sheet, the bank may have to absorb the shock himself if he is isolated outside the interbank system. This negative shock may lead the bank to liquidize the long term asset in a fire sale or even declare bankruptcy. An interbank market can provide bank with risk-sharing among other linked banks. This mechanism could protect bank from further going under. However, the interconnection among banks can also provide a channel for negative shocks to transmit and cause contagion in the interbank market. The literature of applying network analysis in interbank system has grown rapidly in recent years. Network has been applied to many other fields long before its application to the interbank market. The most famous example for its application in social science is the study of the Florence Marriage. Padgett and Ansell(1993) documented the network of marriages between some key families in Florence in the 1430s. The Medici family controlled the business and rose their power during this period. The social importance of Medici family is measured by its centrality in the marriage network structure. In network theory, there are different centrality measures for different means. For example, Between Centrality calculate the the number of shortest paths from all vertices to all others that pass through that node, which measures how important is the node in terms of information transfer. Closeness Centrality is based on the length of the average shortest path between a vertex and all vertices in the graph, which measures its move around ability in the network. Degree Centrality simply measures how

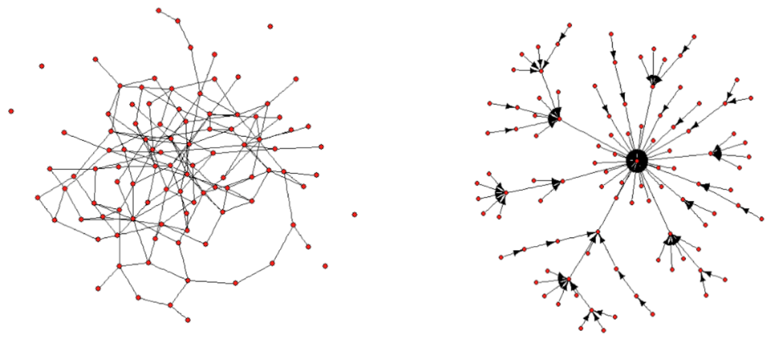

Figure 2: Erdos-Renyi Network Versus Scale Free Network

connected a node is. All centrality measures indicate the Medici family is better positioned than other families in communicating information, brokering business deals, and reaching political decisions. (For your interest: the code for visualization of Florence marriage network is in Appendix)

Network Theory fits well in modeling the interbank system. Individual node presents bank in the system. Link indicates a direct interbank asset and borrowing connection between two banks' balance sheets. The Edge direction indicates an in or out interlink from one bank's liability or asset to another bank's asset or liability. One bank's interbank asset is equal to another bank's interbank liability. If two banks have interbank asset between each other, the link has angles on both direction. The common noticed network formation (mostly used in theory papers) can been illustrated as the follow four formats(Figure.1): The completely connected network; The incomplete cycle network; The disconnected network; The autarkic network.

The most seen network models in modeling interbank markets are Erdos-Renyi Network and Scale Free Network. Erdos-Renyi Network is first introduced in graph theory and named after Paul Erdos and Alfred Renyi, who first introduced the model in 1959. In the Erdos-Renyi Network framework which contains n nodes, each link is formed with a given probability p, and the formation is independent across links. It's a binomial model of link formation with short average paths and low clustering. In this network frame, there is low heterogeneity (most nodes have the same number of connections), the average degree distribution for each node is Poisson approximated when number of nodes n is large and the probability p is small. The other most seen network model is Scale Free network. Barabasi-ALbert model is the algorithm for generating random scale-free networks using a preferential attachment mechanism. Scale-free networks are widely observed in natural and human-made systems. The degree distribution resulting from the Barabasi-ALbert model is a power law distribution. The scale free graph has a few, but significant number of nodes with a lot of connections and a trailing tail of nodes with a very few connections at each level of magnification. Scale free network is especially useful in modeling the financial hubs in the interbank system. Figure.2 is plot of both Erdos-Renyi Network with $n = 100$ and $p = 0.04$. and scale free network with $n = 100, power = 1$. (Please see the Appendix for the R code)

The evolution of international financial network formation from 1985 till 2005 has been studied by Haldane(2009). The paper studied scale and interconnectivity of the global financial network in 18 countries at year 1985, 1995 and 2005. Nodes size are scaled in proportion

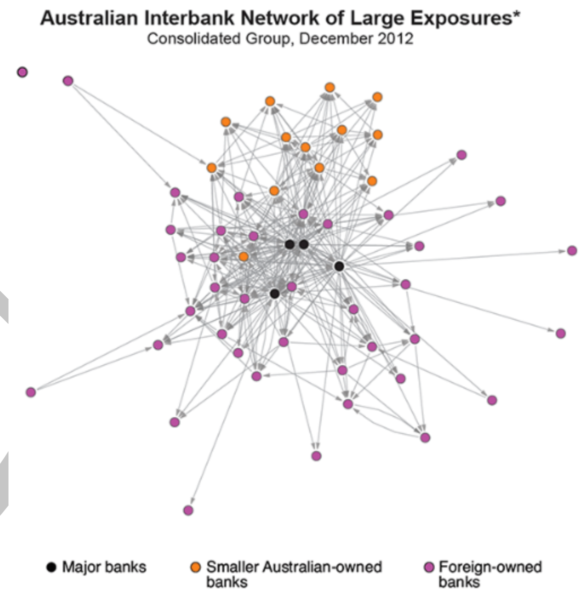

Figure 3: Network of Large Exposures between Australian Banks

to total external financial stocks. Links sickness is proportional to bilateral external financial stocks relative to GDP. Authors draw several conclusions directly from the graphs: First, the international financial network's scale and interconnectivity has increased significantly. Links have become more fatter and also more frequent. The network formation has become more dense and complex. Second, the heterogeneity consideration on degree distribution make sense. Global finance appears to comprise a relatively small number of financial hubs. Third, the average path length of the international financial network has also shrunk over the past twenty years. So based on evidence from a sampled international financial network, the past twenty years have resulted in a financial system with high and rising degrees of interconnection, a long tailed degree distribution and small world properties. From a stability perspective, it translates into a robust-yet-fragile system, susceptible to a loss of confidence in the key financial hubs and with rapid international transmission of disturbances.

The network of large exposures between Australian banks is studied by Tellez(2013), where large exposures include on-balance sheet items such as loans or holdings of debt securities as well as off-balance sheet positions such as those related to financial derivatives. Figure.3 visualizes the network formation, where banks are represented as nodes and links stand for the large exposures between between banks. Nodes which have higher number of links are placed close to the centre of the network. Graph highlights the fact that the major banks are in the centre of the network and connect to most of the other banks. Foreign and smaller Australian-owned banks are linked to only a few other banks, and tend to be more connected with their own kind. Such as: the smaller Australian-owned banks tend to be more connected with other Australian-owned banks, while the foreign-owned banks tend to be more connected with other foreign-owned banks and the major banks.

III. Interbank Stability under Static Simple Network Formations

The most well known papers to model the contagion through the interbank system is Allen and Gale(2000) and Frexias et al(2000). Agents types followed from Diamond and Dybvig(1983), while the major difference is Allen and Gale(2000) deals with time-coordination problem, while Frexias et al(2000) deals with space-coordination problem. Allen and Gale(2000) adopts an economic environment with only four banks involved, and liquidity shocks are negatively correlated with each other. Uncertainty raises from agent type. The incentive for interbank deposit is to insure against the future liquidity demand arise from unexpected early consumers. Interbank system provides the liquidity exchange and resource reallocation channel as: banks with excess liquidity provides liquidity to those banks which have liquidity shortage. Different interbank formations have been studied in this paper. The complete market structure and two incomplete market structures. Non-monotonic result between then completeness and contagion has been found. Only one bank is insolvent in complete interbank network. In the directed cycle interbank network, contagion spreads to all banks. The contagion in the disconnected network is restricted to the sub-network of shock region. Allen and Gale(2000) reveals the fact that network formation matters under the economic environment when banks face uncertainty agents' type. Frexias et al(2000) considered the uncertainty from another prospective. Consumers now are not early or late types, they are travelers or non-travelers. The location for future consumption motivates the interbank system. Three interbank network formations have been studied: the complete network, directed cycle interbank network, and autarkic case. Autarkic formation(Isolated banks with no interbank credit line) backs up the theory on the trade-off between efficiency and stability. The autarkic formation turns out to be the safest formation, while banks will be less efficient in investing fewer money in the risky assets compared to the interbank formation. The diversified network formation is always stable when the nodes number is big enough, which indicates the intuitive explanation that the diversified network allows the insolvent banks to share their losses with its interlinked banks, thus, the system is more resilient to default. The network formations which have been considered in both Allen and Gale(2000) and Frexias et al(2000) are simple ones. In later literature, more implicated network formation has been studied by using numerical simulation methods.

Brusco and Castiglionesi(2007) is an extension of Allen and Gale(2000), which includes Moral Hazard problem. In their model, banks are protected by limited liability and may engage in excessive risk-taking. More precisely, the opportunity to invest in the gambling asset is a random variable and the fraction of the profits is not observable by the depositors, which mainly raises the moral hazard problem. The Allen and Gale(2000) and Brusco and Castiglionesi(2007) is the pair of papers which is comparable to the Diamond and Dybvig(1983) and Kareken and Wallace(1978). Diamond and Dybvig(1983) provides the evidence that the government-supplied deposit insurance is a purely good instrument which can be functioned as ruling out the bad equilibrium among the multiple equilibriums, while Kareken and Wallace(1978) introduce the moral hazard problem by letting government to be required to exercise lender-of-last-resort and bail out facilities, which alter its incentives to undertake risks. Therefore, in Kareken and Wallace(1978), deposit insurance is purely a bad thing. Brusco and Castiglionesi(2007) considers two types of risky assets: one is considered as safe asset with unit return R as in Allen and Gale(2000), the other illiquid asset is considered as gambling asset which generates $\lambda R(\lambda = 1)$ units of good at $t = 2$ for each one unit good invested at $t = 0$ with probability η. There are two types of agents in their economy, the first type the depositor which is the same as Diamond and Dybvig(1983), they creates liquidity shocks. Another type of agents is the investors who receive endowment which allow them to buy the shares of banks which entitled them for dividend. Network formations are considered as completely connected markets and incomplete cycle connected market. The authors showed that by taking moral hazard into an account, the Allen and Gale(2000) result has been reversed: A more connected interbank deposit market is more venerable than the less connected interbank market. However, the source of bankcupty is not the excess aggregate liquidity shock in Allen and Gale(2000), but is the moral hazard problem as banks' investing in gambling asset.

All the models above provide explanations for interbank market fragility under different economic framework. Some extension papers also try to embedded the central bank intervention and monetary policy into the interbank economic framework. In this string of literature, four types of network formations have been considered: Completely connected network, Incompletely connected network which includes incomplete cycle network and incomplete disconnected network, and finally the autarkic network. The limited network formations and the over simplified interbank balance sheet lead the literature into another stage where more complicated network formation and interlinked balance sheet has been modeled. For example: banks strategically decide whether to roll over their credit over time, Banks are heterogeneity with different balance sheet size and interbank condition. The relationship between network properties, nodes heterogeneity and contagion probability has been studied. Some policy suggestions have been drawn on whether it is too-interconnected-to-fail or too-big-to fall.

IV. Connectivity and Heterogeneity under Complex Dynamic Network Formations

The completed network formations on static analysis is illustrated in Nier at.el(2007). The paper provides another insight in understanding the relation between the structure of banking system and the financial stability. They model the balance sheet in the same way as Gai et. al(2010), yet they identify the net worth more specifically in the balance sheet. Paper analyze the network based on aggregate level. By setting the total external assets $E = e_1 + e_2 + ...e_N$. The percentage of external assets in total assets as (A) $\beta = E/A$. Since total asset A is the sum of total external asset and aggregate size of interbank exposure I. Therefore, we have $I = \theta A, \theta = 1 - \beta$, where θ is the percentage of interbank assets in total assets. Erdos-Renyi network model(N, P) provides the total number of links Z in the network, thus the weight(bank-level size) of any directional link is $w = I/Z$. By further assume the net worth as a fixed proportion γ of total assets at bank level $c_i = \gamma a_{i.}$The banking system can be constructed by parameters $(E, N, P, \theta, \gamma)$. The shock transmission has been modeled as the consequence of idiosyncratic shock to the structural parameters of the system, and the priority of customer deposits over bank depositors has been assumed. If shock size s_i cannot be observed by net worth c_i, bank defaults and the residual is transmitted to the creditor banks through interbank liabilities. By using the Erdos-Renyi network model with $N = 25$, $p = 0.20$.They find the following properties for the parameters from numerical simulation. There is a negative relationship between bank's capitalization and contagion probability, but contagion probability is not decrease linearly w.r.t γ. The increase in interbank asset size beyond some threshold may lead to an increase in the threat of contagion. The relationship between connectivity and contagion depends on different probability regimes. For low connectivity regime, an increase in connectivity will increase the number of defaults. For the high connectivity regimes, connectivity increase will make the number of defaults decrease. In the middle regime for connectivity where it's not sufficiently high yet not sufficient low, the increase in connectivity may decrease or increase the system resilience(the M-shape). When those relationship has been modeled in different net worth condition, the simulation indicates an undercapitalized banking systems are more fragile compared to high-capitalized banking system when connectivity is high. The parameter analyze on(E, P, θ, γ) indicates for a given shock size, a more concentrated banking system is more vulnerable to systemic risk. They also analyze the liquidity risk as Gai et. al(2010), they find illiquidity increases contagious default for any level of connectivity, a total breakdown happens even for relatively sizable net worth level, the increases in connectivity are less powerful than in the case without liquidity risk. More concentrated system is more fragile in the liquidity risk case. Authors further analyze the network with tiering, because in the real world, the random graph set up is unrealistic. For example, Boss et al(2003) confirm the Austrian banking system exhibit 'tiering', where the first-tiering are connected to second-tiering as well as to each other, while there is limited connectivity between second-tiering institutions. The similar tiering formate has also been found in UK and German banking markets. Thus, author construct a tiering network and force the banks in the first-tiering to have higher P and one large first-tiering bank. The numerical simulation result indicates the tiering structures are not necessary more prone to systemic risk, whether they are or not depends on the centrality degree. Thus, the high degree tiering systems are not necessarily more fragile than homogenous banking systems.

Gai et. al(2010) models the interbank asset in Erodos-Renyi network, they found the robust-yet-fragile tendency in the financial system, which suggests although the contagion probability is low, the effects can be widely spread when it occurs. The result holds for authors' interbank balance sheet design for bank i is as follow:

lnterbank Balance Sheet

Asset	Liability
Interbank Asset A_i^{IB}	Deposite D_i
External Asset A_i^M	Interbank Liability L_i^{IB}

Bank i's solvent condition is $(1-\phi)A_i^{IB} + qA_i^M + L_i^{IB} - D_i > 0$, where ϕ is the fraction of banks which has default while hold obligation with bank i. q quantifies market condition for illiquid asset. $q = 1$ stands for no fire sale. The important assumption authors apply here is the zero recovery assumption, which indicates once a bank defaults, it's linked bank loses all their interbank asset holds against that bank. Model applies for uniformly distributed interlink asset, which implies $\phi = j$, where j denotes the in-degree for bank i. By calibrate this model with the numerical simulation, authors used Erodos-Renyi Network(uniform Poisson random graph) with equally weighted directed link with probability p, and capital buffer and asset ratio $\frac{K_i}{A_i^{IB}}$is set to be identical among all banks. Each bank's interbank assets are evenly distributed over its incoming links, interbank liability are determined endogenously within the network structure. The benchmark plot implies the robust-yet-fragile tendency, when average degree z is high, especially above 8, contagion seems never occurs more than five times in $1,000$ draws, however, once it happens, every bank in the network fails. This tendency holds still when the nodes in network expends to $10,000$. More results have been drawn when different scenarios on capital buffer and liquidity risk have been taken into account. For the same average degree of z, smaller capital buffer both widens the contagion window and the contagion probability. Liquidity shock has been modeled into $q = e^{-\alpha x}$, where x stands for the fraction of the illiquid assets in the system, α is used to calibrate to make asset price fall 10% when 10% of the system assets have been sold. Simulation result indicates both the contagion probability and contagion window increased (compare to no liquidity case) when liquidity shock has been considered, while robust-yet-fragile tendency still holds in this situation.

By following the same interlinked balance-sheets model and solvency condition from Gai and Kapadia(2010), Caccioli et. al(2011) further answer the target problem of effective policy by considering the real financial network properties such as heterogeneous degree distribution and heterogeneous assets distribution. Authors also consider the degree correlations among connected bank instead of uniform distribution in Gai and Kapadia(2010). Heterogenous degree distribution can be used to capture the characteristic of banks playing the role as financial hubs. By using the power law distribution for the in and out degree, such as $P(z) = z^{-\gamma}$ with $\gamma = 3.0$. By setting the seed randomly, authors found robust-yet-fragile in both networks, but scale free network appears to be more resilient than Erodos-Renyi Network. However, when the seed is chosen to be the most connected node, the probability of contagion in scale free network is much higher than homogeneous one. Thus, those founding confirm that scale free networks are more robust than homogeneous ones with respect to random failures, but more fragile than homogeneous one with respect to target attack, which is in line with Albert et.al(2002). This very fact seems to suggest the policy implication on targeting reserve requirements(capital buffer) in few, most connected banks to increase systemic stability. To test this hypothesis, authors prepare two sets of samples: one is stablished by increasing the capital buffer for top 5% highest degree nodes from 4% to 6%, the other is a compare sample constructed by increasing the capital buffer for random 5% nodes from 4% to 6%, the contagion probability ratio from two samples is almost around 1 in every degree. Therefore, the authors conclude that the target policy is not effective. The scale free network allows nodes to have different degree distributions, which does have a higher contagion probability than Erodos-Renyi network when seed is the most connected nodes. But when the seed is set to be random, the result is opposite, scale free network appears to be the more resilient one. Thus, once the initial failure bank is one of the financial hubs, the contagion will be more probable to happen in the scale free network, however, forcing those hubs to have higher capital buffer will not improve the situation. Authors further analyze the case where the interlinked balance sheets is heterogeneous and characteristic as power law distribution $P(A)A^{-\alpha}$ with $\alpha = 2.5$. The numerical simulation shown in the same random failure Erodos-Renyi framework, uniform asset distribution shortens the contagion window compares to the power law asset distribution case. The situation is even worse when the seed is set to be the biggest bank. When they test the sample policy implication by computing the contagion probability ratio between the capital buffer of 5% random banks and 5% biggest banks, the ratio increases when average degree is high. Thus, the target policy is effective in the high average degree regime. The most highlight in the paper is to answer the question on: whether it is 'too-interconnected-to-fail' or it is 'too-big-to-fall'. Considering now a network with power law distribution on both degree and balance sheet size. By setting the seed as most connected bank and biggest balance sheet bank, authors found two regimes: one for low average degree and the other for high average degree. In the low average degree regime, the contagion probability is higher when the seed is the most connected bank, while in high average degree regime, the contagion probability is higher when seed is the biggest bank. In reality, we know that network appears to be in the high average connectivity regime, we also know that when average degree is high, target policy on capital buffer constrain is effective. Therefore, it indicates 'size' is more important in reducing the contagion probability when average degree is high, in other words, 'too-big-to-fall' is more relevant and this can be controlled by target policy on capital buffer. This shed some lights on Ben Bernanke's comment at September 2010: If the crisis has a single lesson, it is that the too-big-to-fail problem must be solved.

Anand(2012) studied the dynamic topology of interactions and balance sheet. They include the funding maturities, investor's strategic behavior in rollover decisions, and information arrival relative to rollover frequency. The dynamic evolution of network is punctuated by time t where lenders of the bank i engage in a game to decide whether to foreclosure their loans to bank i. The unique equilibrium of the rollover game is defined under threshold of loss c^*(Asset to liability ratio), if loss for bank j is smaller than c^*, bank j will rollover his loans. The adjacency matrix A^t captures the state of interbank network, the balance sheet random variable for both liability and asset are governed by continuous time Poisson process. Loan matures at rate λ, the adverse information about bank i's future loss arrives at random Poisson time with rate v. By numerical simulation, they found, when loss $c < 1$ and loan mature rate λ is small, the network seems to attain in a good state where the network is dense and default free. When $c = 1$ the large loss, even with a small value of λ, the network will stay in the bad state where the default is persistent. Coincide of the common results from equilibrium, authors showed that once funding market freeze, it takes a prolonged time for those markets to re-establish of the normal credit condition.

Another paper worths mentioning is Cohen-Cole et. al(2014). The authors constructed the interbank loan market into both static and dynamic models. Bank balance is designed as Cash, Loans, Interbank Loans on the Assets side, and Deposits, Interbank Borrowing, Equity on the Liability side. The paper defined another source of the shock, which is not emerge from a bankruptcy. Instead it occurs as a result of financial incentives in the absence of default. System illustrates how small changes in uncertainty, risk, or behavior can propagate through a network, which leads to changes in volumes and prices. Authors argue that banks act strategically given the market and regulatory incentives they face. Changes in bank incentives can lead to changes in holdings long before any defaults take place or even in the complete absence of defaults. Authors embed their static model into a complete dynamic model of network formation, where banks form and break links changes the structure of the network. Banks strategically calculate all the possible network configurations and then choose to form or delete the link with bank that gives it the highest profit or reduces the least its profit. The paper stressed the importance of network structural, because it can fundamentally alter incentives and prices. Authors investigated into the impact of the key bank, which will reduces total activity of network once being removed, and concluded a policy design for Central Bank to bail out banks in case of a financial crisis.

V. Future Directions for Research

This paper has surveyed the recent researches of interbank market and network application. We include some stylized and important theoretical papers(Allen and Gale, 2000), which studied the bank runs and contagion in the interbank system. The interbank market is modeled under the simply network formations, which only included the completely connected network, cycle network, and disconnected network. Those papers provided the economic meaning of the interbank markets existence, source of uncertainty(Freixas et al 2000), moral hazard problem(Brusco and Castiglionesi, 2007), agents behavior and contagion conditions. Another stream of papers claim that the interbank market is over-simplified in those models' framework. In reality, interbank market is complex, banks are strategic and not identical in terms of size and credit condition. Thus, the network models together with graph theory can allow us to investigate the contagion and banks' strategic behaviors under complex network structure. By applying power law distribution, bank size and interlink probability are allowed to vary. Robust-yet-fiagile property has been found in the financial system(Gai and Kapadia, 2010). Important questions, such as is it too-big-to-fail or too-connected-to-fall, have been answered by using numerical simulation(Caccioli et al., 2012). Dynamic topology of interactions and balance sheet has also being included(Anand, 2012).

The recent financial crisis has generated substantial amount of new researches. The new method in using network models allow us to study the complex interbank market. The importance of too-big-to-fall is being stressed by using numerical simulation(Caccioli et al., 2012). The theoretical models provide us with the economic explanation in contagion under simple network formation, while simulation-based models allow us investigate into the complex network which is more closer to the real world. There still exists a gap between network structures used in models and real-world evidence. Most existing models form links as homogeneous. However, links in a real world is link-weight heterogeneity. A deeper knowledge in network-formation mechanisms could be a potential topic for future research. Moreover, the interbank system is under the supervision of Central Bank. More focus could also be placed on the role of Central Bank Intervention. Few papers(Freixas et al, 2011 and Allen et al, 2009) have studied the role of interbank market in Central Bank's monetary policy. For the policy makers, it is crucial to understand the mechanism for policy transmission in the interbank market, which further influence the market stability.

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Appendix

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############################
#R Code for Network Formation:#
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library(igraph)

g1=graph.formula(A++B,B++C,C++D,D++A,A++C,B++D)
layout=matrix(c(1,0, 3,0, 3,3, 1,3),byrow=TRUE,nrow=4)
plot.igraph(g1,layout=layout,edge.color="black",vertex.color="white",
vertex.label=c("A","B","C","D"),vertex.size=20,vertex.label.cex=3,
vertex.label.color="black",edge.width=3,edge.arrow.size=1.2,edge.arrow.width=1.2)

g2=graph.formula(A-+B,B-+C,C-+D,D-+A)
plot.igraph(g2,layout=layout,edge.color="black",vertex.color="white",
vertex.label=c("A","B","C","D"),vertex.size=20,vertex.label.cex=3,
vertex.label.color="black",edge.width=3,edge.arrow.size=1.2,edge.arrow.width=1.2)

g3=graph.formula(A++B,C++D)
plot.igraph(g3,layout=layout,edge.color="black",vertex.color="white",
vertex.label=c("A","B","C","D"),vertex.size=20,vertex.label.cex=3,
vertex.label.color="black",edge.width=3,edge.arrow.size=1.2,edge.arrow.width=1.2)

g4=graph.formula()
plot.igraph(g4,layout=layout,edge.color="black",vertex.color="white",
vertex.label=c("A","B","C","D"),vertex.size=20,vertex.label.cex=3,
vertex.label.color="black",edge.width=3,edge.arrow.size=1.2,edge.arrow.width=1.2)



##################
#Florence Marriage#
##################


data("flo")
flomarriage <- network(flo,directed=FALSE)
plot(flomarriage, displaylabels = TRUE, boxed.labels = FALSE)
```

```
##################
#ER VS SF Network#
##################
```

```
g<- barabasi.game(100, power=1,m=1)
igraph.par("plot.layout",layout.fruchterman.reingold)
plot(g, vertex.size=3,
vertex.label=NA,edge.arrow.size=0.7,edge.color="black",vertex.color="red",
frame=TRUE)
is.connected(g)

no.clusters(g)
table(clusters(g)\$csize)
max(degree(g, mode="in"))
max(degree(g, mode="out"))
max(degree(g, mode="all"))

plot(degree.distribution(g, mode="in"), log="xy",ylab = "Frequency", xlab =
"Degree", main = "degree distribution for scale free")

g<- erdos.renyi.game(100, 0.04)

plot(g, vertex.size=3, vertex.label=NA, asp=FALSE,
layout=layout.fruchterman.reingold, edge.color="black",vertex.color="red",
frame=TRUE)

plot(degree.distribution(g, mode="in"), log="xy",ylab = "Frequency", xlab =
"Degree", main = "degree distribution for random network")
```