Ranking Systemic Risks in Bank Networks

Research-in-Progress

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Introduction

The recent global financial tsunami (2007 – present) has been considered by many economists as the worst financial crisis since the Great Depression in the 1930s (Bullard et al. 2009; Pendery 2009). It has resulted in the collapse of major financial institutions like Lehman Brothers, downturns of stock markets around the world, and even breakdowns of financial systems in several countries like Greece and Iceland. Although the immediate cause or trigger for this crisis is the burst of the U.S. housing bubble and the following liquidity shortfall of major banks, the mechanism that spreads and magnifies their impacts is the largely interconnected U.S. bank network (Harrington 2009; Markose et al. 2010). In this network, banks are connected with each other through interbank payments and correlated bank portfolios (i.e. owning the same financial product(s) such as IBM stock) (Elsinger et al. 2006). A bank's solvency largely depends on the interbank payments it received from other banks and the value of its portfolio of financial products. In turn, the value of these payments and its portfolio depends on the financial health of other banks in this bank network. Therefore, correlation in interbank payments and bank portfolio values can contagiously transmit insolvency of single banks to other banks in this network in a domino effect.

Figure 1 shows an example of such contagious failure in a bank network containing three banks A, B and C, and two financial products (e.g., securities, bonds or financial derivatives) X and Y as nodes. There are two types of links/relationships among these nodes. The solid line represents the interbank payment relationships among the three banks, while the dotted line represents the ownership relationship between a bank and a financial product. We use out-links to represent ownership relationship between financial products and banks because only the default of a financial product has impacts on its owner banks, not the other way around. Then this sample bank network illustrates the interbank payment relationships among banks and their interdependencies through shared holdings of financial products. For example, as Figure 1 shows, A has a payment to B and A owns a certain share of financial product X. In addition, an example of the contagious failure may happen as the following: A sudden decrease in the market value of financial product X may cause bank A to default on its payment obligations to bank B. Such a default along with the decreased value of X may lead B to fail its payment obligations to C. A default by C may, in turn, have a major feedback effect on A and potentially bankrupt A. This example illustrates the risk of the collapse of the whole banking system by the default of a single bank through contagious failure process in the bank network. Such risk is often termed as Systemic risk (Bullard et al. 2009; Markose et al. 2010).

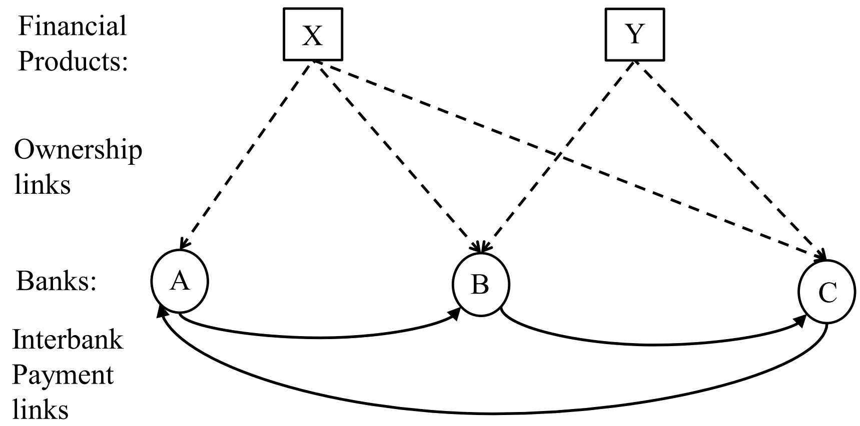

Figure.1. An Example of a Bank Network

In a bank network, systemic risk refers to the risks associated with the interlinkages and interdependencies among banks, where the failure of a single bank or group of banks can cause a cascading failure of other connected banks, which may potentially bring down the entire banking system (network). However, existing research on banking regulation and monitoring mainly focused on the risk at the level of the individual bank (Elsinger et al. 2006) but largely ignored the systemic risk. New models and methods that can discover hidden systemic risks in the bank network are needed to prevent the potential buildup of such risks that may cause the breakdown of the whole banking system.

Therefore, it is important to take a system-wide and network perspective to model and analyze the systemic risks, and devise effective mechanisms to prevent potential breakdown of the banking system. The main modeling challenge, identified by Elsinger et al. (2006), is to effectively capture the two major sources of systemic risk: 1) correlated bank portfolios that may result in simultaneous defaults of multiple banks due to negative shocks in financial markets; 2)Banks may default on their interbank payments and thus cause other banks to default or even bankrupt triggering a domino effect. Elsinger et al. (2006) improved a network-based interbank payment model proposed in Eisenberg and Noe (2001), and adopted simulation methods to study these two sources in Austrian banking system. However, their analysis focused on simulating the system-wide impacts of potential contagious default events on the banks in various stress scenarios. There is a lack of systematic approach to model and assess the level of systemic risk each bank possesses in the bank network.

To address this problem, first we modified Elsinger's interbank payment model to better integrate the other major source of systemic risk – correlated bank portfolios. We then develop a network-based algorithm based on the HITS algorithm (Kleinberg 1999) to rank the systemic risk associated with banks and financial products in the bank network. At last, we use simulation methods to evaluate the effectiveness of our proposed ranking algorithm in different stress scenarios using real-world data on the U.S. banking system.

We claim three major contributions for this research. Firstly, the proposed network-based ranking algorithm can help both individual banks and central bank regulators to devise effective risk mitigation strategies on banks and financial products with high systemic risks, in order to prevent system-wide breakdown in the bank network. Secondly, the modified interbank payment model can better capture the systemic risk associated with the correlated bank portfolios and thus can make the simulation experiments more realistic and accurate. Thirdly, in general, this research contributes to the growing stream of studies on understanding and managing systemic risk in the banking system.

The remainder of this paper is organized as follows. In the next section, we review relevant studies. The third section introduces the modified mathematical model of the banking system. The fourth section describes the proposed network-based ranking algorithm. Then we show our plan to evaluate the effectiveness of our proposed algorithm using simulation techniques. Finally, we discuss the possible implications and potential contributions of our research.

Related Studies

Our study proposes to use a business intelligence approach for managing systemic risk in the bank networks. In this section, we review relevant studies in business intelligence and bank risk management, as well as the network-based ranking algorithm our work is based on.

Business Intelligence and Bank Risk Management

Various business Intelligence (BI) techniques have been employed to manage bank risk, mostly focusing on predictions of bank failures. These studies often adopt Artificial Intelligence and data mining techniques on real-world banking data, aiming to discover the causes of bank failures and successfully predict potential failures. These techniques include Neural Networks (NN), Support Vector Machines (SVM), Bayesian Networks (BN), and other common classification algorithms. Tam et al. (1992) has demonstrated the effectiveness of Neural Networks technique in bank failure predictions. A fuzzy support vector machine method for credit risk assessment in banking industry is proposed in Wang et al. (2005). Sarkar and Sriram (2001) have applied Bayesian Networks models for early warning of bank failures. In addition, Data mining methods have also been used in the research about anti-money laundering (John 2004; Zhongfei et al. 2003). In general, these business intelligence techniques can provide novel insights different from traditional financial risk management techniques for decision makers in the banking industry to achieve better risk measurement, assessment and mitigation.

However, there are mainly two issues for existing research using business intelligence techniques on bank risk management. Firstly, the analyses in these studies mainly focus at the level of individual banks or institutions but largely overlook the systemic risk. Secondly, relevant with the previous issue, the relational (network) data such as interbank payment is rarely studied. Thus network analysis techniques or network-based ranking algorithm is rarely used for bank risk management. Our research aims to address these two issues by 1) adopting a network perspective to model systemic risk associated with interbank payments and correlated bank portfolios, and 2) developing network-based ranking algorithm for systemic risk mitigation in bank networks.

Network-based Ranking Algorithms

With the fast development of digital communication networks such as Internet and World Wide Web (WWW) in the past decades, various network-based algorithms have been developed to rank the node's importance in these networks. These algorithms are widely adopted in modern web search engines which effectively search and rank the web pages on the World Wide Web. Most of such network ranking algorithms are based on link-structure analysis. The most famous two are Google's Pagerank (Brin and Page 1998) and the HITS algorithm developed by Kleinberg (1999). Other link analysis based network algorithms include CLEVER (Chakrabarti et al. 1998) project in IBM, SALSA (Lempel and Moran 2001), as well as TrustRank (Gyöngyi et al. 2004). However, these algorithm are mainly used in information retrieval area, but has rarely been used in other application areas.

Since our proposed systemic risk ranking algorithm is based on the HITS algorithm (Kleinberg 1999), we introduce it in detail as the following. In the HITS algorithm, two scores for each web page are calculated – the authority score and the hub score. The authority score measures the value of the content for the web page, while the hub score estimates the value of the web page's links to other pages. Authority and hub scores are defined in terms of one another in a mutual recursion. An authority score is computed as the sum of the scaled hub scores that point to that page. A hub score is the sum of the scaled authority scores of the pages it points to. Both scores for each web page are normalized for each iteration until they converge.

A Network-based Model of the Banking System

In this research, we developed a network-based model of the banking system mainly for evaluating the effectiveness of our ranking algorithm. We use this model to simulate how our algorithm can help reduce contagious failures in the bank network under various stress scenarios using real-world data. This model is mainly based on the model developed by Eisenberg and Noe (2001) and Elsinger et al. (2006). We extend it to include the systemic risk originated from the correlated bank portfolios.

Considering a set of $\mathrm{N} = \{1,..,N\}$ banks, each bank $\mathrm{i} \in \mathrm{N}$ has a value $\mathrm{e_i}$ which represents the value of this bank's total assets. The total value of the bank is the value of $\mathrm{e_i}$ plus the value of the bank portfolio and the value of all interbank payments received from other banks minus the interbank liabilities this bank has. If the total value of a bank becomes negative, the bank is insolvent. Therefore, there are three components in the total value of a bank – total assets of the bank, the bank's portfolio of financial products, the interbank payments received from other banks or interbank liabilities. We then describe our model of the banking system in the following three sub sections.

Correlated Bank Portfolios

The major difference between our network-based model and the model by Elsinger et al. (2006) is the addition of correlated bank portfolio component. One major source of systemic risk is the shared holdings of same financial product(s) by different banks, especially the ones with interbank payments (liabilities) relationships. A major negative economic shock on the financial market may cause the decrease of the values for certain or most financial products in a bank's portfolio. A typical example is that the burst of housing bubble has caused major banks to suffer heavy loss in many asset-backed securities (ABS) such as Mortgage Backed Securities (MBS), Collateralized Debt Obligations (CDO) (Krahnen and Wilde 2006) and Credit Default Swaps (CDS) (Markose et al. 2010)held by major banks. Along with the interbank payment relationships, such loss in correlated bank portfolios may largely reduce the payment abilities of these banks simultaneously, causing their insolvency. However, Elsinger et al. (2006) did not explicitly include this systemic risk factor in their model of banking system.

Therefore, in our modified model of banking system, we develop a correlated bank portfolio component to represent this source of systemic risk. We define b_i as the value of a bank *i*'s investment on a portfolio of financial products $\mathrm{M} = \{1,...,M\}$ on the observation day. This value is calculated as

$$b_i = \sum_{k \in M}^{M} R_k V_{ik}$$

where R_k is financial product *k*'s market closing price on the observation day and V_{ik} is the volume the bank *i* held that day.

Interbank Payment

To model interbank payments, we use a $N \times N$ matrix L, in which l_{ij} represents bank *i*'s payment obligation towards bank *j*. Therefore, the value of bank *i*'s total obligations towards the rest of the banking system can be denoted as $d_i = \sum_{j=1}^{N} l_{ij}$. We then define a new matrix $\prod \in [0,1]^{N \times N}$ by normalizing the entries by the total obligation d_i:

$$\pi_{ij} = \begin{cases} l_{ij} / d_i & if (d_i > 0) \\ \\ 0 & otherwise \end{cases}$$

Clearing Payment Vector

Then the banking system can be described as the sum of the three aforementioned components – total assets *e*, correlated bank portfolio *b*, and the interbank payment obligations *d*. Following Eisenberg and Noe (2001) and Elsinger et al. (2006), we then define a *clearing payment vector* p^* as

$$p_i^* = \begin{cases} d_i & if \quad \sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i \geq d_i \\ \sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i & if \quad d_i > \sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i \geq 0 \\ 0 & if \quad \sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i < 0 \end{cases}$$

This payment vector p^* is used to represent total interbank payments made by bank *i* to the rest of the banking system under the clearing mechanism. It has limited liability and proportional sharing in case of bankruptcy.

Using this payment vector, we can easily identify the insolvent banks in the system if $p_i^* < d_i$. In that case, the recovery rate will be (p_i^* / d_i). More specifically speaking, a bank default and becomes insolvent if $\sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i - d_i < 0$.

A contagious default may happen on bank *i* in one of the two following situations:

- One or more banks are not be able to keep their payment promises to bank *i*, causing *i*'s insolvency. Using our model to explain, that is $\sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} d_j + e_i - d_i \geq 0$, but $\sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i - d_i < 0$.
- The defaults of the co-related financial products may cause other banks' inability to make their interbank payments and also reduce the value of *i*'s bank portfolio, i.e., $\sum_{k=1}^{M} R_k V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i - d_i \geq 0$, but $\sum_{k=1}^{M} R_k^{'} V_{ik} + \sum_{j=1}^{N} \pi_{ji} p_j^* + e_i - d_i < 0$.

To summarize, this model of the banking system is mainly for simulating the contagious defaults under various stress scenarios and how our ranking algorithm can help reduce systemic risk in the bank network. In addition, the design of the ranking algorithm has also utilized representations developed in this model.

A Network-based Algorithm for Ranking Systemic Risks

Existing risk management research focused on econometric analysis of market and credit risks. Although there are several studies taking a network perspective to study the systemic risks in the banking systems (Eisenberg and Noe 2001; Elsinger et al. 2006; Markose et al. 2010; May and Arinaminpathy 2010), no application mechanisms or algorithms has been proposed to manage such risk. In this study, we developed a network-based algorithm that is based on the famous HITS algorithm developed by Kleinberg (1999) to rank systemic risk in the bank network. This algorithm also mainly considered the two major sources of systemic risk – the correlated bank portfolio and the interbank payment.

Our ranking algorithm is based on both the topological features of the bank networks and financial characteristics of individual banks. As Figure 1 shows, there are two types of nodes – banks and financial products – in the bank network. The financial product nodes only have out-links (owned by banks), while the bank nodes have both in-links (incoming payments) and out-links (outgoing payments or ownership links to financial products).

Measuring Systemic Risk Associated with Financial Product Nodes

We firstly aim to measure the systemic risk associated with the financial product nodes from the banks' perspective. We mainly focused on two factors:

- The likelihood of the default of the underlying financial product. This is often linked to rating scores by credit agencies. We denote the probability of default of financial product *k* as $f_k \quad (k \in M)$.
- The impacts/loss caused by the default of the financial product *k* on its owner bank *i*. We denote that using $\Delta R_k V_{ik} / p_i^*$, where ΔR_k is the change in the price of the product *k* caused by the default event.

Together these two factors determines the impacts (possible loss) of financial product k on its owner bank i as $f_k(\Delta R_k V_{ka} / p_a^*)$.

Measuring Systemic Risk Associated with Interbank Payments

Then we aim to measure the systemic risks associated with the interbank payments among in the bank network. We propose IP_{ij} that intends to measure the impacts (possible loss) caused by the default of an individual bank i on one of its debtor banks j through the interbank payment links between them. That is

$$IP_{ij} = C(l_{ij} / p_j^*),$$

where C is the average default rate for all banks during a certain time period.

Ranking Algorithm Design

After developing two measures for modeling bank systemic risks, we embedded them into the design of our network-based ranking algorithm which is inspired by HITS algorithm (Kleinberg 1999). Similar to HITS, our algorithm has an iterative process with two iterative steps: update hub score and authority score for the two types of nodes. One thing to note is that financial product nodes only has out-links while bank nodes have both in- and out-links. Thus financial nodes only has hub score (FPHUB) and bank nodes have both authority (BANKAU) and hub scores (BANKHUB).

- In the initial step, For each bank i, we calculate the coefficient for the hub score of the financial product k it owns as $\alpha_{ki} = f_k(\Delta R_k V_{ki} / p_i^*)$. Then we set the coefficient for the bank i's hub score to bank j as $\beta_{ij} = IP_{ij} = C(l_{ij} / p_j^*)$.

- Firstly, we start to update bank i's authority score as $BANKAU_i$

$$BANKAU_i = \sum_{k \in M} \alpha_{ki} FPHUB_k + \sum_{j \in N} \beta_{ij} BANKHUB_j$$

where M is the set of financial product owned by bank i, and N is the set of banks that have payment obligations to i. Similar to the HITS algorithm, initially both FPHUB and BANKHUB are set to one. This update process means that the authority score that rank bank i's systemic risk is based on the systemic risks possessed by i's portfolio of financial products, and all the banks that may affect i's cash flow through possible defaults of interbank payments. The coefficients are basically the possible impacts of these two systemic risk sources on bank i.

- Secondly, we update financial product k's hub score as $FPHUB_k$. This score represents the systemic risk financial product k may has (the possible loss of its default) on the whole bank network/system through its owner banks. Therefore, it is calculated as

$$FPHUB_k = \sum_{j \in H} S_{jk} BANKAU_j$$

where S_{jk} is the percentage/share of the product k held by bank j, H is the set of banks that hold k.

- Thirdly, we update bank i's hub score as $BANKHUB_i$. This score represents bank i's systemic risk (the possible loss of its default) on the whole bank network through the banks it has payment obligations. Therefore, it is calculated as

$$BANKHUB_i = \sum_{j \in N'} OP_{ji} BANKAU_j$$

where OP_{ji} is the portion of bank i's payments in the total payments received by bank j, and N' is the set of banks that i has payment obligations.

Then we repeatedly execute the three steps until all three scores converge like HITS algorithm does. We expected these scores will converge after a number of iteration. The converged hub scores for each financial product and bank are our ranking scores for measuring their systemic risks.

Evaluation of the Proposed Algorithm through Simulation

To assess the effectiveness of this the network-based ranking algorithm, we plan to use a simulation approach to generate stress scenarios in which the bank network undergo various types of economic shocks, and contagious bank failures happen through the two systemic risks modeled in the previous section. More specifically speaking, in this simulation, it is assumed that there are two time points: t = 0, the observation day, and t = 1, the payment clearing date, when all interbank payments are settled according to the clearing vector p^* we defined before. At t = 0, the portfolio holdings of financial products b for each bank are observed. In addition, the interbank payments among banks are modeled as a $N \times N$ matrix L. The remaining value of bank assets is represented as e. Both the values of b and e is exposed to various market and credit risk such as the sudden drop of prices for certain financial products held. Therefore, according the clearing payment vector p^* defined before, the value of p^* depends on the realization of such risk factors. To generate a stress scenario, we draw a realization of these risk factors using real-world data such as interest rates or currency exchange rates, and revalue the b and e for each bank to estimate its new value of p^*.

To estimate the effects of our proposed ranking algorithm, we applied it on the data in each generated scenario and get a list of banks and financial products that have high level of systemic risks. We then devise strategies based on this list to reduce the systemic risk in the bank network (e.g., sell the holdings of financial products with high systemic risk). We then compare the number of default banks (caused by contagious failures) between the original scenario and the one which use the algorithm to reduce systemic risk. For multiple scenarios, if the numbers of default banks in original scenarios are consistently and significantly larger than the ones in the scenarios that adopted our ranking algorithm. Then the algorithm will be proven to be effective in reducing systemic risks in bank networks.

Dataset

In this study, we plan to use data from the Bank Regulatory and the Bank Holding Companies Databases in the Wharton Research Data Services (WRDS). The Bank Regulatory Database contains accounting data for bank holding companies, commercial banks, savings banks, and savings and loans institutions. The source data is from the required regulatory forms filed for supervising purposes. The Bank Holding Companies Database collects financial data included in the FRY-9 reports which contain balance sheet, income information, risk-based capital measures and additional supporting schedules. The information in these two databases is mainly used to generate stress scenarios in our simulations of contagious failures in bank networks.

Discussion and Future Work

In summary, we developed a network-based ranking algorithm to rank systemic risk associated with banks and financial products in the bank networks. In addition, we extended Elsinger's (2006) model of the banking system and plan to adopt it on real world banking data to simulate the effects of our proposed algorithm in reducing systemic risk (contagious failures) in the bank network. Our proposed research has both theoretical and practical contributions. Theoretically, it contributes to the research about the causes and mechanisms of contagious bank failures in bank networks. It provides a novel network perspective for researchers to study how system-wide bank failures happen caused by a single bank failure. Empirically, our study intend to provide a network-based ranking mechanism of systemic risk associated with banks and financial products, aiming to help individual banks and central bank regulators devise effective strategies for reducing such systemic risk. The long term goal is to prevent system-wide breakdown in the banking system by identifying banks and financial products with high systemic risk and reducing such risk before total meltdown.

Our future work consists of three parts. Firstly, we need to collect data from the Bank Regulatory and the Bank Holding Companies Databases in WRDS. Secondly, we will construct the bank network and generate various stress scenarios for the banking system. Thirdly, we then compare the numbers of contagious bank failures in original scenarios and in scenarios that adopted our proposed network-based algorithm for systemic risk mitigation. We believe our algorithm may significantly reduce systemic risk (contagious bank failures) in the bank network under various stress scenarios.

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