

# **NETWORK-BASED MODELING AND ANALYSIS OF SYSTEMIC RISK IN BANKING SYSTEMS**

**Daning Hu**

Department of Informatics,  
University of Zurich, Zurich, Switzerland  
[hdaning@ifi.uzh.ch](mailto:hdaning@ifi.uzh.ch)

**J. Leon Zhao**

Department of Information Systems,  
City University of Hong Kong, Hong Kong SAR, China  
[jlzhao@cityu.edu.hk](mailto:jlzhao@cityu.edu.hk)

**Zhimin Hua**

Department of Information Systems,  
City University of Hong Kong, Hong Kong SAR, China  
[zmhua2@student.cityu.edu.hk](mailto:zmhua2@student.cityu.edu.hk)

**Michael C S Wong**

Department of Economics and Finance,  
City University of Hong Kong, Hong Kong SAR, China  
[efmcw103@cityu.edu.hk](mailto:efmcw103@cityu.edu.hk)

## **Abstract**

In the wake of the 2008 financial tsunami, existing methods and tools for managing financial risks have been criticized for weaknesses in monitoring and alleviating risks at the systemic level. A 2009 article in Nature suggested new approaches to modeling economic meltdowns are needed to prevent future financial crises. However, existing studies have not focused on analysis of systemic risk at the individual bank level in a banking network, which is essential for monitoring and mitigating contagious bank failures. To this end, we develop a Network Approach to Risk Management (NARM) for modeling and analyzing systemic risk in banking

systems. NARM views banks as a network that is linked through financial relationships. It incorporates network and financial principles into a Business Intelligence (BI) algorithm to analyze systemic risk attributed to each individual bank via simulations based on real-world data from the Federal Deposit Insurance Corporation. Our research demonstrates the feasibility of modeling and analyzing systemic risk at the individual bank level in a banking network using a BI-based approach. In terms of business impacts, NARM offers a new means for predicting contagious bank failures and determining capital injection priorities in the wake of financial crises. Our simulation study shows that under significant market shocks, the interbank payment relationship becomes more influential than the correlated bank portfolio relationship in determining an individual bank's survival. These insights should help financial regulators devise more effective policies and mechanisms to prevent the collapse of a banking system. Further, NARM and the simulation procedure driven by real-world data proposed in this study have instructional value to similar research areas such as bank stress testing, where time series data and business networks may be studied.

**Keywords:** Systemic risk, contagious bank failures, business intelligence, simulation.

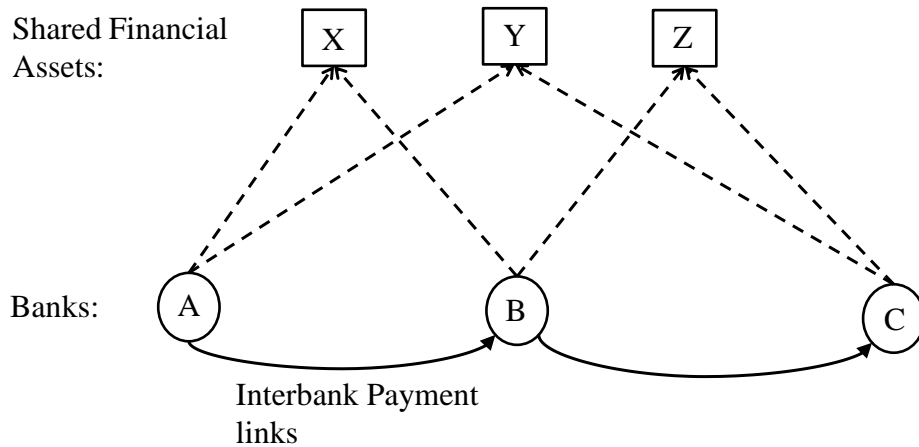
## 1. INTRODUCTION

Many economists consider the recent global financial tsunami to be the worst financial crisis since the Great Depression in the 1930s (Bullard et al. 2009). It was triggered by a liquidity shortfall in the United States (U.S.) banking system and resulted in the bankruptcy of several large financial institutions such as Lehman Brothers, pushing the banking system to the brink of a system-wide collapse. More than 160 U.S. banks failed in 2008 and 2009, while only 11 banks failed between 2003 and 2007 (FDIC 2011). One important consequence of this crisis is the establishment of a new U.S. federal agency – Financial Stability Oversight Council – chartered with monitoring and mitigating systemic risk in the financial system according to the 2010 Dodd–Frank Wall Street Reform and Consumer Protection Act. Systemic risk refers to “the propagation of an agent’s economic distress to other agents that have links with the starting agent through financial transactions” (Rochet and Tirole 1996). In our study, it refers to the risks imposed by interbank relationships in banking systems, where the failure of a single bank or cluster of banks can cause contagious bank failures (i.e., a cascading failure), which could potentially bring down the entire system (Schwarcz 2008).

Our study focuses on systemic risk at the individual bank level, i.e., the systemic risk of a banking system attributed to an individual bank. For simplicity, we refer to the systemic risk at the individual bank level as the *bank systemic risk*, which is defined as the impact of a bank’s economic distress on other banks in the same banking system. In contrast, we refer to the systemic risk of the entire banking system as the *network systemic risk*. The concept of bank systemic risk is critical for central banks to determine which banks should receive capital injections first to stop further contagious bank failures during a financial crisis. In addition, by knowing the

relative magnitude of the influences a bank receives from the economic distresses of its linked banks, central banks can effectively predict which banks are most likely to fail first in possible contagious bank failure scenarios. However, previous research mainly focused on studying the impacts of systemic risk on the whole banking system (Eisenberg and Noe 2001; Elsinger et al. 2006; Kaufman 1995; Kaufman et al. 2003). There is a lack of effective methods and technologies for modeling and analyzing bank systemic risk.

A major challenge for studying bank systemic risk is to model the two main sources of systemic risk in banking systems identified by Elsinger et al. (2006): 1) the correlation relationship between two banks' financial asset portfolios, and 2) the interbank payment relationship that can transmit a single bank's failure to its linked banks. Figure 1 shows an example scenario of how these two relationships can cause contagious bank failures. In this example, three banks, A, B, and C, share three financial assets, represented by X, Y, and Z. The solid lines represent interbank payment obligations and the dotted lines indicate the ownership relationships between the assets and the banks. Assuming a shock in the financial market has largely reduced the price of X, this will cause A, which held a large amount of X, to fail and default on its payment to B. B is affected by both the reduced price of X and Bank A's defaulted payment. If B's loss is greater than its capital, B will fail and then default on its payment to C. This generates a loss for C, and so on, causing contagious bank failures.

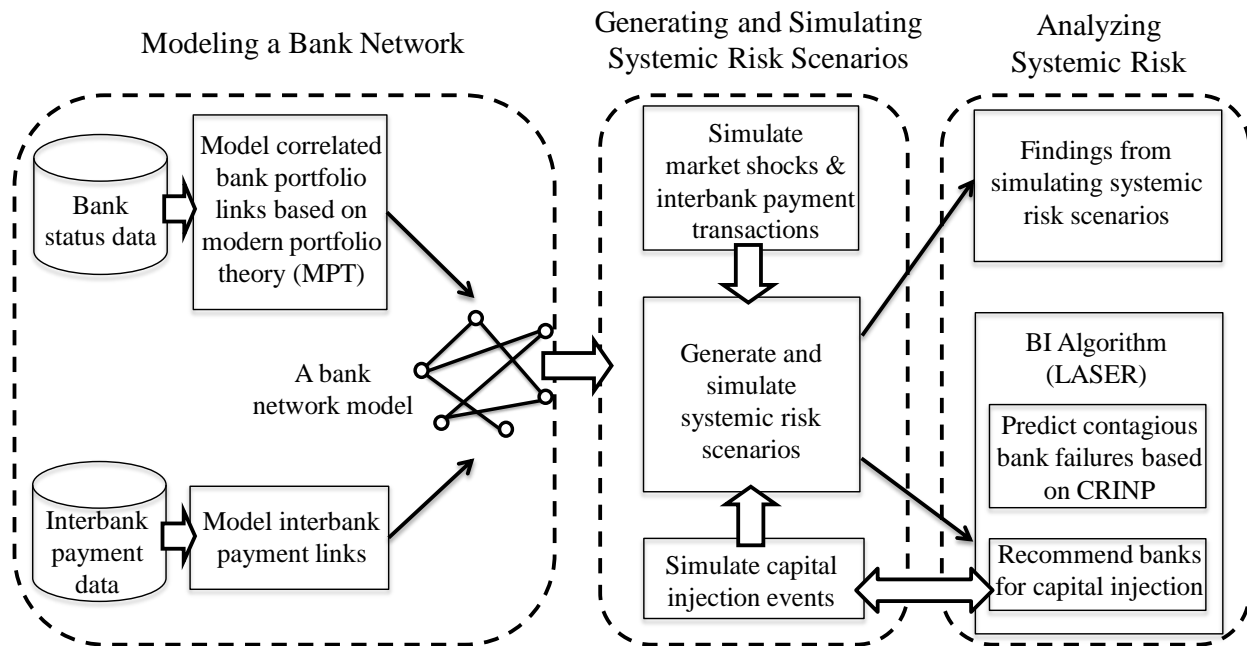


**Figure1. An Example of Contagious Bank Failures**

The above example shows that the systemic risk in banking systems largely depends on both interbank relationships and specific scenarios. This insight helps explain why it is difficult to study bank systemic risk using existing approaches in finance. First, previous systemic risk research focused on modeling interbank payments (Degryse and Nguyen 2004; Sheldon and Maurer 1998; Upper and Worms 2004; Wells 2002) but largely overlooked correlation relationships between bank portfolios, mainly due to data availability issues. Elsinger et al. (2006) have studied both relationships but did not explicitly model the correlation relationship between two banks' financial portfolio values. Second, studies that adopt technological methods to predict bank failures mainly rely on information about individual bank's characteristics rather than interbank relationships (Boyacioglu et al. 2009; Min et al. 2006; Shin et al. 2005; Tam 1991; Tam and Kiang 1990).

To address these issues, we develop a business intelligence (BI) based approach, called Network Approach to Risk Management (NARM), to model and analyze the systemic risk at the individual bank level. BI is commonly used as an umbrella term to describe concepts and methods to improve business decision making, including tools, applications, databases, and

methodologies (Raisinghani 2004). It aims to enable knowledge workers to make faster and better decisions through decision support technologies (Chaudhuri et al. 2011). Figure 2 illustrates the three stages of NARM. First, NARM *models a bank network* using the data about bank status and interbank relationships collected from various data sources. NARM provides a network-based interpretation of the modern portfolio theory (MPT) (Markowitz 1952). Based on this interpretation, it successfully models the correlation relationship between two banks' financial asset portfolios and the systemic risk originating from such relationships. We then construct a bank network model in which the links are the positive correlations between two banks' portfolios and interbank payment obligations. In the second stage, NARM uses discrete event simulation techniques to *generate and simulate systemic risk scenarios* based on the real-world bank data collected from the first stage. These simulated scenarios allow central banks to evaluate the effectiveness of different methods in terms of predicting contagious bank failures and determining capital injection priorities. In the third stage, NARM *analyzes systemic risk* in the simulated scenarios using a BI algorithm - Link-Aware Systemic Estimation of Risks (LASER) - we developed based on a network principle embedded in banking systems' systemic risk called Correlative Rank-In-Network Principle (CRINP).



**Figure 2. An Illustration of the Network Approach to Risk Management**

We also conducted an evaluation study to compare the performance of LASER with several other network-based algorithms in the simulated scenarios based on data collected from 281,401 Federal Deposit Insurance Corporation (FDIC) Call reports for 7,822 banks from 2001 to 2010. The results show that LASER outperforms other network-based algorithms and the most widely used bank risk measure – capital adequacy ratio (CAR). Moreover, we found that the relative predictive power of correlated bank portfolios and interbank payments largely depends on the magnitude of the market shocks. These business insights can help regulators devise better policies to prevent banking crises.

Our NARM approach is unique in several ways. From the modeling perspective, NARM provides a novel network-based view of classic financial theories and risk measures, which leads to new models and methods for studying systemic risk at the level of individual banks. From the information systems (IS) researchers perspective, previous BI studies on predicting bank failures mainly applied data mining algorithms on historical data of individual banks' financial ratios (e.g.,

capital adequacy ratio) (Boyacioglu et al. 2009). To the best of our knowledge, LASER is the first BI algorithm that incorporates both network (CRINP) and financial (MPT-based systemic risk model) principles to analyze systemic risk. It opens new possibilities for IS researchers to contribute to one of the most important research problems for today's world economy – systemic risk management in banking systems. From the business perspective, NARM provides central banks an effective BI-based approach to utilize the data they have for monitoring systemic risk at the individual bank level and determining capital injection priorities.

The remainder of this paper is structured as follows. In Section 2, we review the studies that are relevant to this research. Section 3 describes our bank network model and the interbank payment clearing mechanism. In Section 4, we discuss the details of the LASER algorithm. In Section 5, we present the design and results of a simulation-based evaluation study. Then we discuss the implications of our findings in the context of systemic risk management. We summarize our findings in Section 6.

## **2. RELATED WORK**

### **2.1 Modeling the Sources of Systemic Risk in Banking Systems**

Systemic risk in banking systems is rooted in interbank relationships (Elsinger et al. 2006; Kaufman et al. 2003). Existing bank risk management techniques or measurements were mainly developed for individual banks. Thus they are not very effective in modeling and analyzing systemic risk. Elsinger et al. (2006) suggested the major challenge for modeling systemic risks and capturing the two risk sources: 1) an insolvent bank may default on its interbank payment obligations to other banks and cause more banks to fail, thereby triggering a domino effect which is often called contagious bank failure (Aghion et al. 2000); 2) an adverse economic shock may



cause significant losses in banks' correlated financial asset portfolios and result in simultaneous failures of multiple banks. These two systemic risk sources are not independent of each other and often exist at the same time.

### **2.1.1 Modeling Interbank Payment Relationships**

The first source of systemic risk – the interbank payment obligations -- has been well studied in financial literature. Rochet and Tirole (1996) studied the relationship between interbank loans and systemic risk. Angelini et al. (1996) studied an interbank payment network and found that on average the failure of 4% of network participants can trigger contagious bank failures. Eisenberg and Noe (2001) analyzed the properties of inter-firm cash flows featuring cyclical interdependence. In addition, since contagious bank failures are very rare in real-world banking systems, there is little empirical data available for studying systemic risk. Thus Sheldon and Maurer (1998), Degryse and Nguyen (2004), Wells (2002), and Upper and Worms (2004) all use simulation methods to study contagious bank failures. However, these studies mainly focused on the interbank payment relationships, largely ignoring the other important source of systemic risk – the correlated bank financial asset portfolios.

### **2.1.2 Modeling Correlated Bank Financial Asset Portfolios**

Elsinger et al. (2006) conducted a study which combines the analysis of interbank payment relationships and correlated financial portfolios. They adopted a simulation approach to studying these two risk sources using a unique data set from the Austrian Central Bank. In their study, it was found that banks' exposures to market risk through the correlated financial asset portfolios have substantial impacts on the risk concealed in the network of interbank payment obligations. Their simulation study also provided an estimate of the amount of capital injection needed to

avoid contagious bank failures, which is 0.01% of the banking system's total assets. Although focusing on the same two systemic risk sources, our study differs from theirs mainly from two aspects. First, Elsinger et al. (2006) focused on studying the impacts of systemic risk on the whole banking system, while we mainly aim to model and analyze systemic risk at the individual bank level. One of our research goals is to develop a method that can rank individual banks based on the level of systemic risk they contribute to the banking system. Such a method can support central banks' decisions regarding appropriate capital injection priorities during financial crises to avoid further contagious bank failures. Second, Elsinger et al. (2006) did not explicitly model and analyze the correlation relationship between two banks' financial asset portfolios, which is critical for studying the systemic risk at the individual bank level. The major modeling challenge is that the composition of a bank's financial asset portfolio is often confidential information. In this study, we develop a method based on Markowitz's modern portfolio theory (MPT) (1952) to model the correlated relationship without the composition information and measure the systemic risk at the individual bank level. Next, we review MPT to lay the ground for our modeling method described in Section 3.

### **2.1.3 Modern Portfolio Theory**

Modern portfolio theory (Markowitz 1952) defines a financial asset's risk as the standard deviation of its return and models the risk of a financial asset portfolio (i.e., weighted combination of assets) as the variance of this portfolio's return. The idea behind MPT is that the risk of an asset portfolio not only depends on each individual asset's risk, but also on how each asset's return changes relative to how every other asset in the portfolio changes. For instance, if different types of assets in a portfolio often change in value in opposite ways, it is possible that the variance of this portfolio's return will be lower than the variance of each individual asset.

Therefore, the portfolio return variance (i.e., portfolio risk) can be reduced by including different assets whose returns are not positively correlated into the portfolio. The variance of a portfolio R's return  $\sigma_R^2$  (i.e., portfolio R's risk) is calculated as:

$$\sigma_R^2 = \sum_{i \in D} w_i^2 \sigma_i^2 + 2 \sum_{i \in D} \sum_{j \in D, j > i} w_i w_j \sigma_i \sigma_j \rho_{ij} \quad (1)$$

where  $D$  is the set of assets in portfolio  $R$ ,  $w_i$  is the percentage of  $R$ 's total value that is invested in the asset  $i$ ,  $\sigma_i$  is the standard deviation of  $i$ 's return, and  $\rho_{ij}$  is the correlation coefficient between the returns on assets  $i$  and  $j$ .

Equation (1) shows that the variance of an asset portfolio largely depends on the correlation coefficients  $\rho$  between all pairs of its assets' returns. The more correlated the portfolio assets' returns are, the larger the portfolio risk is. Since the assumptions about market and investors in MPT also apply to banks' financial assets, the portfolio risk measure (Equation 1) has great potential for modeling the systemic risk originating from banks' correlated financial asset portfolios. That is, the more similar the market risk exposures of the banks' portfolios are, the greater the systemic risk the banking system has.

## **2.2 Analyzing Systemic Risk with Business Intelligence Methods**

Recent years have witnessed a growing interest in studying systemic risk in banking systems from a network perspective (Elsinger et al. 2006; Furfine 2003; Iyer and Peydró 2011; Simon 2004). These studies mainly focused on the empirical mappings of interbank markets to financial networks in several major banking systems such as United States (Furfine 2003), United Kingdom (Simon 2004), Switzerland (Sheldon and Maurer 1998), Austria (Elsinger et al. 2006), and India (Iyer and Peydró 2011). Their analyses aim to discover the roles of such financial

networks in contagious bank failures. Their findings largely depend on specific empirical settings such as time periods and market conditions. For instance, Furfine (2003) studied interbank funds transactions in Fed wire across 719 U.S. commercial banks in February, 1998. The results show that the interbank payment relationship does not have significant impact on the stability of the U.S. banking system. But the liquidity shortfall of the U.S. banking system during the recent financial crisis indicates that this finding may not always hold under extreme market conditions. Thus, empirical analyses of limited historical data are inadequate for predicting contagious bank failures in financial crises. Moreover, nowadays central banks need the capabilities of real-time data analysis for devising systemic risk mitigation strategies (e.g., determining capital injection priorities). Therefore, an effective approach that can enable the central banks to conduct timely analyses and examine systemic risk mitigation strategies in different crisis scenarios is greatly needed.

Business Intelligence (BI) is an ideal approach for achieving the above goals. BI is an umbrella term for describing “concepts and methods to improve business decision making,” concerning tools, applications, databases, and methodologies (Raisinghani 2004). As a data-centric approach, BI’s main objectives are to enable easy access to diverse business data, enable transformation of these data, and provide business managers the ability to conduct timely data analyses and take appropriate actions (Turban et al. 2008). The findings from such analyses are the products of BI which enable businesses to predict the behaviors of their environments (Jourdan et al. 2008; Lönnqvist and Pirttimäki 2006; Martinsons 1994). A stream of studies that is most relevant to our research focuses on applying BI algorithms on historical data of financial ratios of individual banks, aiming to predict bank failures (Boyacioglu et al. 2009; Min et al. 2006; Shin et al. 2005; Tam 1991; Tam and Kiang 1990; Wang et al. 2005; Wu et al. 2007). These ratios (e.g., capital

adequacy ratio) have captured certain financial principles embedded in individual bank's risks. However, they are not designed for predicting contagious bank failures since systemic risk largely depends on interbank relationships. Therefore, BI methods that can incorporate the network principles behind systemic risk are needed for effectively predicting contagious bank failures.

### 2.2.1 Hyperlink-Induced Topic Search (HITS)-related Algorithms

In this section, we review the Hyperlink-Induced Topic Search (HITS) algorithm as well as its extensions, mainly because the network principle behind it can be applied to model how systemic risk is transmitted through interbank relationships. In addition, the design of the weighted HITS algorithm has great potential for integrating multiple factors or principles that affect systemic risk. Kleinberg (1999) developed HITS to rank the importance of web pages. Its assumption is that a hyperlink transmits recognition from one web page to another. The collective recognitions from all of the incoming hyperlinks of a web page build up its relative importance in the World Wide Web. HITS introduces two scores for measuring a web page's relative importance and recognition influence respectively: 1) the authority score, which estimates the relative importance of this web page, and 2) the hub score, which estimates the relative recognition influence this web page's hyperlink has on another page. The authority score of a web page  $i$  is computed as the sum of the normalized hub scores for web pages that link to  $i$ . On the other hand  $i$ 's hub score is the sum of the normalized authority scores of the pages that  $i$  links to. More specifically, a web page  $i$ 's authority score  $Au_i$  and hub score  $Hub_i$  can be calculated as:

$$Au_i = \sum_{j \in A} Hub_j, Hub_i = \sum_{j \in C} Au_j \quad (2)$$

where  $A$  is the set of nodes that links to  $i$ , and  $C$  is the set of nodes that  $i$  links to.

Several extensions of the HITS algorithm have been developed to improve its performance in ranking web pages. These HITS-related algorithms focused on adding weights to the two scores based on contextual information on the Internet. There are two main types of weights. The first type of weights often reflects the value of a web page's content (Deng et al. 2009; Zhang et al. 2007). From the algorithmic perspective, these weights are associated with the nodes in the network. The second type of weights represents the value of a hyperlink relative to its peers (i.e., links from the same web page) (Bharat and Henzinger 1998; Li et al. 2002) and is often associated with the links in the networks. Such added weights aim to incorporate the factors, principles, or mechanisms within the application domain that affect the importance of the nodes.

### **2.3 Research Gaps and Research Objectives**

To summarize, previous studies have not focused on the systemic risk at the individual bank level, i.e., bank systemic risk. However, the modeling and analysis of bank systemic risk is essential for monitoring and mitigating contagious bank failures and determining capital injection priorities. Moreover, previous systemic risk studies were not targeted to help central banks conduct timely data analysis and mitigate bank systemic risk in the face of a financial crisis. Further, Business Intelligence studies on bank failure predictions mainly focused on modeling various financial risks of individual banks but largely ignored the relation-induced systemic risk.

In summary, there is a research opportunity for studying bank systemic risk via Business Intelligence methods in light of interbank relationships for purposes of supporting capital injection decisions. Thus, we set two research objectives in this paper. First, we aim to model bank systemic risk through its correlated financial asset portfolio links. Second, we will develop a BI approach that incorporates both network and financial principles for predicting contagious bank failures and determining capital injection priorities.

### **3. A NETWORK APPROACH TO RISK MANAGEMENT (NARM)**

To achieve these two objectives, we proposed a BI approach called the Network Approach to Risk Management (NARM), which consists of 1) a bank network model in which links are correlated bank portfolios and interbank payment obligations, 2) a BI algorithm called Link-Aware Systemic Estimation of Risks (LASER) which incorporates both network and financial principles for ranking individual banks based on their systemic risk levels, and 3) a simulation-based approach for evaluating LASER's performances in predicting contagious bank failures and determining capital injection priorities. In this section, we will describe the bank network model in NARM that is based on a novel network-based interpretation of modern portfolio theory. In addition, we present our interbank payment clearing mechanism which explicitly models the correlated bank financial asset portfolio relationship.

#### **3.1 Modeling Systemic Risk from Correlated Bank Financial Asset Portfolios**

As suggested in Section 2, the major challenge for modeling systemic risk originating from correlated bank financial asset portfolios is the lack of information about their composition. A bank's financial asset portfolio consists of various types of assets that can be traded in financial markets, such as mortgage-backed securities, cash instruments, and financial derivatives. However, information about a bank's holdings of specific assets is often not publicly available, which makes it very difficult to model the correlation relationships among bank portfolios at the individual asset level. We then develop a method that models such relationships at the portfolio level.

As shown in Equation 1, Modern Portfolio Theory (MPT) perceives that the market risk of a financial asset portfolio depends on the correlations among its assets' returns. In this research,

we can view a banking system as a large portfolio in which each asset is a bank's financial asset portfolio. Then MPT's risk perception, that portfolio risk depends on the correlation relationships among its assets, is consistent with the finding in previous banking research (Eisenberg and Noe 2001; Elsinger et al. 2006) that one major source of systemic risk is the correlated bank portfolios. However, to adopt this MPT-based perspective for modeling systemic risk, two issues need to be addressed. First, MPT makes certain assumptions about investors and markets. These assumptions need to be checked. Second, MPT focuses on modeling the risks at the portfolio level (system level in this research), while our study focuses on studying systemic risk at the individual bank level.

### **3.1.1 Assumptions for Modern Portfolio Theory**

MPT mainly has two types of assumptions for investors and markets respectively. First, MPT assumes that all investors are 1) rational and risk-averse, 2) aim to maximize economic utility, and 3) have access to the same market information at the same time (Markowitz 1952). These three assumptions are also found in Fama's (1970) efficient-market hypothesis which suggests that financial markets are "informationally efficient." In this study, the investors are professional managers who manage the banks' financial asset portfolios. They are usually experienced and well informed. With the advance of the Internet and other information technologies, these institutional investors usually have access to the same public information when it becomes available. Thus we also adopt the three above assumptions in this study. In addition, MPT also assumes that asset returns are normally distributed random variables. In reality, these assumptions are not entirely true and sometimes are violated by rare events like insider trading. Such limitations will compromise MPT to a certain degree. However, considering the small probability of such events, we suggest the adoption of MPT is appropriate for this study.



Second, from the market perspective, MPT assumes that the correlations between assets are fixed and constant over the observation period. This assumption is based on the idea that the correlations depend on systemic relationships among the component assets. It is consistent with the main assumption of this study, that is, the strong correlation between two bank portfolio returns reflects similar risk preferences of the management teams between these two banks. Our study aims to model and utilize such patterns to predict how two banks' portfolio returns change during financial crises.

### 3.1.2 Modeling Systemic Risk at the Individual Bank Level

As suggested earlier, we need to develop an approach based on MPT for modeling bank systemic risk originating from the correlated bank portfolios between two banks. MPT uses the variance of a portfolio  $R$ 's returns  $\sigma_R^2$  as the proxy for its risk (Markowitz 1952), calculated as:

$$\sigma_R^2 = \sum_{i \in D} \sum_{j \in D} w_i w_j \sigma_i \sigma_j \rho_{i,j} \quad (3)$$

where  $D$  is the set of assets in portfolio  $R$ ; all other notations have the same meanings with Equation 1.

After adopting the MPT assumptions described in Section 3.1.1, we can view a banking system as an asset portfolio in which each bank's portfolio is an asset. Then the systemic risk of a banking system  $B$  originating from the correlated bank portfolios can be viewed as the risk of the asset portfolio  $B$ . Based on Equation (3), we define the systemic risk of a banking system as follows.

**Definition 1:** The **systemic risk of a banking system** (i.e., network systemic risk)  $B$  originating from the correlated bank portfolios is calculated as the variance of  $B$ 's returns:

$$\sigma_B^2 = \sum_{i \in N} \sum_{j \in N} w_i w_j \sigma_i \sigma_j \rho_{ij} \quad (4)$$

where  $N$  is the set of banks in this banking system  $B$ ,  $w_i$  is the weight of bank  $i$ 's portfolio value in  $B$ ,  $\sigma_i$  is the standard deviation of  $i$ 's portfolio returns over the observation period,  $\rho_{ij}$  is the correlation coefficient between the portfolio returns of banks  $i$  and  $j$ .

Such a relation-based definition makes network modeling a natural choice for further decomposing the network systemic risk into the individual bank level. We model the whole banking system as a network, in which the bank portfolios are nodes and their correlation relationships are undirected links. Based on this network model and Equation (4), we then define the systemic risk at the individual bank level as follows.

**Definition 2:** The systemic risk bank  $i$  contributes to the banking system (i.e.,  $i$ 's **bank systemic risk**) originating from  $i$ 's correlation relationships with other banks' portfolios,  $G(i)$ , is calculated as:

$$G(i) = \sum_{j \in L} w_i w_j \sigma_i \sigma_j \rho_{ij} \quad (5)$$

where  $L$  is the set of banks that have correlated portfolio links with bank  $i$ .

Then  $G(i)$  is the sum of the weighted co-variances between the returns of bank  $i$  and all of its linked banks. The weighted co-variance between the portfolio returns of banks  $i$  and  $j$  can be viewed as the systemic risk bank  $i$  contributes to the banking system through its correlated portfolio link with  $j$ . Based on this interpretation, we can further model the systemic risk from the individual bank level to the dyadic level. We define the dyadic measure of systemic risk as follows.

**Definition 3:** The systemic risk associated with the correlated portfolio relationship between a dyad of banks  $i$  and  $j$ , i.e., the **dyadic measure of systemic risk**,  $S_{ij}$ , is calculated as:

$$S_{ij} = w_i w_j \sigma_i \sigma_j \rho_{ij} \text{ where } i \neq j \quad (6)$$

### 3.1.3 Modeling a Correlated Bank Portfolio Network

As Equation (6) shows, the systemic risk associated with each correlated portfolio link between two banks  $i$  and  $j$ ,  $S_{ij}$ , depends on the correlation coefficient for their portfolio returns  $\rho_{ij}$ . A positive correlation coefficient  $\rho_{ij}$  means that the portfolio returns between banks  $i$  and  $j$  vary together over time, indicating they are generally exposed to similar types of risks over the observation period. In this study, we excluded such negative correlated relationships from our bank portfolio network model, primarily because the effects of such negative correlations between bank portfolio returns tend to become smaller during a financial crisis than in normal times. The values of most bank portfolios will be largely reduced in a financial crisis and become more positively correlated.

Therefore, we construct the correlated bank portfolio network by including links (i.e., dyads of bank portfolios) only if the correlation coefficients for their returns are larger than a positive threshold value  $\rho_s$  ( $\rho_{i,j} > \rho_s$ ). This construction process is done by 1) determining the synchronous correlation coefficient of the logarithmic value difference of a bank portfolio over a selected observation time period  $T$ , and 2) selecting dyads of banks with correlation coefficients larger than the threshold value  $\rho_s$  as the links in our correlated bank portfolio network.

To calculate the correlation coefficients for two banks' portfolio returns over the observation period  $T$ , we adopted the operational definition of the correlation coefficient for two financial asset returns developed by Bonanno et al. (2004) as follows:

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{(\langle r_i^2 \rangle - \langle r_i \rangle^2)(\langle r_j^2 \rangle - \langle r_j \rangle^2)}} \quad (7)$$

$$r_i = \ln F_i(t) - \ln F_i(t - \Delta t) \quad t \in T \quad (8)$$

where  $i$  and  $j$  are banks;  $F_i(t)$  is the market value of bank  $i$ 's financial asset portfolio at time  $t$ , and  $\Delta t$  is the time horizon selected to observe the changes in the return of a bank portfolio. The logarithmic value difference of a portfolio  $i$ 's return  $r_i$  over the time period  $\Delta t$  is calculated as a proxy of the percentage changes of bank  $i$ 's portfolio returns. In addition, the correlation coefficient  $\rho_{ij}$  is computed between all possible pairs of bank portfolios present in the selected data sample. The statistical average, as indicated with the notation  $\langle \rangle$ , is a temporal average calculated over the time period  $T$ .

According to Equation (7),  $\rho$  measures the strength of the linear dependence between the changes of two banks' portfolio returns. It aims to capture the similarities between two banks' long-term investment preferences and behaviors, which largely determine the correlations in their portfolio returns. For instance, the managers of two banks both prefer to include mortgage-backed securities in their banks' financial asset portfolios. Then the burst of the housing bubble will cause similar negative impacts on their portfolio returns, resulting in a positive correlation coefficient.

In this study, we set the threshold value  $\rho_s$  for the correlation coefficient as 0.5 (i.e.,  $\rho_{ij} \geq \rho_s$ ) for the following reasons. First, Elsinger et al. (2006) found that the changes in the majority of the 881 Austrian banks' portfolio returns are highly correlated to the aggregate market profits and losses of the Austrian banking system. The mean correlation coefficient is 0.48, indicating that in general banks' financial asset portfolio returns tend to be positively correlated with each other. Second, when  $\rho_{ij} < 0.5$ , we need at least 20 data points for each pair of banks to test the statistical significance of  $\rho_{ij}$ . However, we may not have more than 20 data points for many banks in our empirical data set. Therefore, 0.5 is an appropriate threshold value for our empirical evaluation study. In addition, we tested the robustness of our correlated portfolio network model and the LASER algorithm with different threshold values  $\rho_s$  in our evaluation study. The results are reported in Section 5.2 and support the choice of setting  $\rho_s$  as 0.5.

### 3.2 Modeling the Interbank Payment Network and Clearing Mechanism

Interbank payment relationships are another major source of systemic risk in banking systems (Eisenberg and Noe 2001; Elsinger et al. 2006; Kaufman et al. 2003). Similar to Elsinger's approach (2006), we define a bank  $i$ 's interbank payment obligation to a bank  $j$  as a directed link from node  $i$  to  $j$  in the interbank payment network. To model the interbank payment network, we use a  $N \times N$  matrix  $L$ , in which  $l_{ij}$  represents the value of bank  $i$ 's payment obligation towards bank  $j$ . Therefore, the value of bank  $i$ 's total payment obligations towards other banks can be computed as  $d_i = \sum_{j=1}^N l_{ij}$ , where  $N$  is the set of banks that bank  $i$  owes. We further define a normalized matrix  $\Pi \in [0,1]^{N \times N}$  by dividing each entry  $l_{ij}$  over the relevant total obligation  $d_i$ :

$$\pi_{ij} = \begin{cases} l_{ij} / d_i & \text{if } (d_i > 0) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

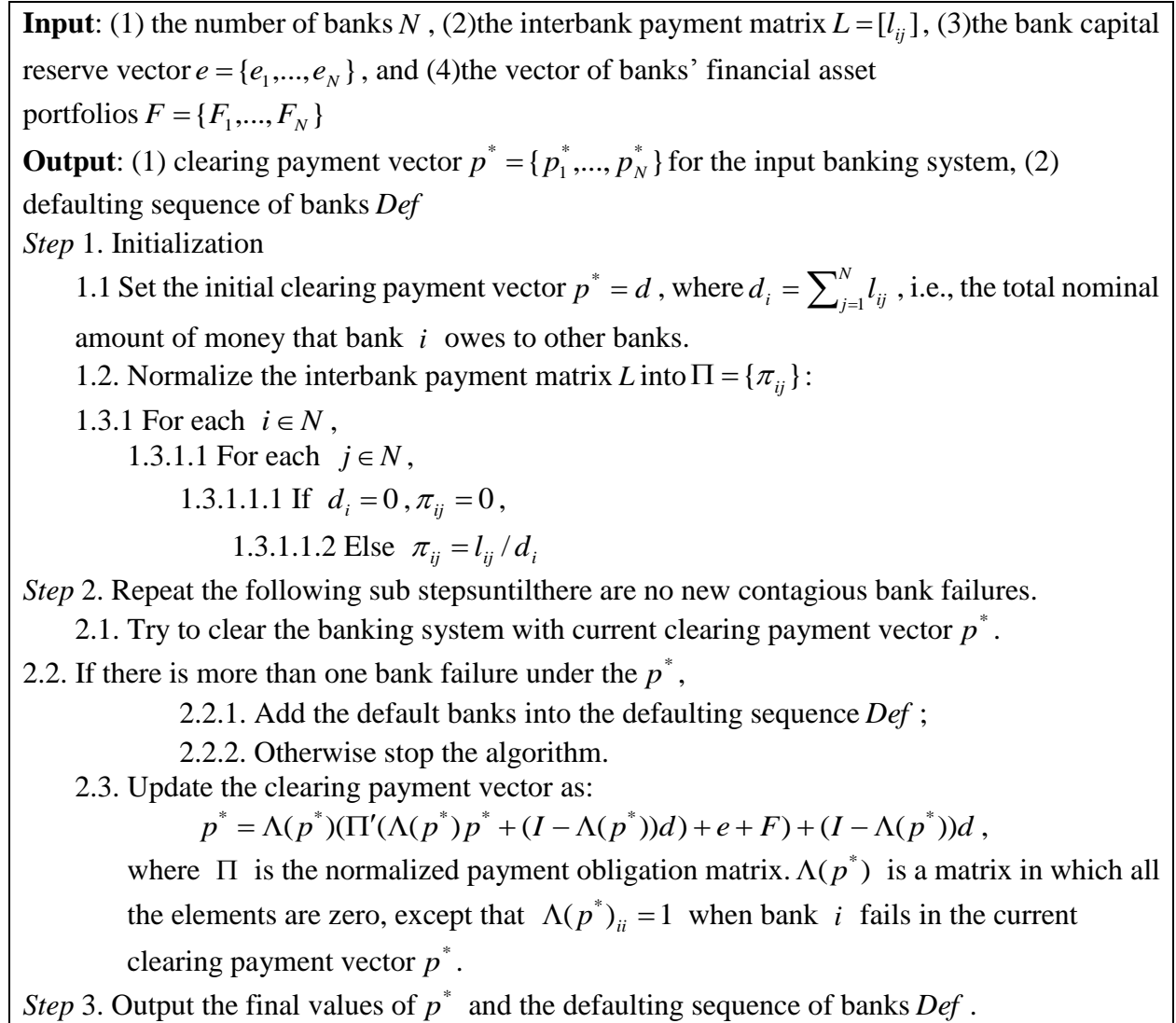
The clearing mechanism in Elsinger et al. (2006) does not explicitly models each bank's financial portfolio value. But our modeling method described in Equations (7) and (8) requires the value of each individual bank  $i$ 's financial asset portfolio  $F_i$ . Thus we developed a clearing mechanism that mainly differs from Elsinger's by explicitly modeling the values of bank financial asset portfolios. Consider a set of  $N$  banks, each bank  $i \in N$  has a clearing payment vector  $p_i^*$ , which represents  $i$ 's ability to pay off its payment obligations to other banks.

$p_i^*$  consists of three major components. The first two components are 1) bank  $i$ 's financial asset portfolio  $F_i$ ; and 2)  $i$ 's capital reserve  $e_i$ . The third component  $\sum_{j=1}^N \pi_{ji} p_j^*$  is the total amount of the interbank payments  $i$  receives from other banks. Thus bank  $i$ 's clearing payment vector  $p_i^*$  can be defined as follows:

$$p_i^* = \begin{cases} d_i & \text{if } F_i + \sum_{j=1}^N \pi_{ji} p_j^* + e_i \geq d_i \\ F_i + \sum_{j=1}^N \pi_{ji} p_j^* + e_i & \text{if } d_i > F_i + \sum_{j=1}^N \pi_{ji} p_j^* + e_i \geq 0 \\ 0 & \text{if } F_i + \sum_{j=1}^N \pi_{ji} p_j^* + e_i < 0 \end{cases} \quad (10)$$

The assumption is that each bank has limited liability and requires proportional sharing of assets in case of a bank failure. Thus the amount of payment  $i$  can receive from its counterparty bank  $j$  depends on  $j$ 's actual payment ability  $\pi_{ji} p_j^*$  instead of the nominal value of payment obligation  $\pi_{ji} d_j$ . According to Eisenberg and Noe (2001), there is a unique clearing payment vector for each risk scenario. We implement this clearing payment vector through the following

algorithm based on Eisenberg and Noe's (2001) fictitious default algorithm. We explain this algorithm in detail in Figure 3.



**Figure 3. The Algorithm for the Payment Clearing Process**

## 4. A NETWORK-BASED ALGORITHM FOR ANALYZING BANK SYSTEMIC RISK

### 4.1 The Correlative Rank-In-Network Principle (CRINP)

As summarized in Section 2.3, there is a research opportunity for analyzing bank systemic risk via network-based Business Intelligence approaches. By reviewing literature on network-based algorithms, we gained two important insights from analyzing the similarities between measuring bank systemic risk and a web page's importance using the HITS algorithm. First, from the network perspective, a bank's systemic risk, like a web page's importance, is based on the relational influences from its linked banks or web pages. For HITS, the relational influence is a source web page's recognition of other pages transmitted through its outgoing hyperlinks. Thus, the more recognition a web page receives from other pages through the incoming hyperlinks, the more important this page becomes. For bank systemic risk, a source bank's economic distress can impose negative relational influence on other banks through interbank relationships and may cause contagious bank failures. Thus when a bank has more interbank relationships, its failure will have greater negative influence on other banks in the banking system. Second, such relational influence largely depends on the source node's characteristics (e.g., systemic risk) and will affect the same characteristics of the target node. In HITS, the more important the source page is, the more recognition its outgoing hyperlinks will impose on the linked pages. In a banking system, a bank with higher bank systemic risk indicates its failure will have larger negative influences on its linked banks, and thus is more likely to cause contagious bank failures.

To summarize, there is a common network phenomenon in both networks of web pages and banks: *a node transmits its relational influences through its outgoing links and result in the status change of its linked nodes.* This phenomenon has resulted in a network principle we define as follows:



**Definition 4:** A node's prominence in a characteristic depends on 1) the number of incoming links which transmitted the corresponding relational influences, and 2) the prominence of this characteristic of the source nodes.

In our study, this network principle is called as the **Correlative Rank-In-Network Principle (CRINP)**. CRINP has also been used in citation analysis to develop the famous "impact factor" for measuring the prominence of scientific journals (Garfield 1972) and in social network analysis to identify cliques (Hubbell 1965). But to the best of our knowledge, it was not formally defined and studied before, especially in banking-related research.

The bank network in this study is much more complex than the Internet since the former contains two types of links with different levels of relational influences. Bigger banks often have more interbank transactions and larger correlated exposures in their asset portfolios than smaller banks. Thus CRINP needs to be adapted to the bank network in this study. Therefore, the systemic risk a bank receives in the banking system depends on 1) the number and the amount of incoming interbank payments from other banks; 2) the number and the levels of its correlation relationships with other banks' financial asset portfolios; and 3) the systemic risk levels of the linked banks. Thus the standard HITS ranking algorithm cannot be directly applied to this bank network. An algorithm based on CRINP that can account for both types of interbank relationships with heterogeneous relational influences is needed.

#### **4.2 Link-Aware Systemic Estimation of Risks (LASER) Algorithm**

We developed a B algorithm called Link-Aware Systemic Estimation of Risks (LASER) that incorporates both the network principle (CRINP) and the financial principle (MPT-based bank systemic risk measure in Definition 2) to account for the influences of the systemic risk originating from the two interbank relationships. The LASER algorithm aims to rank banks

based on the relative levels of systemic risk these banks contribute to (or receive from) their linked banks in the banking system. Like HITS, the LASER algorithm provides two scores for each bank – the authority score and the hub score. A bank’s LASER authority score represents the level of systemic risk it received from other banks in the banking system. A bank’s hub score represents the level of systemic risk it imposed on other banks.

#### 4.2.1 Node-Weighted HITS Algorithm

As mentioned in Section 4.1, a major challenge for designing a bank systemic risk ranking algorithm is to factor in the heterogeneous influences associated with the two types of bank network links. The MPT-based bank systemic risk measure we developed in Section 3.1.2 provides us an effective approach to modeling the bidirectional influences of bank systemic risk originating from correlated bank portfolio relationships. As defined in Equation (5), a node  $i$ ’s bank systemic risk (i.e., negative influence imposed on the banking system due to  $i$ ’s failure) can be calculated as  $G(i)$ . Following Bharat and Henzinger (1998),  $G(i)$  can be embedded into the HITS algorithm as a node’s weight to account for the influence of the systemic risk originating from correlated bank portfolio links. We defined such an algorithm as the node-weighted HITS algorithm which is written as:

$$Au_i = \sum_{j \in A} G(j)Hub_j, Hub_i = \sum_{j \in C} G(j)Au_j \quad (11)$$

where  $A$  is the set of banks from which  $i$  receives interbank payments, and  $C$  is the set of banks that  $i$  has interbank payment obligations to.  $Au_i$  is bank  $i$ ’s authority score, while  $Hub_i$  is  $i$ ’s hub score. The design of this node-weighted HITS aims to account for the influences of a bank’s systemic risk originating from the correlated bank portfolio links.

#### 4.2.2 Link-Weighted HITS Algorithm

However, the influences of the different amounts of interbank payments are ignored in the node-weighted HITS algorithm. To address this, a link-weighted HITS algorithm can be developed by following the weighting approach in several HITS-related algorithms (Li et al. 2002; Xing and Ghorbani 2004). The resulting link-weighted HITS algorithm can be written as:

$$Au_i = \sum_{j \in A} \frac{O_{ji}}{\sum_{u \in U} O_{ui}} Hub_j, Hub_i = \sum_{j \in C} \frac{I_{ij}}{\sum_{v \in V} I_{iv}} Au_j \quad (12)$$

where  $O_{ji}$  is the average value of interbank payments (per transaction) made from bank  $j$  to  $i$  over the observed time period.  $\sum_{u \in U} O_{ui}$  calculates the total amount of average payment values bank  $i$  received from the set of its linked banks  $U$ . Thus the link weight  $\frac{O_{ji}}{\sum_{u \in U} O_{ui}}$  measures the proportion of negative influence  $i$  receives from bank  $j$ 's failure through their interbank payment link. On the other hand,  $I_{ij}$  is the average value of payments bank  $i$  (per transaction) made to other banks. Then the link weight  $\frac{I_{ij}}{\sum_{v \in V} I_{iv}}$  measures the proportion of negative influence that bank  $i$ 's failure imposes on bank  $j$ . However, such link weights alone cannot account for systemic risk originating from the correlated bank portfolio links.

#### **4.2.3 Incorporating Network and Financial Principles to Measure Bank Systemic Risk**

Neither a node- nor link-weighted HITS algorithm alone can fully account for the impacts of bank systemic risk originating from the two types of interbank relationships in this study. Therefore, we adopt a combined approach similar to the one used in both Zhang et al. (2007) and Deng et al. (2009) to design a BI algorithm for measuring bank systemic risk. This approach assigns appropriate weights to both nodes and links in a HITS algorithm, aiming to rank a web page's importance based on both the value of its contents and hyperlinks. We use this combined

approach to incorporating the influences of the bank systemic risk originating from the two interbank relationships into the design of a weighted HITS algorithm. The bank systemic risk measure (Definition 2) reflects the financial principles embedded in modern portfolio theory (MPT) and systemic risk originating from the correlated bank portfolios. On the other hand, the interbank payment relationship is mainly responsible for explicitly transmitting the influence of a bank's economic distress to its linked banks based on CRINP.

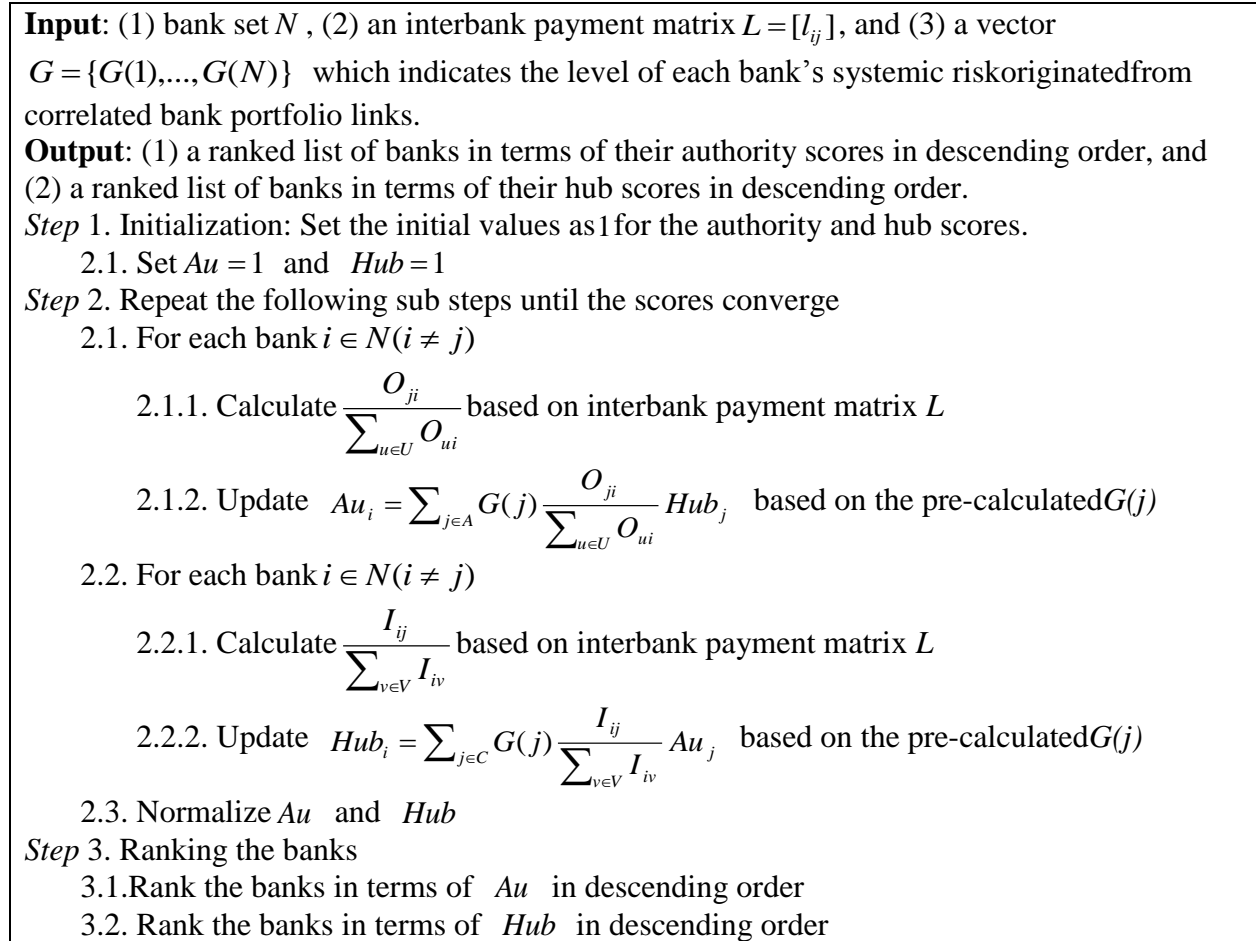
Using the combined approach, we incorporate both the network principle, CRINP, and the financial principle, bank systemic risk measure, into the design of a systemic risk ranking algorithm which we call Link-Aware Systemic Estimation of Risks (LASER). It can be written as:

$$Au_i = \sum_{j \in A} G(j) \frac{O_{ji}}{\sum_{u \in U} O_{ui}} Hub_j, \quad Hub_i = \sum_{j \in C} G(j) \frac{I_{ij}}{\sum_{v \in V} I_{iv}} Au_j, \quad G(i) = \sum_{y \in Y} w_i w_y \sigma_i \sigma_y \rho_{iy} \quad (13)$$

where  $A$  is the set of banks that sent payments to  $i$ ;  $C$  is the set of banks that  $i$  sent payments to, and  $Y$  is the set of banks that have correlated portfolio links with  $i$ . Other notations have the same meanings as in Equation (5), (11), and (12). The influence of bank  $i$ 's systemic risk originating from correlated bank portfolio links is reflected by the node weight  $G(i)$ . Similar to HITS, both the authority and hub scores are calculated for multiple iterations and eventually converge (Bharat and Henzinger 1998; Golub and Van Loan 1996).

These two scores rank banks based on the relative levels of the system risk they receive from (contribute to) their linked banks in the banking system. The higher a bank's authority score is, the bigger the influences it receives from other banks' failures through interbank relationships. In the evaluation study described in Section 5, the authority score is used to predict the banks that are most likely to fail in the contagious bank failure scenarios. On the other hand, the higher a

bank's hub score is, the bigger the influence its failure will impose on its linked banks. The hub score is used to identify banks whose failures will have the largest negative impacts on the banking system during a financial crisis. Injecting capital to these banks may effectively stop further contagious bank failures and stabilize the banking system. The main steps of LASER are described in Figure 4.



**Figure 4. The Main Steps of the LASER Algorithm**

## 5. A SIMULATION-BASED EVALUATION STUDY

We conduct a study using both real-world and simulated data to evaluate the performances of LASER with other methods in terms of predicting contagious bank failures and determining

capital injection priorities. This simulation-based evaluation study consists of two steps. In the first step, we extract information from U.S. FDIC banking regulatory reports and the Federal Reserve Wire Network (Fedwire) to create a set of base scenarios at a series of reporting dates (denoted as  $t_k$ ). In the second step, for each base scenario, we generate systemic risk scenarios on  $(t_k + 1)$  day in which various financial market shocks and events such as contagious bank failures and capital injections are simulated.

For each systemic risk scenario, we construct a correlated bank financial asset portfolio network and an interbank payment network using the U.S. banking information. Based on these two networks, the LASER algorithm generates two ranked lists of banks. The list of banks ranked by the LASER authority scores predicts which banks are most likely to fail in the given scenario. The other list ranked by the LASER hub scores shows which banks may impose the largest negative influence on the banking system. Injecting capital to these banks with the highest hub scores may effectively stabilize the banking system. To evaluate LASER's prediction performance, we compared the list of the banks that actually failed in the simulated scenario with the list of banks ranked by LASER's authority scores. The prediction performances of several methods, including the well-known bank financial ratio - capital adequacy ratio (CAR), were examined against LASER for comparison purposes. Moreover, we evaluated the effects of the capital injection strategies based on LASER hub scores against several other methods in the simulated systemic risk scenarios.

## **5.1 Data Sets and Simulation Scenario Generation**

### **5.1.1 Data Sets**

Two data sets were used in this study: an interbank payment dataset from Fedwire and a bank call reports dataset provided by the U.S. Federal Deposit Insurance Corporation (FDIC). Fedwire is a real-time gross settlement system provided by the Federal Reserve Banks for more than 7,500 financial institutions, mostly banks, to process large-value inter-institution payments. Such payments include “the settlement of interbank purchases and sales of federal funds; the disbursement or repayment of interbank loans; and the settlement of real estate transactions” (Soramäki et al. 2007). The Fedwire dataset provides system-level statistics such as average daily volumes and values of payments for each quarter from 1992 to 2010. Using this data set and the empirical findings from previous studies (May et al. 2008; Soramäki et al. 2007) on the Fedwire network topology, we can simulate the Fedwire interbank payment transactions and network.

The FDIC dataset contains information extracted from quarterly reports of major U.S. banks’ condition and income (i.e., call reports). These call reports include banks’ balance sheets, income statements, and other supervisory reports. They are prepared by banks on the last day of each calendar quarter. These reports contain an extensive set of banking information such as capital adequacy statistics and market risk exposures. Such information is widely used by the federal and state authorities, rating agencies, and the academic community as an important data source for monitoring and studying bank financial risks. In summary, call reports are a timely and critical data source of information about the U.S. banking system (FDIC 2010). With these two data sets, we evaluate the performance of the LASER algorithm in simulated systemic risk scenarios.

### **5.1.2 Setting up Base Scenarios**

We first set up a set of base scenarios as the start states of our simulation-based evaluation study. Each base scenario at time  $t_K$  contains two types of information: 1) bank status such as value of

capital reserve; and 2) a correlated financial asset portfolio network constructed using the FDIC data set. The FDIC dataset contains information for 38 quarters ( $t_1, \dots, t_{38}$ ) from March 31, 2001 to June 30, 2010. We use bank status information from the most recent 18 quarters (from  $t_{21}$  to  $t_{38}$ ) to set up the 18 base scenarios in our simulation experiment.

### **Extracting Bank Status Information**

According to our payment clearing mechanism (Equation (10)), the capital reserve  $e$  is retrieved from the data item - Tier 1 capital - in the regulatory capital section of a FDIC call report. Tier 1 capital is defined in both the Basel I and II Accords and mainly includes a bank's equity capital and disclosed reserves. It measures a bank's ability to sustain unexpected loss and serves as a safety net for bank solvency. Financial regulators in many countries require banks to keep a certain level of Tier 1 capital as protection against various banking risks including systemic risk.

To obtain the value of a bank  $i$ 's financial asset portfolio  $F_i$ , we select three accounting items from the FDIC call reports: (1) held-to-maturity securities, (2) trading assets (minus trading liabilities), and (3) available-for-sale securities. The Statement of Financial Accounting Standards No. 115 requires each bank holding company to report these three items in order to classify its investment in equity securities. In this study, the sum of these three items is used as the value of a bank's financial asset portfolio.

### **Constructing Correlated Financial Asset Portfolio Networks**

For each of the 18 base scenarios  $t_K$  ( $21 \leq K \leq 38$ ), we constructed the correlated bank portfolio links by calculating the correlation coefficients between banks' financial asset portfolio returns using Equation (7) over a predetermined observation period  $C$  (from  $t_{K-C}$  to  $t_{K-1}$ ). Based on our domain expert's recommendation,  $C$  was set as 20 quarters (i.e., 5 years). The assumption is that



the correlated portfolio relationship between two banks is largely affected by factors such as the management teams' investment risk preferences. Moreover, banks that engaged in mergers and acquisitions are excluded from our analysis because such transactions may temporarily distort bank performance measures in FDIC call reports.

Then for each of base scenario (at time  $t_k$ ), we only include banks that have filed FDIC call reports with these three accounting items for the past 5 years. For instance, among the 7,321 banks that filed an FDIC report on December 31<sup>st</sup>, 2009 ( $t_{36}$ ), 7,167 banks that filed call reports over the past 5 years (from  $t_{16}$  to  $t_{35}$ ) are included in the base scenario at  $t_{36}$ . Eventually we extracted 281,401 FDIC call reports filed by 7,822 distinct banks across the 38 quarters.

**Table 1. Basic Statistics of the Selected Data Sample from FDIC Data Set**

Time span	Number of selected reports	Total number of selected reporting banks	Number of reporting quarters	Average number of reporting banks per quarter
03.2001- 06.2010	281,401	7,822	38	7,405

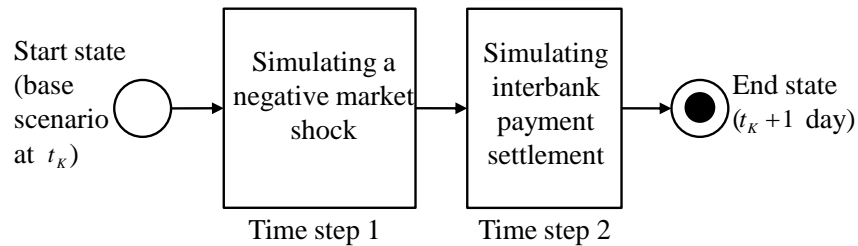
### 5.1.3 Generating Systemic Risk Scenarios for Discrete Event Simulation

Our main simulation approach is discrete event simulation. It is defined as “the variation in a model caused by a chronological sequence of events operating on it” (Sokolowski and Banks 2009). The events are instantaneous occurrences that will change the states of a banking system. Therefore, generating systemic risk scenarios with discrete event simulation involves simulating a sequence of events that may change the value of  $F$  and eventually cause contagious bank failures in a banking system. In this study, three types of events were included in a simulated systemic risk scenario: 1) financial market shock(s); 2) the interbank payment

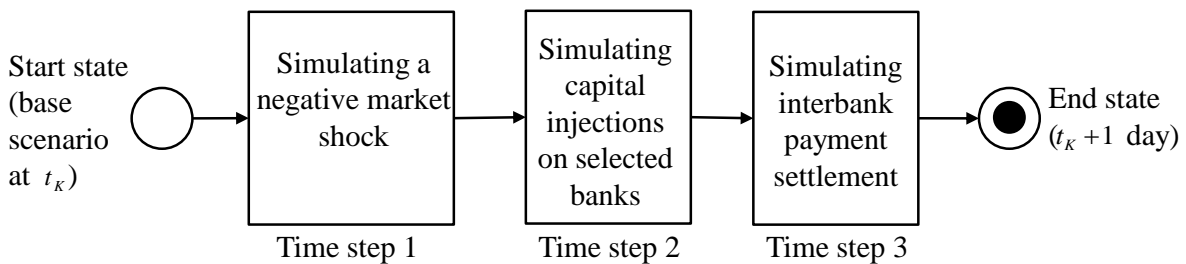
settlement; and 3) capital injections to selected banks. The state of the banking system is described by the clearing payment vector  $p^*$  defined in Equation (10).

Following the timesetting described in Section 5.1.2, each systemic risk scenario is simulating a set of events within one day ( $t_k + 1$ ). At the start time  $t_k$ , the initial values of a bank  $i$ 's financial portfolio and capital reserve ( $F_i$  and  $e_i$ ) are extracted from FDIC call reports to set up the base scenario. Then we start to simulate events that will affect the value of  $F_i$ .  $e_i$  is assumed to remain constant. Based on Equation (10), the resulting values of  $F_i'$  and  $i$ 's incoming payments  $\sum_{j=1}^N \pi_{ji} p_j^* + e_i$  will determine bank  $i$ 's payment ability  $p_i'$  at the end of the day

( $t_k + 1$ ).



**Figure 5a. A Systemic Risk Scenario for Predicting Contagious Bank Failures**



**Figure 5b. A Systemic Risk Scenario for Determining Capital Injection Priorities**

Two designs of systemic risk scenarios are illustrated in Figure 5a and 5b using the modeling method of discrete event simulation. These two types of scenarios will be simulated using

real-world data for evaluating the performances of LASER against other methods, in terms of predicting contagious bank failures and identifying capital injection priorities. In reality, the market shocks and interbank payment settlement events may arrive randomly at any time in a day. However, the interbank payment settling system we aim to simulate – U.S. Fedwire– can provide intraday credit to banks through the central bank. Thus different sequences of the shock and settlement events within a business day will not affect the banks’ day-end payment ability. Thus we can design the events to happen in the sequences as shown in Figure 5. The same type of events is set to happen at the same instantaneous time step.

As Figure 5a shows, a negative financial market shock can consist of major economic events that are assumed to happen at the first time step of the simulation day  $t_k + 1$ , causing big losses for banks. A recent example is that the news of the 2011 Japan nuclear crisis caused the Nikkei stock market index to drop 10.6% on March 15<sup>th</sup>. Such a market shock caused significant losses for many banks’ correlated portfolios that contain Japan-related financial assets. At the second time step, the banks that suffer from such losses may not be able to settle their payment obligations to other banks, thereby causing contagious bank failures. In this design, we compared the bank failures predicted by LASER authority scores against the actual failures in the simulations. The design in Figure 5b adds the capital injection events after the market shock events. We use multiple methods, including the LASER hub scores, to select the banks for capital injections and observe their effects in reducing contagious bank failures in the simulations.

### **Simulating a Negative Market Shock**

To simulate the impacts of a negative financial market shock on a bank’s financial asset portfolio value  $F$ , we adopt two mechanisms. The first mechanism follows Elsinger’s historical simulation approach (2006) and aims to simulate the random changes in banks’ portfolio values  $F$  due to

various market risks. This mechanism will generate a distribution of bank portfolio returns estimated using the capital asset pricing model (CAPM) based on real-world data. The CAPM developed by William Sharpe (1964) and John Lintner (1965) is one of the most widely used finance models for estimating the return for an individual financial asset based on its sensitivity to the market risks. Since CAPM is built on modern portfolio theory (MPT) and shares its assumptions, it also works without MPT-based correlated bank portfolio network model. Based on the CAPM equation, the expected portfolio return of bank  $i$  -  $E(R_i)$  - is calculated as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \quad (14)$$

where  $R_f$  is the risk-free rate of interest,  $E(R_m)$  is the expected return of the market, and  $\beta_i$  is the sensitivity of  $i$ 's expected excess return to the expected excess market return. In our simulation,  $R_f$  is set as the rate of return of U.S. Treasury Bills. Moreover, we use Dow Jones Industrial Average (DJIA) data to calculate the market return  $R_m$  and estimate  $E(R_m)$ . We collected daily data about U.S. Treasury Bills and DJIA from March 2001 to June 2010 (2,325 trading days). For each bank  $i$ ,  $\beta_i$  is calculated as Equation (15) shows using the data on  $i$ 's quarterly returns  $R_i$  from the FDIC data set along with the corresponding quarterly market returns  $R_m$ .

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\sigma^2(R_m)} \quad (15)$$

Then we rescale these returns assuming that a quarter consists of 61 trading days and use Equation (14) to estimate the quarterly expected value for bank portfolio returns. As a result, we construct a  $7,822$  (banks)  $\times$   $2,264$  (days) matrix  $D$  of expected bank portfolio returns. Following Elsinger's simulation approach, for each of the 18 base scenarios, we made 1,000 draws from

this estimated distribution of bank portfolio returns to generate 1000 systemic risk scenarios. To illustrate this procedure which aims to simulate the uncertainties in  $F$ , let  $D_s$  be one such draw (i.e., a column vector from the matrix  $D$ ). It represents one randomly drawn scenario of expected quarterly returns (i.e.,  $E(R_j)$ ) for all 7,822 banks from the estimated distribution  $D$  based on CAPM. Let  $F_{t_k}$  denote the vector of the initial values of bank financial portfolios at the start time of the base scenario at  $t_k$ . Then the vector  $D_s F_{t_k}$  contains the profits or losses for each bank realized under the scenario  $D_s$  at time  $t_k + 1$ . For each of the base scenarios, we repeat this procedure 1,000 times and get a distribution of profits and losses of the banks in this base scenario.

The second mechanism aims to simulate a significant negative shock on selected banks' financial asset portfolios caused by sources other than stock market risks. This mechanism is analogous to how the recent subprime mortgage crisis has imposed economic shocks on the U.S. banking system. The collapse of the housing bubble in 2007 caused the value of financial assets and products linked to real estate prices to plummet. Major U.S. banks with huge exposures to these assets and products were affected first and suffered great losses. Some of these banks could not afford such losses and failed, which further affected other banks through correlated financial asset portfolios and interbank payment obligations. To emulate this propagation of bank failures starting from a small set of banks, we select the top 5% of the banks with the largest financial asset portfolio values at time  $t_k$  as a seed set and simulate that each of them will suffer a loss for a percentage  $S$  (defined as shock rate) of its portfolio value due to a negative shock. We choose the top 5% because Angelini et al. (1996) found that contagious bank failure can be triggered by the failure of as little as 4% of the banks in the system.

## **Simulating Capital Injections**

The scenario design in Figure 5b aims to examine the effects of capital injections guided by different methods, including the LASER algorithm. In this design, 5% of the banks are selected for capital injections in the generated systemic risk scenario based on a ranking method. The amount injected for each bank is expressed as a percentage of this bank's financial asset portfolio value at the day  $t_k + 1$ , called capital injection rate  $\delta$ . This injection approach is consistent with the strategy of the Troubled Asset Relief Program (TARP) which allows the U.S. Government to purchase "troubled assets" of selected key banks in order to provide liquidity and stabilize the banking system.

## **Simulating Interbank Payment Settlements**

Since the Fedwire dataset only provides consolidated system-level statistics on interbank payments, we need to simulate transaction-level interbank payment settlements based on such statistics. First, we simulate a network which represents the interbank payment relationships in the banking system over one quarter (from  $t_{k-1}$  to  $t_k$ ). This time period is chosen mainly because interbank payment relationships are often affected by short-term factors. For instance, at the end of each year, many multinational corporations often have large amounts of funds transferred across countries for tax benefits, resulting in unusual patterns for interbank payment activities in the short term.

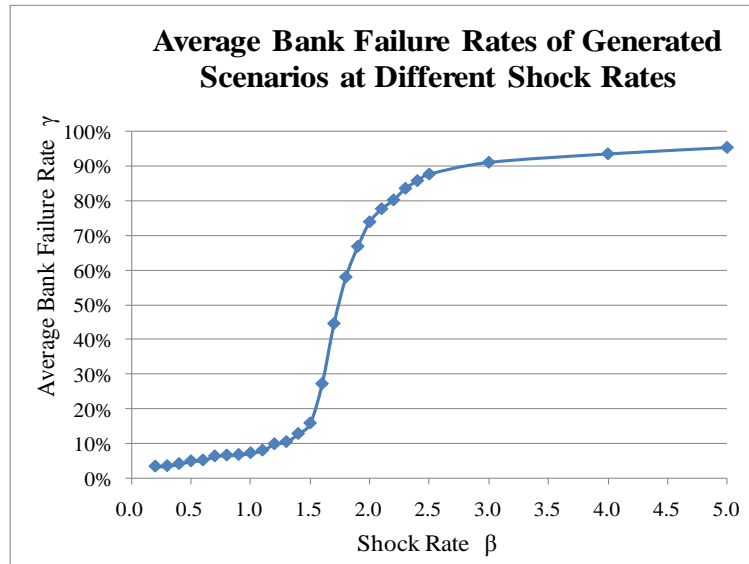
This Fedwire network is simulated based on the empirical findings from Soramäki's study (2007) on the network topology of interbank payments among 7,584 banks in the Fedwire system for the first quarter of 2004, since the 7,822 banks in our FDIC dataset also use the Fedwire system. Like Soramäki's network, the average degree for our simulated Fedwire network is set to be 15

and the connectivity is 0.3%. The average daily number of payments is set to be 345,000 and the average value per payment is \$3 million. The payment frequency distribution, degree distribution, and the distribution of payment values are also extracted from Soramäki's study (2007). The assignment of an average payment value to a link is constrained by the capital reserve of the source bank at time  $t_K$ .

Moreover, to examine the robustness of the LASER algorithm, for each of the 18 base scenarios, we simulate 1,000 such payment networks, in which a directed link from bank  $i$  to  $j$  represents that  $i$  has made one or more payments to  $j$  during the quarter (from  $t_{K-1}$  to  $t_K$ ). The link weight is set to be the average value per payment for this interbank payment relationship and selected from the empirical distribution reported in Soramäki (2007). For each of the interbank payment networks, we also generate 1,000 configurations for assigning the payment value distributions to the network links on day  $t_K + 1$ . Each configuration is considered as a systemic risk scenario. In such a scenario  $l$ , we can calculate the bank failure rate as  $bf_l = x/N$ , where  $x$  is the number of failed banks and  $N$  is the total number of banks in that scenario  $l$ . An average bank failure rate  $\gamma$  across the set of all scenarios  $L$  can be calculated

as  $\gamma = \sum_l bf_l / M$  ( $l \in L$ ), where  $M$  is the total number of generated scenarios.

### **Comparing Average Bank Failure Rates at Different Shock Rates**



**Figure 6. Average Bank Failure Rates for Generated Scenarios at Different Shock Rates**

Figure 6 shows the average bank failure rates  $\gamma$  resulting from the generated scenarios using the setting in Figure 5a. The shock rate  $\beta$  can be larger than 1 since the trading liabilities of a financial asset portfolio may exceed its nominal value due to excessive leverage in financial derivative products. As the figure shows, when  $\beta$  is relatively low (0.1 to 1.4), the average bank failure rate  $\gamma$  is relatively low, ranging from 2.9% to 12.8%. Starting at  $\beta = 1.5$ ,  $\gamma$  began to increase drastically. When  $\beta$  reaches 2.0, more than 70% of the banks failed, indicating a system-wide collapse of the banking system.

These results show that the banking system can sustain relatively mild negative market shocks when  $0 < \beta \leq 1.4$ . However, when the shock rate exceeds a threshold value ( $\beta \geq 1.5$ ),  $\gamma$  starts to increase at a much faster rate, leading to the collapse of the banking system. Further, when  $\beta \geq 2.0$ , the effects of negative market shocks become marginal since most banks in the system already failed. Therefore, in our evaluation experiment of the LASER algorithm, we focus on the results in the scenarios when  $\beta$  is between 1.5 and 1.9.



## 5.2 Evaluation of the Link-Aware Systemic Estimation of Risks (LASER) Algorithm

We then evaluate the performance of the LASER algorithm in 1) predicting contagious bank failures and 2) determining capital injection priorities in the generated systemic risk scenarios. Performances of the standard HITS (Equation (2)), node-weighted (Equation (11)) and link-weighted HITS (Equation (12)), as well as the widely used bank liquidity risk measure, capital adequacy ratio (CAR), were also studied for comparison purposes. Since bank systemic risk is often in the form of liquidity shortfall under extreme market conditions, CAR is used as a proxy measure and defined as follows:

$$\text{Capital Adequacy Ratio} = \frac{\text{Tier 1 Capital} + \text{Tier 2 Capital}}{\text{Risk Weighted Assets}} \quad (16)$$

where Tier 1 capital is denoted as  $e$  in our clearing payment vector. Tier 2 capital is supplementary capital, which is categorized in the Basel I Accord as undisclosed reserves, revaluation reserves, general provisions, hybrid instruments, and subordinated term debt. A bank's risk-weighted assets are fund-based assets such as cash, loans, investments, and other assets.

### 5.2.1 Predicting Contagious Bank Failures

In each of the generated scenarios, the data about the correlated bank portfolio links and interbank transaction links is used as input for the LASER algorithm. After simulating the events described in Figure 5a, the contagious bank failures that occurred at the time  $t_K + 1$  are treated as the “unknown” future events to evaluate the prediction capability of LASER. Then LASER was set to generate a ranked list of  $\eta$  banks in terms of their authority scores in a descending order. Bank  $i$ 's LASER authority score  $Au_i$  represents the systemic risk it receives from the banking

system. The higher a bank's authority score is, the more likely it will fail due to liquidity shortage caused by other banks' failures and negative market shocks. This ranked list predicts which banks are most likely to fail in the generated scenarios. Another four ranked lists were generated based on the three other HITS-related algorithms and the capital adequacy ratio for comparison purposes. We then check the banks in these lists with the banks that failed in the generated scenarios to evaluate their prediction performances. We adopted the following prediction-quality metrics from Breese et al. (1998) for evaluating LASER and the other four methods. Precision score mainly measures the accuracy of the predictions, while recall score focuses on the coverage. F-measure, which combines precision and recall, is the harmonic mean of these two scores.

$$\text{Precision: } Pr_l = \frac{\text{Number of predicted banks that failed in the current scenario}}{\text{Total number of predicted banks in the list } (\eta)} \quad (17)$$

$$\text{Recall: } Rc_l = \frac{\text{Number of predicted banks that failed in the current scenario}}{\text{Total number of bank failures in the current scenario}} \quad (18)$$

$$\text{F-measure: } Fm_l = \frac{2 \times Pr_l \times Rc_l}{Pr_l + Rc_l} \quad (19)$$

where  $l$  is a generated scenario. When the shock rate  $\beta \geq 1.4$ , the average bank failure rate becomes larger than 15%. Thus we set the length of the prediction list for LASER  $\eta$  as 1,110 (i.e., 15% of the average number of 7,405 reporting banks). We also repeated the experiments for three other different settings of  $\eta$  (500, 1500, and 2000) and got similar results, indicating LASER performs better than the other four methods. As suggested in Section 5.1.3, our experiments focus on scenarios with shock rates ranging from 1.5 to 1.9. For the precision, recall,

and F-measure, average values across all the generated scenarios were calculated as the main performance measures for LASER's predictions of contagious bank failures.

**Table2. Prediction Performance Measures**

Shock Rate	Ranking Methods	Precision	Recall	F-Measure
1.5	LASER	<b>0.2297</b>	<b>0.2064</b>	<b>0.2073</b>
	HITS	0.1674	0.1476	0.1455
	Node-Weighted HITS	0.1947	0.1792	0.1783
	Link-Weighted HITS	0.1789	0.1631	0.1658
	Capital Adequacy Ratio	0.1526	0.1387	0.1355
1.6	LASER	<b>0.3609</b>	<b>0.1875</b>	<b>0.2378</b>
	HITS	0.2967	0.1529	0.1947
	Node-Weighted HITS	0.3243	0.1688	0.2113
	Link-Weighted HITS	0.3079	0.1594	0.2037
	Capital Adequacy Ratio	0.2673	0.1343	0.1689
1.7	LASER	<b>0.5231</b>	<b>0.2765</b>	<b>0.3518</b>
	HITS	0.4632	0.2433	0.3078
	Node-Weighted HITS	0.4815	0.2536	0.3212
	Link-Weighted HITS	0.4694	0.2483	0.3145
	Capital Adequacy Ratio	0.4303	0.2254	0.2858
1.8	LASER	<b>0.6832</b>	<b>0.3609</b>	<b>0.4673</b>
	HITS	0.6247	0.3308	0.4217
	Node-Weighted HITS	0.6293	0.3345	0.4259
	Link-Weighted HITS	0.6512	0.3461	0.4405
	Capital Adequacy Ratio	0.5503	0.2829	0.3611
1.9	LASER	<b>0.7713</b>	<b>0.4005</b>	<b>0.5201</b>
	HITS	0.6821	0.3608	0.4621
	Node-Weighted HITS	0.7037	0.3742	0.4772
	Link-Weighted HITS	0.7426	0.3963	0.5085
	Capital Adequacy Ratio	0.6327	0.3335	0.4272

The results are presented in Table 2. First, we observe that the LASER algorithm outperformed the other four methods in all three performance measures across all five shock rates. Second, the performances of capital adequacy ratio are the worst among all five methods, indicating this widely adopted risk measure is less useful in measuring bank systemic risk compared with LASER and other methods. Third, both LASER and the two weighted HITS algorithms perform better than the standard HITS algorithm. This indicates that the weight information based on the nodes and links can improve the performance of HITS in predicting contagious bank failures. These findings together indicate that the LASER algorithm is capable of exploring and integrating the underlying financial and network principles. These principles govern the emergence and distribution of systemic risk in banking systems through the two types of interbank links, which to a certain extent are not fully captured by other HITS-related algorithms and the capital adequacy ratio.

In addition, the performances of the node- and link-weighted HITS largely depend on the magnitudes of the simulated market shocks. As Table 2 shows, when shock rates are relatively low, ranging from 1.5 to 1.7, the node-weighted HITS algorithm performs better than the link-weighted algorithm. But when the shock rates are at 1.8 and 1.9, the link-weighted HITS provides better predictions than the node-weighted one. We conjecture that is because when the shock rates are relatively low, the correlation relationship among bank portfolios returns is strong and remains the main source of systemic risk for individual banks. On the other hand, when the magnitude of a market shock reaches a certain level, a significant number of bank portfolio values were largely reduced and all of them tend to become positively correlated. This sudden change may not fit the general patterns of banks' past correlated portfolio relationships which the node-weighted HITS depends on. In such scenarios, interbank payment links become the

dominating source of systemic risk for the banking system. This process is consistent with what we observed during the 2007 financial tsunami, that the U.S. banks became extremely cautious about their interbank cash flow management after the initial shocks (e.g., the collapse of Lehman Brothers), causing a system-wide liquidity shortage. From an individual bank's perspective, such managerial actions are effective in reducing banks' systemic risk. However, from the regulator's perspective, such actions largely increase the system-level liquidity risks. For this reason, providing liquidity through capital injections to the banking system is a rational choice and can effectively stabilize the bank system.

### **5.2.2 Preventing Contagious Bank Failures through Capital Injections**

One of the research goals is to explore how NARMA as a BI approach can be used by financial regulators to mitigate bank systemic risk, in another word, preventing contagious bank failures. When contagious bank failures happen, financial regulators need to provide liquidity to the banking system often by injecting capital to key banks. Since the amount of such capital is often limited, one critical question for regulators is which banks should receive the injections in order to prevent further contagious bank failures. The U.S. Troubled Asset Relief Program (TARP) implemented in 2008 is a form of capital injections. Although it achieved its goal of providing liquidity to the banking system, the regulators have acknowledged it is difficult to evaluate the bailout's effectiveness.

To address this problem, we use the LASER hub score as a measure of the negative influence a bank's failure may impose on other banks through the two sources of systemic risk – interbank payments and correlated bank portfolios. In the scenarios generated based on Figure 5b, a certain amount of capital is injected to the banks selected based on hub scores from LASER and the other three HITS-related algorithms. The amount of capital injection is expressed as a percentage

of the value of a bank’s financial asset portfolio, defined as capital injection rate  $\delta$ . Based on our domain experts’ opinion, we set  $\delta$  at 100%, 200%, 300%, 400%, and 500% for different experimental configurations. The results are consistent across different configurations. When  $\delta$  exceeds 500%, the effects of capital injections based on LASER become marginal. Therefore, in Table 3 we only report the results with capital injection rates of 100%, 300%, and 500%, and shock rates ranging from 1.5 to 1.9. Based on domain experts’ opinion, the number of banks selected for capital injection is the same as the number of banks (i.e., 5% of all banks) being shocked in each scenario. We then observe the changes in the average bank failure rates of the simulated scenarios with or without capital injections, given everything else is the same. Table 3 reports the average reduction rates for the scenarios with different experimental settings. The reduction rate  $\lambda$  for each scenario is calculated as  $\lambda = (\gamma_a - \gamma_b) / \gamma_b$ , where  $\gamma_a$  is the average bank failure rate in the scenario without capital injections and  $\gamma_b$  is the one with capital injections. The average reduction rate  $\bar{\lambda}$  is calculated across all simulated scenarios. The average reduction rates in bold font indicate the capital injection strategy with the best performance across all five methods.

**Table 3. Performance Measures for Different Capital Injection Strategies**

Shock Rate	Ranking Methods	Average Reduction Rate $\bar{\lambda}$		
		$\delta = 100\%$	$\delta = 300\%$	$\delta = 500\%$
1.5	LASER	<b>-13.23%</b>	<b>-21.87%</b>	<b>-34.59%</b>
	HITS	-10.91%	-14.84%	-19.32%
	Node-Weighted HITS	-12.48%	-18.73%	-26.51%
	Link-Weighted HITS	-12.03%	-17.90%	-24.89%
	Capital Adequacy Ratio	-1.86%	-3.12%	-3.98%
1.6	LASER	<b>-14.95%</b>	<b>-24.38%</b>	<b>-38.31%</b>
	HITS	-10.64%	-13.82%	-18.41%

	Node-Weighted HITS	-12.67%	-15.87%	-26.53%
	Link-Weighted HITS	-13.14%	-16.36%	-28.82%
	Capital Adequacy Ratio	-2.05%	-2.93%	-3.62%
1.7	LASER	<b>-16.28%</b>	<b>-25.84%</b>	<b>-37.81%</b>
	HITS	-11.85%	-14.12%	-18.53%
	Node-Weighted HITS	-12.13%	-15.24%	-25.48%
	Link-Weighted HITS	-14.71%	-17.97%	-30.24%
	Capital Adequacy Ratio	-1.48%	-3.59%	-4.56%
1.8	LASER	<b>-16.83%</b>	<b>-26.24%</b>	<b>-38.07%</b>
	HITS	-10.77%	-14.36%	-17.49%
	Node-Weighted HITS	-12.37%	-15.88%	-25.72%
	Link-Weighted HITS	-15.12%	-18.33%	-31.96%
	Capital Adequacy Ratio	-1.25%	-3.30%	-4.29%
1.9	LASER	<b>-16.31%</b>	<b>-27.09%</b>	<b>-37.52%</b>
	HITS	-11.90%	-15.26%	-17.92%
	Node-Weighted HITS	-11.85%	-16.92%	-18.33%
	Link-Weighted HITS	-14.89%	-18.54%	-30.22%
	Capital Adequacy Ratio	-1.82%	-3.88%	-4.81%

Table 3 shows that LASER's average reduction rates are significantly larger than other methods at all shock rates and capital injection rates. This means capital injections based on LASER's hub score can save more banks from contagious bank failures than the other four methods in the simulated systemic risk scenarios. It was also found that the average reduction rates of capital injections based on capital adequacy ratio were much smaller than the other methods. We conjecture this is mainly because CAR is the only method among the five that does not model any interbank relationships but only reflects a bank's own liquidity status. As suggested earlier, in systemic risk scenarios, a bank's survival largely depends on its relationships with other banks.

Thus CAR, as a non-relational and static bank risk measure, may not be useful in determining a bank's priority for receiving capital injection.

In addition, the link-weighted HITS in general saves more banks than the node-weighted HITS in the simulated scenarios. The performance difference between these two becomes larger when the shock rate increases. This is consistent with the finding mentioned above, that interbank payment links become the dominating systemic risk sources under large market shocks. The intuition is that when the values of financial asset portfolios are already largely reduced by market shocks, banks with large amounts of outgoing payments will become more influential in terms of facilitating contagious bank failures. Under such conditions the link-weighted HITS, which depends on interbank payment links, performs better than the node-weighted HITS in identifying key banks for capital injections. Moreover, the average reduction rates for all the methods increase as more capital is injected into the banking system. To check for robustness of our findings, we repeat the experiment with 9 different threshold values for  $\rho_{ij} - \rho_s$  from 0.1 to 0.9. The results show that, under the same shock rate, when the threshold value for  $\rho_s$  increases from 0.1 to 0.7, the precision, recall, and F scores of the LASER algorithm are rather stable within a narrow range. When  $\rho_s$  is larger than 0.8, all three scores decrease. This is mainly because large threshold values will drastically reduce the number of constructed correlated portfolio links. Based on Equation (1), this reduction then causes the weighting value  $G(i)$  for bank  $i$ 's authority and hub scores to become closer to the bank's own variance  $w_i^2 \sigma_i^2$ . Then the heterogeneity of the correlated portfolio relationships cannot be effectively captured by the LASER algorithm under such conditions. Therefore, we present the set of representative results when setting  $\rho_s$  as 0.5 (i.e.,  $\rho_{ij} \geq 0.5$ ). In addition, we also repeat the experiment with



different values for shock rates, number of banks to shock, capital injection rates, and numbers of banks receiving capital injections. The results are consistent with the ones presented in Table 3, that LASER outperforms the other methods in terms of predicting and preventing contagious bank failures.

## 6. CONCLUSIONS

In this paper, we develop a BI-based approach called NARM to support central banks in monitoring and mitigating bank systemic risk. We adopt a network view of the modern portfolio theory (MPT) to model bank systemic risk. To do so, we conceptualize the network principle –Correlative Rank-In-Network Principle (CRINP)–for modeling the impact of interbank relationships on bank systemic risk. By incorporating CRINP and MPT, we developed the LASER algorithm to rank banks according to their relative systemic risk levels. We use discrete event simulation techniques to evaluate LASER in monitoring and mitigating systemic risk in comparison with other methods. The results of our simulations show that LASER outperforms other HITS-related algorithms and the capital adequacy ratio.

In addition, we also found that bank systemic risk levels are largely affected by market conditions. In our simulation, the banking system can sustain mild market shocks. However, when the magnitude of a market shock exceeds a certain threshold, contagious bank failures will happen with accelerating speed. In such scenarios, systemic risk originating from interbank payment links becomes more important than correlated bank portfolio links in determining a bank's survival. These business insights should help central banks devise better policies and mechanisms to prevent breakdown of banking systems.

We claim two research contributions. First, our work initiates a new research direction in the study of systemic risk at the individual bank level with a network perspective for mitigating contagious bank failures in the face of a financial crisis. We developed a BI algorithm that incorporates network and financial principles into a systemic risk analysis framework of a banking network. As a result, our work lays the foundation towards a practical approach for central banks to better monitor and manage systemic risk. Second, our research has potential impacts on the modeling and analysis methods of various business networks. The CRINP network principle we conceptualized in this research has instructional value to research in other domains such as citation analysis. In addition, our data analysis and simulation methods can be applied to similar research areas such as bank stress testing where time series data and business networks may be studied to analyze various financial risks.

We acknowledge that this research has some limitations. First, certain assumptions of modern portfolio theory we adopted are simplifications of reality. For instance, MPT assumes that there are no taxes or transaction costs, while real financial assets are often subject to both. Each of these assumptions compromises MPT to some degree. Second, LASER requires high-quality financial data quality. For central banks that do not have such data on market risk and interbank transactions, LASER's performance may degrade. Third, our evaluation study focuses on commercial banking systems mainly because of data availability issues. However, other types of financial institutions like hedge funds are becoming more connected with banking systems and should be included in systemic risk monitoring and analysis.

Our future research will focus on improving NARM to allow users to validate various risk management theories and methods for applications in systemic risk management. We also plan to improve the LASER algorithm for experiments with other bank datasets from the European Union

and Hong Kong. In addition, we intend to explore other BI techniques for further exploiting the network-related information associated with interbank relationships as sources of systemic risk.

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## **Author Biographies**

Dr. Daning Hu is an Assistant Professor of the Department of Informatics at University of Zurich and Head of the Business Intelligence Research Group. He holds his Ph.D. degree in Management Information Systems (minor in Finance) from the University of Arizona, and B.S. degree in Computer Science from Zhejiang University. His research goal is to derive analytical and empirical insights from the analyses of various real-world networks such as organization networks, communication networks, and social networks. Based on such insights, He aims to develop network-based business intelligence techniques and information systems for supporting decision making in various application domains. He has published in Decision Support Systems, Journal of the Association for Information Systems, Journal of the American Society for Information Science and Technology, and Information Systems Frontiers.

Dr. J. Leon Zhao is Chair Professor and Head of the Department of Information Systems at City University of Hong Kong. He was Interim Head and Eller Professor in MIS, University of Arizona and taught previously at HKUST and College of William and Mary, respectively. He holds Ph.D. and M.S. degrees from the Haas School of Business, UC Berkeley, M.S. degree from UC Davis, and B.S. degree from Beijing Institute of Agricultural Mechanization. His research is on information technology and management, with a particular focus on workflow technology and applications in knowledge distribution, e-learning, supply chain management, organizational performance management, and services computing. Leon's research has been supported by NSF, SAP, and other sponsors. Leon has been associate editor of ACM Transactions on MIS, Information Systems Research, IEEE Transactions on Services Computing,



Decision Support Systems, Electronic Commerce Research and Applications, International Journal of Business Process Integration and Management, International Journal of Web and Grid Services, and International Journal of Web Services Research and is on the editorial board of Journal of Database Management. He has co-edited over ten special issues in various IS journals. Leon has been a chair or program chair for numerous conferences including the 2012 IEEE International Conference on Service Economics, the 2011 CIO Symposium, International Conference on Information Systems, the 2010 International Conference on Design Science Research in Information Systems and Technology, the 2009 IEEE International Conference on Services Computing, the 2008 IEEE Symposium on Advanced Management of Information for Globalized Enterprises (AMIGE'08), the 2008 Arizona Exposium on Frontiers of Information Technology and Applications (FITA'08), the 2007 China Summer Workshop on Information Management (CSWIM'07), the 2006 IEEE Conference on Services Computing (SCC'06), the 2005 Workshop on Information Technology and Systems (WITS'05), and the 2003 Workshop on E-Business (WEB'03) among others. He received an IBM Faculty Award in 2005 for his work in business process management and services computing. He received IBM Faculty Award in 2005 and National "Chang Jiang Scholars" Chair Professorship at Tsinghua University in 2009.

Zhimin Hua is a doctoral student in the Department of Information Systems, College of Business, at the City University of Hong Kong. He received a B.S. in Computer Science from the University of Electronic Science and Technology of China. His research interests include Business Intelligence, Financial Information Services, Business Process Management, etc. His work has appeared in ICIS, WITS, etc. He is a student member of the INFORMS and AIS.

Dr. Michael C S Wong is an associate professor of the Department of Economics & Finance at City University of Hong Kong (CityU). He is a pioneer in risk management education in Asia. Since 1994 he has trained more than 6,000 risk managers and regulators on global practices of risk management. In 1998 Dr. Wong joined the Education Committee and FRM Committee of Global Association of Risk Professionals, developing and promoting the FRM examination. The examination has now become an international standard of risk management education. In 2003-2010, Dr. Wong advised many banks to rebuild their risk management systems, including first Basel-standard and Hong Kong Monetary Authority (HKMA)-approved internal credit ratings system, and investment services due diligence systems after the collapse of Lehman Brothers. In 2007, with the support by the University, he established CTRISKS, a credit ratings agency (CRA) for Asia. In June 2011, CTRISKS formally becomes one of the five CRAs licensed under the Hong Kong Securities and Futures Ordinance.

Dr. Wong graduated from University of Cambridge, University of Essex and Chinese University of Hong Kong and is an elected Fellow of Royal Statistical Society (UK). Prior to his academic and consulting career, he spent seven years on investment banking, specializing on currencies, precious metals and derivatives trading. Dr. Wong served as a member of examination panel of Hong Kong Institute of Bankers, Hong Kong Securities Institute and Stock Exchange of Hong Kong. He has published more than 60 academic papers in Finance and Risk Management and frequently serves as an invited speaker in professional risk conferences in Asian region.