

Credit Risk Spillovers among Financial Institutions around the Global Credit Crisis: Firm-Level Evidence

Jian Yang

The Business School, University of Colorado Denver, Denver, CO 80217-3364, USA
Email: Jian.Yang@ucdenver.edu Tel: (303) 315-8423; Fax: (303) 315-8084

Yinggang Zhou

The Faculty of Business Administration, Chinese University of Hong Kong,
Hong Kong, P.R. China
Email: ygzhou@baf.cuhk.edu.hk Tel: (852) 3943 8780; Fax: (852) 2603 7724

This Draft: January 6, 2012

Abstract

Using credit default swap data, we propose a novel empirical framework to identify the structure of credit risk networks across international major financial institutions around the recent global credit crisis. The findings shed light on the credit risk transmission process and helps identify key financial institutions. Specifically, we identify three groups of players including prime senders, exchange centers and prime receivers of credit risk information. Leverage ratios and particularly the short-term debt ratio appear to be significant determinants of the roles of financial institutions in credit risk transfer, while corporate governance indexes, size, liquidity and asset write-downs are not significant.

Key Words: credit risk; financial network; directed acyclic graphs; structural VAR

JEL Classifications: G01, G15, G32

We gratefully acknowledge helpful comments on earlier versions from Warren Bailey, Douglas Diamond, Mathias Drehmann (discussant), Robert Engle, Stijn Ferrari, Philipp Hartmann, Scott Henry (discussant), Andrew Karolyi, Jan Pieter Krahenen, Francis Longstaff, David Ng, Meijun Qian (discussant), Fan Yu, Gaiyan Zhang, Hao Zhou, Haibin Zhu, and seminar/session participants at Australian National University, Central Bank of China, Chinese Academy of Science, Chinese University of Hong Kong, the ECB-CFS-CEPR conference “Macro-prudential Regulation as an Approach to Contain Systemic Risk”, the FDIC-Cornell-University of Houston Derivative Securities and Risk Management Conference, NFA meeting in Vancouver, National University of Singapore 4th annual Risk Management conference, University of Colorado Denver, and the University of New South Wales conference on “Systemic Risk, Basel III, Financial Stability and Regulation”. We are particularly thankful to Zijun Wang for invaluable computational assistance. An earlier version of this paper was in circulation under the title “Finding Systemically Important Financial Institutions around the Global Credit Crisis: Evidence from Credit Default Swaps.” Yang acknowledges partial financial support from the UC Denver Faculty Research & Scholarship Completion Fund. Zhou acknowledges financial support from a Hong Kong RGC Research Grant (Project # 459510).

Credit Risk Spillovers among Financial Institutions around the Global Credit Crisis: Firm-Level Evidence

1. Introduction

During the 2007-2008 global credit crisis, the comovement of financial institutions' assets and liabilities increased dramatically. Increased comovement heightens the risk that financial distress originating in a handful institutions can spread to many others and distort the supply of credit and capital to the real economy. Understanding the nature of this systemic risk is the key to understanding the occurrence and propagation of financial crises.¹ The recent crisis underscores the importance of systemic risk and exposes critical weakness in the financial regulatory system. As a result, top-down system-wide marco-prudential approaches have been proposed to supplement the traditional bottom-up micro-prudential approach focusing on the soundness of individual banks.

While the literature (Jarrow and Yu, 2001; Allen, Babus, and Carletti, 2009; Cossin and Schellhorn, 2007; Elsinger, Lehar, and Summer, 2006) theoretically demonstrates credit risk transfer in a network structure due to tangible connections (such as interbank lending) between individual firms, other types of systemic risk can also be reflected by the comovement of credit risk or other asset prices of financial institutions. For example, Elsinger, Lehar, and Summer (2006) provide evidence that correlation in banks' asset portfolios dominates contagion as the main source of systemic risk, while contagion is rare but can nonetheless wipe out a major part of the banking system, which is consistent with Jorion and Zhang (2007, 2009) and Longstaff

¹ According to Allen, Babus, and Carletti (2009), there are at least three types of systemic risk. The first is a common asset shock such as a fall in real estate or stock market prices. The second is the danger of contagion where the failure of one financial institution leads to the failure of another due to investor panics or other psychological factors. A third type of systemic risk is the failure of one financial institution which likely coincides with the failure of many others due to the more correlated portfolios and enhanced financial connections of individual financial institutions resulting from their individual original incentive to diversify.

(2010). As a first step towards understanding of systemic risk, it is worthy to identify the structure of international risk transmission across major financial institutions before we investigate different causes or channels that generate systemic risk.

This paper uses a dataset of international credit default swaps to identify the structure of credit risk transmission across major financial institutions on the eve of Lehman Brothers' failure. The paper contributes to the literature in the following aspects. First, this study is perhaps the first study to provide a data-determined identification of the structure of credit risk transmission. Such an investigation is important itself, as it is directly motivated by earlier theoretical work on credit risk in a network economy (e.g., Jarrow and Yu, 2001; Allen, Babus, and Carletti, 2009; Cossin and Schellhorn, 2007; Elsinger, Lehar, and Summer, 2006) and furthers our understanding of credit risk transfer (e.g., Allen and Carletti, 2006).² It is also informative to investors for their decisions about international equity and credit markets. Equally important, our work enhances recent efforts to identify systemically important financial institutions (SIFIs) and to design and deploy macro-prudential regulation (e.g., Adrian and Brunnermeier, 2009). More specifically, we focus on a particular major criterion for identifying SIFIs, their connectedness with other financial institutions. Interconnectedness describes situations when financial distress in one institution materially raises the likelihood of financial distress in other institutions.³ In this context, SIFIs arguably can be those financial institutions which are prime senders or

² For example, the identification of prime senders and prime receivers of credit information in our empirical framework corresponds to primary and secondary firms in the theoretical model of Jarrow and Yu (2001). We thank Fan Yu for pointing this out. Our empirical framework also corresponds to the theoretical discussion on (clustered and unclustered) credit risk network in the literature (e.g., Allen, Babus, and Carletti, 2009; Cossin and Schellhorn, 2007).

³ From the perspective of interconnectedness, financial institutions which are prime senders of credit risk information might well be identified as the SIFIs, as they would influence credit risk of other financial institutions. The institutions which are the exchange center of credit risk information could also be systemically important. By contrast, those institutions which are prime receivers of credit risk information might less likely be systemically important, as they simply respond to new information about credit risk from others.

exchange centers, but not prime receivers of credit risk information.⁴ Meanwhile, our work extends the literature on international asset return spillover (e.g., Eun and Shim, 1989; Gagnon and Karolyi, 2009) to the credit market (rather than the stock market) and at the firm level (rather than the country level).⁵

Second, we propose an innovative empirical framework of combining cluster analysis, principal component analysis (PCA), a relatively new causal modeling technique (i.e., the direct acyclic graph (DAG))⁶, and structural vector autoregression (VAR) analysis to identify the credit risk transmission network. Specifically, we classify international financial institutions into several clusters, extract the major driving force behind the changes of CDS spreads in each cluster using principal components, and apply DAG-based structural VAR analysis to identify the structure of credit risk spillover within each cluster while controlling for the influence of the other clusters. Our empirical work is directly motivated by much theoretical work on credit risk transfer, but also extends existing empirical work using VAR and causality analysis (e.g., Longstaff, 2010). In particular, DAG analysis naturally provides a structure of causality between credit risk shocks to financial institutions and allows us to uncover the financial network of credit risk in the contemporaneous time. The DAG is further crucial in subsequent structural VAR analysis, which yields insights on the economic significance of financial connections in the credit risk network and also allows for lagged transmission of credit risk. In this context, we also

⁴ There are alternative systemic importance measures, such as CoVAR by Adrian and Brunnermeier (2009) or MES by Acharya, Pederson, Philippon, and Richardson (2010), which address how an institution contributes to the financial system's overall risk contemporaneously. The perspective of interconnectedness in this study is different from these studies and the empirical framework also allows for the transmission of credit risk with time lags.

⁵ As mentioned earlier, the structure of credit risk spillover could be due to either contagion or the link by fundamentals. It is beyond the scope of this paper to distinguish these different channels. See Forbes and Rigobon (2002) and Bae, Karolyi, and Stulz (2003) for recent works on financial contagion.

⁶ Causality is a fundamental and yet a controversial concept. DAG analysis (Pearl, 2000; Spirtes et al., 2000) represents a recent advance in probabilistic approaches to model causality, with the main focus on obtaining causal conclusions from observational data rather than experimental data. As discussed in more details below, probabilistic conditional independences are the key concept in such analysis.

extend the data-determined structural vector autoregression (VAR) analysis first proposed in Swanson and Granger (1997) to a setting of a high-dimensional system, which may have wide applications.⁷

Third, we explore the credit default swap (CDS) data of international financial institutions, which has been little studied. The CDS market came to prominence during the recent global credit crisis (Stulz, 2010). Compared to the corporate bond market, CDS spreads are found to have a number of advantages in representing credit risk, including more accurate and efficient measurement of default risk, higher liquidity, and no confounding tax issues (Longstaff, Mithdal, and Nies, 2005; Blanco et al., 2005; Ericsson, Jacobs, and Oviedo, 2009; Zhang, Zhou, and Zhu, 2009; Li, Zhang, and Kim, 2011). Nevertheless, despite the growing interest in the CDS market, there are relatively few empirical studies using firm-level CDS data and even fewer using international firm-level CDS data. Recently, Huang, Zhou, and Zhu (2009) use US CDS spreads to assess the systemic risk of US major financial institutions. Another work more closely related to ours is Eichengreen, Mody, Nedljkovic, and Sarno (2009), who use international CDS spreads to study whether contagion rather than economic fundamental linkages led the subprime crisis to propagate internationally. However, their paper does not aim to identify credit risk networks at the firm level.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 discusses the empirical methodology. Section 4 presents empirical findings and Section 5 offers robustness checks and further analysis. Finally, Section 6 concludes.

⁷ The VAR analysis of Sims (1980) has been a workhorse in macroeconomics and financial economics. As discussed in more details below, the meaningfulness of its structural/economic interpretation, however, critically depends on the appropriate decomposition of (typically significantly cross-correlated) VAR residuals. Swanson and Granger (1997) propose to uncover contemporaneous causal orderings of VAR residuals in a data-determined and, thus, less ad hoc manner.

2. Data

Following Eichengreen et al. (2009), we select the 43 largest financial institutions across the US, the UK, Germany, Switzerland, France, Italy, Netherlands, Spain, and Portugal.⁸ All these institutions can be considered to “too big to fail.” After controlling for size, we want to search for the SIFIs among these big institutions. From Bloomberg, the raw data are end-of-day CMA⁹ mid-quotes as well as bid and ask prices for 5-year CDS spreads, the most widely traded maturity.¹⁰ A CDS contract offers protection against default losses of an underlying entity. CDS payments are denominated in either US dollar or Euro while the spreads are in basis points. Following Forbes and Rigobon (2002), we compute rolling-average, two-day changes of CDS spreads to control for the fact that CDS markets for financial institutions from different countries may not operate during the same trading hours.¹¹ Such practice is also helpful to smooth out sharp daily movements and irregular trading (Eichengreen et al., 2009). We also compute the difference between ask and bid prices and normalize it by dividing the corresponding mid-quote. The sample runs from January 2007 to early September 2008 before the Lehman’s failure. This period has seen the unfolding of the crisis until it infected the entire U.S. and global financial system (Brunnermeier, 2009).¹² It is ideal for investigating how the crisis spread and which SIFIs played an important role.

[Table 1 here]

⁸ The two exceptions are Munchner Hypoth and LCL for which we can’t find the data from the Bloomberg any more.

⁹ The CMA is a credit information specialist headquartered in London with offices in New York and Singapore. It is a wholly owned subsidiary of CME Group, the largest and most diverse derivatives exchange in the world.

¹⁰ Missing data are less than 1% of the total observations during the sample period and thus negligible. We fill missing data with the mid-quotes for spreads of the previous trading day.

¹¹ Similarly, Forbes and Rigobon (2002) use the two-day average stock returns to address nonsynchronous trading of international stock markets due to different time zones.

¹² The first trigger for the crisis was an increase in subprime mortgage default, which was first noted in February 2007.

Table 1 reports summary statistics on spreads for 43 financial institutions. The CDS spreads over the sample period have significant cross-section and time series variation. Among them, the average mid-quotes for CDS spreads for US investment-banks are the highest, above 100 basis points except for Goldman Sachs. For each CDS, the spread is also volatile with its standard deviation close to its mean. The minimum and maximum values of the mid-quotes further highlight the considerable change over time. For example, the spread for Bear Sterns ranges from 21 to 727 points and for HBOS from 5 to 253 points.¹³ The bid-ask- differences are about 4.56 points and, in normalized terms, an average about 0.15.

3. Empirical Methodology

We combine cluster analysis, principal component analysis (PCA), DAG analysis and VAR models. Cluster analysis and PCA reduce the dimension of VAR analysis. For SIFIs from different clusters, we apply the DAG technique again to explore their interdependent structure.

3.1. Cluster Analysis and Principle Component Analysis

Cluster analysis refers to statistical methods which search for distinct groups or clusters of variables (or observations). The most commonly used clustering methods lead to a series of hierarchical (or nested) classifications of variables (or observations), beginning at the stage where each variable (or observation) is considered a separate group, and ending with one group containing all variables (or observations). Similar to Leuz, Nanda, and Wysocki (2003), to form clusters using a hierarchical cluster analysis, one must select: (1) A criterion for determining similarity or distance between two cases; (2) a criterion for determining which clusters are merged at successive steps; and (3) a criterion for determining the number of clusters.

¹³ Similar to Blanco et al. (2005), there is evidence of nonstationarity of CDS spreads. Focusing on the level of CDS spreads during the crisis period might thus suffer from well-known the spurious regression/correlation problem. Accordingly, similar to Eichengreen et al. (2009), we use the change of CDS spreads to ensure stationarity.

First, hierarchical clustering methods use a distance matrix as their starting point. The

most common distance measure is Euclidean which is calculated as $d_{ij} = \sqrt{\sum_{t=1}^T (x_{it} - x_{jt})^2}$ where

x_{it} and x_{jt} are the variable values for individuals i and j at time t .

Second, there are a variety of ways to measure how different two clusters are. This depends on the distance between cluster pairs: (1) single linkage defines intergroup distance as the distance between their closest members; (2) complete linkage uses the distance between the most remote pair of observations, one from each group; and (3) average linkage considers the average of the distances between all pairs of observations where members of a pair are in different groups. It uses information about all pairs of distances, not just the nearest or the furthest. For this reason, it is usually preferred to the single and complete linkage methods.

Third, an index that can be used for choosing the number of clusters is the cubic clustering criterion (CCC). This is a comparative measure of the deviation of the clusters from the distribution expected if data points were obtained from a uniform (no clusters) distribution.

The criterion is calculated as

$$CCC = \ln \left[\frac{1 - E(R^2)}{1 - R^2} \right] \times K$$

where $E(R^2)$ is the expected R -squared¹⁴ and K is the variance-stabilizing transformation.¹⁵ Larger positive values of the CCC indicate a better solution, as it shows a larger difference from a uniform (no clusters) distribution.

¹⁴ R^2 = Between-cluster sum-of-squares / total-sample sum-of-squares, which has the usual interpretation of the proportion of variance accounted for by the clusters.

¹⁵ K is an empirical parameter adopted to stabilize the variance across different numbers of observations, variables and clusters.

Principal component analysis (PCA) (e.g., Ludvigson and Ng, 2009), is an orthogonal linear transformation for dimensionality reduction. Given a set of data, the first component (the eigenvector with the largest eigenvalue) corresponds to a line that passes through the mean and minimizes sum squared error with these points. The second principal component corresponds to the same concept after all correlation with the first principal component has been subtracted out from the points. Essentially, PCA rotates the set of points around their mean in order to align with the first few principal components, which can explain a majority of the total variation of the data. The cumulative fraction of the total variation explained by the first few principal components is computed as the ratio between the sum of the first few largest eigenvalues divided by the sum of all eigenvalues.

3.2. VAR Models and Innovation Accounting

Let X_t denote a vector of stationary changes in CDS spreads, which can be modeled in a vector autoregressive model (VAR) following Sims (1980):

$$(1) \quad X_t = \sum_{i=1}^{k-1} \Gamma_i X_{t-i} + \mu + e_t (t = 1, \dots, T).$$

Because the individual dynamic coefficients of Γ do not have a straightforward interpretation, we use the innovation accounting method to summarize the dynamic structure and provide appropriate economic interpretation. Specifically, we can rewrite equation (1) as an infinite moving average process:

$$(2) \quad X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \quad t = 1, 2, \dots, T.$$

The error from the forecast of X_t at the n-step-ahead horizon, conditional on information available at t-1, Ω_{t-1} , is as follows:

$$(3) \quad \xi_{t,n} = \sum_{l=0}^n A_l \varepsilon_{t+n-l} .$$

Therefore, the variance-covariance matrix of the total forecasting error is computed as

$$(4) \quad Cov(\xi_{t,n}) = \sum_{l=0}^n A_l \Sigma A_l' ,$$

where Σ is the variance-covariance matrix of the error term in equation (1), e_t . The remaining basic problem is how to orthogonalize the VAR residuals. Sims (1980) proposes the Cholesky factorization to achieve a just-identified system in contemporaneous time, which leads to the following variance decomposition for the forecasting error:

$$\theta_{ij}^c(n) = \frac{\sum_{l=0}^n (e_i' A_l \Sigma P e_j)^2}{\sum_{l=0}^n (e_i' A_l \Sigma A_l' e_i)} ,$$

where P is the Cholesky factor of the residual variance-covariance matrix Σ , and e_i is a selection vector, with the i th cohort equal to 1 and all the other cohorts equal to 0. Therefore, $\theta_{ij}^c(n)$ measures the contribution of the j th-orthogonalized innovation to the variance of the total n -step-ahead forecasting error for the variable X_{it} .

Note, however, that we assume that there exists a particular recursive contemporaneous causal structure in the Cholesky decomposition. The assumption obviously is restrictive and often unrealistic (Swanson and Granger, 1997). More fundamentally, economic theories rarely provide guidance for contemporaneous causal orderings, and VAR practitioners usually need to rely on various stories to determine them arbitrarily. As pointed out in Hoover (2005), it is probably (more or less) ironic that the VAR method that originated as a way of getting away from incredible identifying restrictions on large scale macroeconomic models has to rely heavily

on hardly more-credible arguments to identify contemporaneous causal orderings. However, as advocated by Swanson and Granger (1997), the directed acyclic graphs (DAG) can be used to uncover contemporaneous causal orderings in a data-determined and, thus, less ad hoc manner.

3.3. Directed Acyclic Graphs Analysis

The DAG technique (Pearl, 2000; Spirtes et al., 2000), which is also termed Bayesian Network, is a recent advance in causality analysis. The basic idea of DAG builds on the insight of a non-time sequence asymmetry in causal relations, which contrasts with the well-known Granger causality, exploiting the time sequence asymmetry that a cause precedes its associated effect (and thus an effect does not precede its cause). In this subsection, we briefly describe how we conduct the DAG analysis using the variance-covariance matrix of the VAR residuals in equation (1). See, for example, Hoover (2005) for more related discussion.

A directed graph is essentially an assignment of the contemporaneous causal flow (or lack thereof) among a set of variables (or vertices) based on observed correlations and partial correlations. The “edge” relation characterizing each pair of variables represents the causal relation (or lack thereof) between these variables. Relevant to this study, possible edge relationships in DAG analysis are: (1) No edge ($X \perp Y$) indicates (conditional) independence between two variables. (2) Directed edge ($Y \rightarrow X$) suggests that a variation in Y , with all other variables held constant, produces a (linear) variation in X that is not mediated by any other variable in the system. Alternatively, for this paper’s purpose, a DAG may represent a recursive linear structural system with observables at the nodes, and edges encoding directional causality correspond to nonzero structural coefficients, with jointly independent unobservables are not represented in the DAG (see, e.g., Swanson and Granger, 1997).

Although correlation does not necessarily imply causation, under some circumstances DAG analysis can derive causality from correlation. As an illustration of the basic idea (Pearl, 2000), consider a causally sufficient set of three variables X , Y , and Z . A causal fork that X causes Y and Z can be illustrated as $Y \leftarrow X \rightarrow Z$. Here the unconditional association/correlation between Y and Z is nonzero (as both Y and Z have a common cause in X), but the conditional association/correlation between Y and Z , given knowledge of the common cause X , is zero. In other words, common causes screen-off associations or correlation between their joint effects. Now consider the so-called inverted causal fork, that X and Z cause Y , as $X \rightarrow Y \leftarrow Z$. Here the unconditional association or correlation between X and Z is zero, but the conditional association or correlation between X and Z , given the common effect Y , is not zero. Thus, common effects do not screen-off association between their joint causes. The reader is referred to Pearl (2000) and Spirtes et al. (2000) for more discussion on DAG.

Assuming that the information set, Ω_{t-1} , is causally sufficient, Spirtes et al. (2000) provide a powerful directed graph algorithm (i.e., PC algorithm) for removing edges between variables and directing causal flows of information between variables.¹⁶ The PC algorithm begins with an undirected graph in which each variable is connected with all the other variables. It then proceeds in two stages: elimination and orientation. In the elimination stage, the algorithm removes edges from the undirected graph, based on unconditional correlations between pairs of variables: Edges are removed if they connect variables that have zero correlation. The remaining edges are then checked for whether the first-order partial correlation

¹⁶ The causal sufficiency may to a large extent apply in this study. Longstaff, Mithdal, and Nies (2005) do not find any clear lead of the stock market with respect to the CDS market or vice versa. More relevantly, Acharya and Johnson (2007) document that the information flow from the CDS market to the US stock market is greater for subsamples when firms experience credit deterioration and they have high CDS levels, which certainly characterize the sample period of the crisis as used in this study. At the minimum, such a finding on prima facie causality is interesting in itself as the initial effort to detect credit risk transfer network.

(correlation between two variables conditional on a third variable) is equal to zero. If it is zero, the edges connecting the two variables are removed. The remaining edges are then checked against zero second-order conditional correlation and so on. The algorithm continues to check up to $(N - 2)$ th-order conditional correlation for N variables. Fisher's z statistic is applied to test whether conditional correlations are significantly different from zero.

Once the elimination stage is completed, the algorithm proceeds to the orientation stage, where the notion of *sepset* is used to assign the direction of contemporaneous causal flow between variables remaining connected after we check for all possible conditional correlations. The *sepset* of a pair of variables whose edge has been removed is the conditioning variable(s) on the removed edge between two variables. For vanishing zero-order conditioning (unconditional correlation), the *sepset* is an empty set. Edges remaining connected are directed by considering triples $X - Y - Z$, in which the pair X and Y and the pair Y and Z are adjacent but X and Z are not. Edges are directed between triples $X - Y - Z$ as $X \rightarrow Y \leftarrow Z$ if Y is not in the *sepset* of X and Z . If (1) $X \rightarrow Y$, (2) Y and Z are adjacent, (3) X and Z are not adjacent, and (4) there is no arrowhead at Y , then $Y - Z$ should be positioned as $Y \rightarrow Z$. If there is a directed path from X to Y and an edge between X and Y , then $X - Y$ should be positioned as $X \rightarrow Y$. The PC algorithm discussed above is popular and has been programmed in the software Tetrad III (<http://www.phil.cmu.edu/projects/tetrad/tet3/master.htm>), which is also used for the DAG analysis in this paper.

4. Empirical Results

4.1. Cluster Analysis and PCA Results

We apply hierarchical cluster analysis to the 2-day average changes of CDS spreads for all 43 largest financial institutions in our sample. With the average linkage clustering, CCC takes

its highest value when there are four clusters. The dendrogram also tends to suggest a four-group solution. As shown in Table 2, all European financial institutions belong to one group (“EU Financial Institutions”) while US financial institutions form the other three clusters. Interestingly, US commercial banks and investment banks are in one group (“US Banks”), insurance companies and American express in another (“US Insurance”), and Fannie Mae and Freddie Mac fall in the last group (“US GSEs”). The classification for US financial institutions is meaningful because different groups have different business operation models and is confirmed by the subsequent analysis below.

[Table 2 here]

Next, we use PCA to extract the common factors underlying variations in the 2-day average changes of CDS spreads for each cluster. Table 3 reports the cumulative fractions of the total variations explained by the first 5 principal components. The first component in each cluster can explain more than 60% of the total variations. Although the cumulative fractions vary across clusters, it is clear that the first component is the major driving force. Additional analysis is also conducted below to ensure the robustness of the main findings.

[Table 3 here]

4.2. DAG and Structural VAR Results

The optimal lag in Equation (1) is selected by minimizing the Schwarz's Bayesian Criterion (SBC) and the maximum lag is set at 15 days (three trading weeks). The SBC suggests the optimal lag of $k=3$ for all the model specifications under consideration, which is consistent with somewhat slow changes in CDS spreads across countries.¹⁷ Lagrangian multiplier tests on

¹⁷ We selected this lag initially based on a parsimonious VAR system only including the four first principal components from each cluster, which are proxies (albeit imperfect) for the common credit risk information for each group of financial institutions. Additional analysis shows that alternative lags do not appear to affect the main findings.

autocorrelation of the residuals cannot reject the null of white noise residuals at any conventional significance levels. In the analysis below, we investigate contemporaneous casual patterns among individual financial institutions within each of the clusters (while controlling the influence of the other clusters) to uncover the structure of credit risk network at the firm level. The investigation can also be motivated by the evidence that the common CDS spread variation in each cluster is explained predominately by its own earlier shocks.¹⁸

Firstly, the 5-variable VAR with the lag of 3 is estimated and used to summarize dynamic interactions among Fannie Mae, Freddie Mac, and the first components of the three other clusters. Equation (5) gives the lower triangular elements of the VAR residual correlation matrix with the following order: Fannie Mae, Freddie Mac, US banks, US insurance companies, and EU financial Institutions.

$$(5) \quad V = \begin{bmatrix} 1 & & & & \\ 0.73 & 1 & & & \\ 0.25 & 0.26 & 1 & & \\ 0.22 & 0.29 & 0.24 & 1 & \\ 0.16 & 0.17 & 0.18 & -.05 & 1 \end{bmatrix}$$

The matrix provides the starting point for the analysis of the contemporaneous causal pattern. The analysis is conducted using Tetrad III and the resulting graph at the 10% significance level is shown in Figure 1.¹⁹ We see contemporaneous causality from US insurance companies to US banks, from US banks to Fannie Mae, from Fannie Mae to Freddie Mac, from US insurance companies to Freddie Mac and from EU financial institutions to US banks.

[Figure 1]

¹⁸ The evidence is based on additional analysis focusing on only the four first principal components from each cluster, which is to be discussed briefly as a robustness check.

¹⁹ Due to somewhat low power of the PC algorithm and rather limited number of observations used in the DAG analysis, the conventional significance level of 10% seems to be the most appropriate for the sample size in this study (Spirtes, Glymour, and Scheines, 2000).

As vigorously argued in Swanson and Granger (1997), the contemporaneous casual pattern as identified through the DAG analysis of the correlation matrix provides a data-determined solution to the basic problem of orthogonalization of VAR residuals and thus is critical to forecast error variance decomposition of a VAR. There are two major advantages of employing the forecast error variance decomposition: (1) allowance for time-lagged information transmission in addition to contemporaneous information transmission; (2) description of economic significance of dynamic causal linkages.

Based on the directed graph result in Figure 1, forecast error variance decompositions are shown in Table 4. Entries in Table 4 give percentage of forecast error variance (standard deviation in the table) at horizon k , which is attributable to earlier shocks (surprises) from each other series (including itself). We list steps or horizons of 0 (contemporaneous time), 1 and 2 days (short horizon), and 10 and 30 days ahead (longer horizon). The shock to Fannie Mae very substantially explain about 44-48% of the CDS spread variation in Freddie Mac at all horizons, while the reverse is much weaker (about 11% at the longer horizon). Also, shocks to Fannie Mae and Freddie Mac together can explain little of the common CDS spread variation of any other groups, even at the longer horizon. European financial institutions have noticeable influence (6-11%) on the credit risk of the two GSEs.

It is also interesting to note that the first principal component of the other three clusters is explained primarily by itself both in contemporaneous time and at short horizons, with the possible exception of the US banks, where about 10-13% of its common credit risk variations can be explained by US insurance companies and European financial institutions. At the longer horizon of 30 days ahead, the US insurance companies and European financial institutions exhibit more pronounced influences on common credit risk variations of the US banks (about 8%

each). The European financial institutions stand out to explain about 12% of the common variation in the CDS spreads of US insurance companies at the 30-day horizon. By contrast, about 8% of the common credit risk variations of the European financial institutions at the 30-day horizon can be explained by US financial institutions and particularly US banks (about 4%). This suggests an interesting role of the European financial institutions before the global credit crisis worsened because of the collapse of Lehman Brothers, which probably has not received much attention. The evidence also implies that regional (or country) factors might have played an more important role than conventionally perceived during this stage of the crisis development, which is in line with the fact many European financial institutions had much exposure to Eastern European economies while US financial institutions were primarily exposed to the US subprime loan problem. In addition, different market-based assessments of probability of government bailout for financial institutions in different countries might also factor in the change of CDS spreads.

[Table 4]

Secondly, the 12-variable VAR with the lag of 3 is estimated and used to summarize dynamic interactions among 9 US banks as well as the first components of the three other clusters. Equation (7) gives the lower triangular elements of the innovation correlation matrix with the following order: US GSEs, US insurance companies, EU financial Institutions, Lehman Brothers, Bear Sterns, Goldman Sachs, Merrill Lynch, Morgan Stanley, Wachovia, Citigroup, JPMorgan, and Bank of America.

The resulting directed graph at the 10% significance level is shown in Figure 2. While no contemporaneous relation is identified between individual US banks and the common CDS

number of other commercial banks (i.e., Citigroup, Wachovia, and JPMorgan). Similarly, Bank of America and Bear Sterns also appear to be the exchange center of credit risk information.

In contrast, some other commercial banks appear to be prime receivers of credit risk information in contemporaneous time. For example, Citigroup receives credit risk information from Lehman Brothers, Goldman Sachs, Bank of America, and Wachovia and spreads it out to JPMorgan only. Similarly, influenced by Bear Sterns, Lehman Brothers, and Goldman Sachs, Wachovia affects Citigroup only. The most endogenous case is JPMorgan, which is affected by Bank of America, Citigroup, Goldman Sachs, and Morgan Stanley but has no impact on any others in contemporaneous time.

[Figure 2 here]

The information about Goldman Sachs in Figure 2 provides more details for the edge running from the US Banks to the US GSEs in Figure 1. Also enriching our understanding for the edge running from US insurance companies to US banks in Figure 1, it is shown that US insurance companies spread their common credit risk information to many other banks directly through Lehman Brothers. Such a unique information role of Lehman Brothers would be further collaborated and most clearly revealed in Table 5. Moreover, consistent with Figure 1, US GSEs receive shocks from US insurance companies in the contemporaneous time, which is further validated in the subsequent analysis (Figure 3).

Based on the directed graph result of Figure 2, forecast error variance decomposition is also conducted and reported in Table 5. The most striking firm-level evidence is that, even with allowance for the influence of US insurance companies and other banks, Lehman Brothers exerts strong effects on Bear Sterns (29-33%), Goldman Sachs (35-42%), Merrill Lynch (21-26%), Wachovia (22-27%), Citigroup (9-12%), and JPMorgan (about 10%) at all horizons. No other

US financial institutions under consideration have exhibited such an extensive and significant role of credit risk information spillover, which suggests that the decision not to bail out Lehman Brothers was probably a serious mistake and certainly worsened the global credit crisis. Similarly, Morgan Stanley, as another prime sender of credit risk information, indeed exerts nontrivial influence on other banks at all horizons, including Lehman Brothers (7-8%), Goldman Sachs (5-7%), Merrill Lynch (5-8%), Citigroup (6-11%), JPMorgan (10-13%), and Bank of America (11-12%). As an exchange center, Goldman Sachs is influenced by other four major investment banks in contemporaneous time as 42%, 7%, 4% and 5% of its CDS spread variations are explained by shocks to Lehman Brothers, Bear Sterns, Merrill Lynch, Morgan Stanley, respectively. As the horizon increases, while the contributions of other investment banks largely remain similar, shocks to two US commercial banks (i.e., JP Morgan and Bank of America) together explain about 8% of the variation in Goldman Sachs. On the other hand, Goldman Sachs exhibits noticeable influence and its role as the exchange center of credit risk information is more significant at the longer horizon of 30 days ahead, explaining about 5%, 10%, and 9% of US GSEs, Wachovia, and JPMorgan CDS variations, respectively. Consistent with the earlier observation that JPMorgan is the most endogenous in the contemporaneous time, at a longer 30-day horizon, it has the lowest percentage of CDS spread variations explained by its own shocks. Lastly, consistent with Figure 1 and Table 4, US insurance companies do exert noticeable influence on some banks. Nevertheless, even at the longer horizon, the influence of European financial institutions on individual banks is smaller, compared to its influence on US banks as a group in Table 4, perhaps because that the proxy used earlier only represents about 63% of the common credit risk variation for the cluster.

[Table 5 here]

In Figure 3, it is revealed now that such contemporaneous causality is channeled directly through Chubb, AIG, and American Express, which extends the finding of the edge running from US insurance companies to US GSEs in Figure 3, Also enriching our understanding for the edge running from US insurance companies to US banks in Figures 1-2, it is shown that US insurance companies contemporaneously spread the common credit risk information to US banks directly through AIG, American Express, and Met Life. European financial institutions are also exogenous in the sense that its credit risk information directly flows to US GSEs and American Express without inflow from others.

[Figure 4 here]

Table 6 presents results on forecast error variance decomposition based on the directed graph result of Figure 3. Noteworthy, Chubb and Safeco are confirmed to be the prime senders of credit risk information even at the longer horizon. Safeco has persistent and significant effect on all other five firms in the cluster at all horizons, i.e., American Express (6-8%), AIG (8-10%), Chubb (34-41%), Met Life (19-24%), and Hartford (41-54%), in addition to US GSEs (7-8%) and US banks (7-10%). Chubb also exerts noticeable impacts on most of the other firms at all horizons, including American Express (4-6%), AIG (14-15%), Met Life (22-29%), and Hartford (16-17%), as well as US GSEs (8-9%) and US banks (9-10%). The evidence for AIG as a prime sender of credit risk information however is weaker. Nevertheless, it still has nontrivial effects on American Express (5%), Met Life (6%) and US banks (14%), at the longer horizon. Hartford as a prime receiver of credit risk information is also easily confirmed as within the group it has the lowest percentage of CDS spread variations explained by its own shocks at a longer 30-day horizon. There is also some evidence for Met Life as the exchange center of credit risk information, while such is more mixed for American Express. Specifically, at the short and

longer horizons, Met Life receives credit shocks from AIG (6%), Chubb (22-26%), and Safeco (about 19-24%) and its shock affects Hartford (about 6-7%) and US banks (about 5%).

Moreover, consistent with the findings discussed above, European financial institutions exhibit noticeable effects at the longer 30-day horizon. The shock to European financial institutions as a group explains about 14%, 16%, 14%, 15%, 12%, and 6% of CDS spread variations of American Express, AIG, Chubb, Met Life, Hartford, and Safeco, respectively.

[Table 7 here]

Finally, we estimate a 29-variable VAR with the lag of 3 for 26 European financial institutions together with the first components of the three US clusters. Figure 4 shows contemporaneous causal patterns based on the VAR residuals.²⁰ The European financial institutions are well connected to each other and the edges are all directed (with the exception of the edges related to the three US clusters). Noteworthy, UBS only affects but is not affected by other institutions in the contemporaneous time, suggesting its role as a prime sender of credit risk information. Similarly, BNP Paribas has the contemporaneous causal effects on six other institutions (ING, Rabobank, Credit Agricole, Societe Generale, Banco Santander, and HVB) while it is only affected by UBS. A similar point may be made for Dresdner and to a lesser extent for Lloyds TSB. By comparison, ABN AMRO, ING, Rabobank, and Deutsche Bank may be considered as the prime receivers of credit risk information as they only directly receive but not send out credit risk shocks. Barclays, Commerzbank, RBS, and HVB appear to be the exchange center of credit risk information, as they receive credit risk shocks from some firms and send out the shock to an equal number of other firms. It is also interesting to note that Standard Chartered

²⁰ Note that the result for this part of the analysis should be interpreted with some caution, as we are not aware of any simulation evidence on the performance of the PC algorithm applied to such a high dimensional system. Due to the same reason and further constrained by the programming capacity of the algorithm (up to 32 variables), we do not explore the potentially interesting case where all 43 financial institutions are included in one large system.

is the only European financial institution connected with US banks in the contemporaneous time, although the casual relationship is undirected. Obviously, future research is needed to further investigate the issue.

[Figure 5 here]

We also conduct the forecast error variance decomposition analysis using the estimated VAR parameters and the orthogonalized shocks based on Figure 4. To conserve the space, the detailed decompositions are not tabulated here but are available upon request. Briefly, in the short terms, none of the three groups of US financial institution have a significant impact on the 26 European financial institutions, consistent with the observations in Tables 4-6. At the 30-day horizon, US GSEs explain 2.5%-7.5% of credit risk variations in some of the individual 26 institutions. By contrast, the explanatory power of US banks is typically negligible (less than 1%). The effect of US insurances on some individual European financial institutions is more mixed and largely falls in the range of 1% and 3.5%.

5. Robustness Checks and Further Analysis

5.1. Robustness checks

We conduct many robustness checks on the main results as follows. First, the four-variable VAR with the lag of 3 is estimated to summarize dynamic interactions among four first principal components. It should be noted that in some cases such results based on (somewhat imperfect) proxies of the common credit risk variation of each cluster (group) may be somewhat different from firm-level results, which is based on richer and firm-specific information. Nevertheless, the results based on the four first principal components (available on request), apparently an oversimplified empirical model, is generally in line with the main findings based on larger models using firm-level data (as reported above) (although no information on the firm-

level network is revealed by such an analysis). Regarding the contemporaneous causality pattern, all directed edges are consistent with Figure 1 where the group of GSEs is the focus. One possible exception may be the only undirected edge between US GSEs and US insurance companies, which should be assumed to run from US insurance companies to US GSEs and consistent with the directed edge from US insurance companies to Freddie Mac in Figure 1. Also, the common credit risk variations of the European financial institutions as a group are highly exogenous in the contemporaneous time, which is generally consistent with Figures 1, 3, and 4.

The resulting error variance decomposition results confirms that every first principal component of the four clusters is explained primarily by itself both in contemporaneous time and at short and longer horizons, with some proportions explained by innovations in other clusters, particularly at the longer horizon. The result generally confirms the appropriateness of the cluster analysis result of classifying the financial institutions into 4 groups and the result in Table 4. At 30 days ahead, US banks and US insurance companies together explain about 6 percent of the common CDS spread variation of the European financial institutions, while the European financial institutions also have a noticeable (about 8-10%) impact on the common credit risk variations of other groups at the longer horizon within the four clusters. The evidence is again generally in line with Tables 4, 5, and 6, particularly in light of the fact that the first principal component alone is an imperfect proxy even for the common variation in credit risk.

Second, we also re-estimate all the models related to US banks, US insurances and EU financial institutions by including second principal components of each cluster (the first principal component alone already explain 90% of the US GSEs cluster). In the main analysis above, for the purpose of the model parsimony, we have only included the first principal component in the

VAR model specifications, which explains more than 60% variations for each cluster. With one principal component for each cluster in the models, it is straightforward to interpret the results of DAG and variance decompositions. With more than one principal component for the same cluster included in the models, the interpretation of the empirical results is a little more complicated. For the consideration of the simplicity, we add up the decompositions of both principal components of the same cluster of financial institutions as the influence of the particular cluster. The result (not reported here but available upon request) confirms that the above finding based on the first principal components alone generally hold.

Third, we conduct a small scale simulation to assess the effectiveness of the PC algorithm in DAG analysis in this study. Specifically, based on the estimated 12-variable VAR model of US Banks with the lag of 3, we bootstrap a set of pseudo residuals of the same length as the realized sample. These residuals are then used to sequentially generate a pseudo sample of CDS spread changes for the 12 financial institutions using the estimated autoregressive parameters. We generate a total of 100 such pseudo samples. For each sample, a VAR model with a lag length of three is estimated. The estimated VAR residuals are retained and Tetrad III is run for each realization using the PC algorithm and assuming causal sufficiency. Again, the chosen significance level for DAG analysis is 10%. When there is no edge between two variables in the true data generating process (DGPs), the PC algorithm is very successful in excluding the edge in the simulated data, with an average success rate of 96.0%. When there is an edge, the algorithm can both detect the existence of the edge and direct it correctly up to 60% of times. Furthermore, it can on average correctly identify the existence of all edges in the true DGPs (i.e., the skeleton of the causal graph) 76.3% of times (with the median success rate is 86.0%).

Finally, we also consider an alternative sample period. In particular, the sample contains an unusual episode of the fall of Bear Sterns. To examine whether the inclusion of the data after the fall of Bear Sterns has had a significant effect of the main results we have obtained, we also re-estimate the 12-variable VAR(3) for the US banks using the subsample of January 1, 2007 through –March 14, 2008 when the Bear Sterns was rescued. While the untabulated result shows less strong evidence of credit risk network for the group of US banks due to the use of much fewer data points, most of the main results, such as Lehman Brothers, Morgan Stanley and Goldman Sachs as either prime senders or exchange center of credit risk information, remain unchanged.

5.2. Driving Forces of Credit Risk Transfer

We have investigated how CDS spread changes as a proxy of credit risk transmitted among 43 individual financial institutions. A natural question is the economic intuition for why we would expect the spillovers to be more intense in one direction than another. Note also that such analysis can serve as further robustness check on the above main result of the credit risk transfer pattern, as random errors possibly introduced in the multi-step procedure (despite many robustness checks above), if substantial, should be biased toward no significant relationship between credit risk transfer and potential economic factors.

Toward this end, we conduct the following preliminary analysis. First, based on the identified contemporaneous causal patterns among financial institutions, we construct an index (called as I-index) to measure the importance of financial institutions from the perspective of interconnectedness as follows.²¹ (1) Being assigned to be 3, the prime senders of credit risk

²¹ As discussed earlier, prime senders, exchange centers and prime receivers identified based on contemporaneous causal patterns are generally confirmed in the forecast error variance decompositions. We also conduct additional analysis to confirm the robustness of the result below. For example, when Fannie Mae is classified as a prime sender

information are those who send out at least two more shocks than their receipts. Specifically, Lehman Brothers, Morgan Stanley, Sefeco, Chubb, and possibly AIG in the US and BNP Paribs, Dresdner bank, and UBS in the Europe belong to this category. (2) The exchange centers of credit risk information are assigned to be 2. Goldman Sachs, Bear Sterns, Bank of America, and Metlife in the US and Barclays, RBS, Commerzbank, and HVB in the Europe play the role of the exchange center on the credit market by intensively receiving from at least 2 financial institutions and then transferring credit risk information to at least 2 others. (3) The prime receivers of credit risk information are assigned to be 0, such as Citigroup, Wachovia, JPMorgan and Hartford in the US, and ABN AMRO, ING, Rabobank, and Deutsche Bank in the Europe. These institutions receive at least two more shocks than what they spread out. (4) The institutions other than the above three categories are assigned to be 1. Table 8 shows the value of I-index for each individual institution. The higher the value, the more likely an institution transfers credit risk information to others and thus plays a more active role in the interconnected financial network.

Second, we analyze the relationship between our I-index and various factors. Given a small sample size with (at most) 43 observations, it is probably most appropriate to focus on the simple regressions and 10 percent significance level (or lower). Table 9 summarizes the simple regression results of I-index on various variables, with White's (1980) robust standard errors. The first factor under consideration is the size, the coefficient of which is however not statistically significant at any conventional significance levels, regardless of using the values in any year of 2006-08. Actually, these (insignificant) coefficient estimates are all negative. As the financial institutions under study are all among the largest in the world, the result thus does not

instead, the results hold even better. Also, as mentioned earlier, our identification of "senders" and "receivers" of credit information is similar to primary and secondary firms in Jarrow and Fu's (2001) model, respectively.

mean that the size does not matter in affecting the roles of credit risk transfer. Nevertheless, it does imply that among the largest financial institutions, their roles of credit risk transfer may not be related to their further somewhat differences in their sizes. Hence, from the perspective of interconnectedness, the evidence suggests a caveat for the conventional argument of “too big to fail.”

In contrast to size, the leverage and particularly short-term leverage ratios show their importance in credit risk spillovers. Collin-Dufresne and Goldstein (2001) argue that a firm’s leverage ratios have a significant impact on credit spread predictions. More relevant to this study, both Diamond and Rajan (2009) and Acharya and Viswanathan (2011) emphasize the role of short-term debt in affecting asset market liquidity under the crisis scenario. We employ several leverage ratios including the ratios of total debt to total asset, short-term debt to total debt, total debt to common equity, and short-term debt to common equity. The regression results are all significantly positive for both debt to common equity ratios at (at least) the 10% levels across three years of 2006-08, with short-term debt to equity ratios in 2006 and 2007 particularly significant in predicting the cross-sectional differences in importance of credit risk transfer. The ratio of short-term debt to total asset is also generally significant, while the ratio of total debt to total asset is not significant in any case, perhaps because it is a noisier and less relevant measure of the leverage to financial institutions. Thus, consistent with Collin-Dufresne and Goldstein (2001) and particularly Diamond and Rajan (2009) and Acharya and Viswanathan (2011), the result suggests that an institution with a higher leverage ratio and particularly a short-term leverage ratio is more likely to transfer credit risk information to others and thus is more important in the credit risk network from the perspective of interconnectedness. Arguably, a financial institution with a higher leverage ratio might have more incentive to collect private

information about credit risk, or other financial institutions including its counterparties might simply be more sensitive to the new information about credit risk of the more highly leverage financial institution around the global credit crisis.

We further examine whether the roles of credit risk transfer is related to corporate governance, as it is well documented that corporate governance may affect many aspects of corporate performance including credit spreads (e.g., Qiu and Yu, 2009) and thus possibly credit risk spillover. Various corporate governance measures are considered as follows: G-index is Gompers, Ishii and Metrick's (2003) measure of shareholders rights and E-index is Bebchuk, Cohen and Ferrell's (2009) measure of entrenchment, both of which are only available for US firms. There are other corporate governance measures as follows: the board size is the total number of directors in the firm; % independent director is the percentage of outside directors who have no significant connection with the firm. None of these corporate governance indicators are significant even at the 10% significant level. The result should be interpreted with caution, as the data are only available for some firms and the sample is very small.

Another dimension of the driving forces of CDS spread change spillover might be (il)liquidity as part of CDS spread change (albeit small) might be related to expected liquidity premium (see, e.g., Bongaerts, de Jong, and Driessen, 2011). Given the data availability, we construct two measures for illiquidity: one is the average difference between ask and bid prices and the other is average percentage ask-bid spread normalized by the corresponding mid-quote. The average ask-bid spread increased from 3.27 points in 2007 to 6.48 points in 2008 while the average normalized ask-bid decreased from 20.5% in 2007 to 6.9% in 2008. However, both measures are not statistically significant in predicting cross sectional variations of our I-index, indicating that illiquidity might be not a major driving force of credit risk transfer among largest

financial institutions. Certainly, the result does not mean that the liquidity premium does not exist on the CDS market. Nevertheless, it might not be substantial for these largest financial institutions, which is generally consistent with the findings that the effect of liquidity is either statistically insignificant for most widely traded CDS spreads (Acharya and Johnson, 2007) or statistically significant but economically small even for a large cross-section of CDS spreads (Bongaerts, de Jong, and Driessen, 2011).

Finally, we conduct the analysis on how asset write-downs by financial institutions might affect the roles of credit risk transfer. From the Bloomberg, the absolute values of write-down²² and the percentage values normalized by total asset and/or market value are potentially direct measures of how hard an institution was hit in the credit crunch and could be to some extent proxies for counter party risk as discussed in Jorion and Zhang (2009). However, as shown in Table 9, the results are all insignificant. The result, while it could be due to the relatively small sample, may be consistent with the observation that write-down more likely reflects opportunistic reporting by managers rather than the provision of their private information (Riedl, 2004) or that financial contagion was not propagated through a correlated-information channel (Longstaff, 2010). The above analysis is obviously preliminary, and further research is needed to examine the issue in more depth.

6. Conclusions

This study uses credit default spreads to sort out the structure of credit risk spillovers among the 43 largest international financial institutions around the recent global credit crisis. We propose and apply a relatively novel empirical framework that combines cluster analysis, principle component analysis, and DAG-based VAR analysis. Using hierarchical cluster analysis,

²² The total magnitude of losses in all firms covered by Bloomberg is about US \$1,000 billion for our sample period. Bloomberg collects write downs by quarter and also classifies them into various groups based on company disclosure. For simplicity, we aggregate write downs by year for each financial institution.

we classify financial institutions into four clusters based on their credit risk: US GSEs, US banks, US insurance companies, and European financial institutions. The first component in each cluster is also found to be the major driving force, explaining more than 60% of total variation.

To investigate the structure of credit risk spillover at the firm level, we consider interactions among individual financial institutions within a particular cluster while controlling for the influence of the other clusters. We are able to identify three groups of players including prime senders, exchange centers and prime receivers of credit risk information. Noticeably, before its collapse, Lehman Brothers already surpassed all other US banks under consideration to exert a pervasive impact on credit risk of US banks. Credit risk shocks to European financial institutions as a group often has a noticeable impact on individual US GSEs and US insurance companies, but not on individual US banks, even at the longer horizon. The main findings are quite reliable based on the simulation evidence and generally robust against alternative model specifications and sample periods. Further analysis shows that consistent with the literature (e.g., Acharya and Viswanathan, 2011; Collin-Dufresne and Goldstein, 2001; Diamond and Rajan, 2009), leverage ratios and particularly short-term debt ratios appear to be significant determinants of identified different roles of financial institutions in credit risk transfer. There is little preliminary evidence that other factors including corporate governance indexes, size, liquidity and write-downs can explain the cross-sectional differences of the credit risk transfer roles among these financial institutions, which is also consistent with many earlier works (e.g., Acharya and Johnson, 2007; Bongaerts, de Jong, and Driessen, 2011; Riedl, 2004).

The findings of this study provide considerable information to policymakers, as they shed light on the structure of the credit risk network among financial institutions and the identification of SIFIs from the perspective of interconnectedness with the focus on credit risk. The current key

policy initiative to address the SIFIs is to use a basket of measures to identify these SIFIs and impose additional capital surcharge of 1% to 2.5% of risk-weighted assets. Our findings also offer more specific implications for regulation, suggesting that capital surcharge should be particularly based on short-term debt ratio. Further research may be fruitful to more thoroughly examine different firm characteristics and different channels affecting the role of individual financial institutions in credit risk transfer (e.g., Beltratti and Stulz, 2010).

References

- Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M. (2010), "Measuring Systemic Risk," Working Paper, New York University.
- Acharya, V.V., Viswanathan, S., (2011). "Leverage, Moral Hazard and Liquidity," *Journal of Finance*, 66, 99-138.
- Acharya, V.V., Johnson, T., (2007) "Insider Trading in Credit Derivatives," *Journal of Financial Economics*, 84, 110-141.
- Adrian, T, Brunnermeier, M.K. (2009), "CoVAR," Working Paper, University of Princeton.
- Allen, F., Babus, A., Carletti, E. (2009), "Financial Connections and Systemic Risk," Working Paper, University of Pennsylvania.
- Allen, F., Carletti, E., (2006). "Credit risk transfer and contagion," *Journal of Monetary Economics*, 53, 89-111.
- Bae, K-H, Karolyi, G.A., and Stulz, R.M. (2003), "A New Approach to Measuring Financial Contagion," *Review of Financial Studies*, 16, 717-763.
- Bebchuk, L., Cohen, A., Ferrell, A. (2009), "What Matters in Corporate Governance," *Review of Financial Studies*, 22, 783-827
- Beltratti, A., Stulz, R.M., (2010). "The credit crisis around the globe: Why did some banks perform better?" Working Paper, Ohio State University.
- Blanco, R. Brennan, S., and March, I.W.(2005). "An Empirical Analysis of the Dynamic Relationship Between Investment-Grade Bonds and Credit Default Swaps," *Journal of Finance*, 60, 2255-2281.
- Bongaerts, D., F. de Jong, and J. Driessen, (2011). "Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market." *Journal of Finance*, 66, 203-240.

- Brunnermeier, M.K. (2009), “Deciphering the Liquidity and Credit Crunch 2007-2008,” *Journal of Economic Perspectives*, 23, 77-100.
- Collin-Dufresne, P., and Goldstein, B. (2001). “Do credit spreads reflect stationary leverage ratios.” *Journal of Finance*, 56, 2177–208.
- Cossin, D., Schellhorn, H., (2007). “Credit Risk in a Network Economy,” *Management Science*, 53, 1604-1617.
- Diamond, D. W., Rajan, R.G. (2009). “The Credit Crisis: Conjectures about Causes and Remedies,” *American Economic Review Papers and Proceedings*, 99, 606-610.
- Eichengreen, B., Mody, A., Nedljkovic, M., and Sarno, L. (2009), “How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads,” NBER working paper 14904.
- Elsinger, H., Lehar, A., and Summer, M. (2006). “Risk Assessment for Banking Systems.” *Management Science*, 52, 1301–1314.
- Ericsson, J., Jacobs, K., and Oviedo, R. (2009), “The determinants of credit default swap premia,” *Journal of Financial and Quantitative Analysis*, 44, 109-132.
- Eun, C., Shim, S. (1989), “International transmission of stock market movements,” *Journal of Financial and Quantitative Analysis*, 24, 241-256.
- Forbes, K. J., Rigobon, R.(2002) “No contagion, only interdependence: measuring stock market comovements,” *Journal of Finance*, 57, 2223-2261.
- Gagnon, L., Karolyi, G.A., (2009). “Information, Trading Volume, and International Stock Return Comovements: Evidence from Cross-listed Stocks”, *Journal of Financial and Quantitative Analysis*, 44, 953-986.

- Gompers, P., Ishii, J. Metrick, A. (2003). "Corporate Governance and Equity Prices," *Quarterly Journal of Economics*, 116, 107-155
- Hoover, K.D., (2005). "Automatic inference of the contemporaneous causal order of a system of equations." *Econometric Theory*, 21, 69-77.
- Huang, X., Zhou, H., Zhu, H.(2009), "A Framework for assessing the Systematic Risk of Major Financial Institutions," *Journal of Banking and Finance*, 33, 2036-2049.
- Jarrow, R., Yu, F. (2001) "Counterparty Risk and the Pricing of Defaultable Securities." *Journal of Finance*, 56, 1765-1799.
- Jorion, P., Zhang, G. (2007). "Good and bad credit contagion: Evidence from credit default swaps," *Journal of Financial Economics*, 84, 860-883.
- Jorion, P., Zhang, G., (2009). "Credit Contagion from Counterparty Risk." *Journal of Finance*, 64, 2053-2087.
- Li, H., Zhang, W., and Kim, G. (2011). "The CDS-Bond Basis and the Cross Section of Corporate Bond Returns." Working paper, University of Michigan and National University of Singapore.
- Leuz, C., Nanda, D. and Wysocki, P.D. (2003). "Earnings management and investor protection: An international comparison." *Journal of Financial Economics*, 69, 505-527.
- Longstaff, F.A., (2010). "The Subprime Credit Crisis and Contagion in Financial Markets," *Journal of Financial Economics*, 97, 436-450.
- Longstaff, F.A., Mithdal, S. and Nies, E. (2005), "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default-Swap Market," *Journal of Finance*, 60, 2213-2253.
- Ludvigson, S. C., and S. Ng. (2009). "Macro factors in bond risk premia." *Review of Financial*

- Studies*, 22, 5027-5067.
- Pearl, J., (2000). *Causality: Models, Reasoning, and Inference*. Cambridge University Press, Cambridge.
- Qiu, J., Yu, F. (2009). "The market for corporate control and the cost of debt," *Journal of Financial Economics*, 93, 505-524.
- Riedl, E.,(2004). "An examination of long-lived asset impairments," *The Accounting Review*, 79, 823-852.
- Sims, C., (1980). "Macroeconomics and reality." *Econometrica*, 48, 1-48.
- Spirtes, P., Glymour, C., Scheines, R. (2000), *Causation, Prediction, and Search*. MIT Press, Cambridge.
- Stulz, R.M., (2010). "Credit Default Swaps and the Credit Crisis," *Journal of Economic Perspectives*, 24 (Winter), 73-92.
- Swanson, N., Granger, C.W.J. (1997), "Impulse response functions based on a causal approach to residual orthogonalization in vector autoregression," *Journal of the American Statistical Association*, 92, 357-367.
- White, H., (1980). "A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity." *Econometrica*, 48, 817-838.
- Zhang, B., Zhou, H., and Zhu, H. (2009), "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms," *Review of Financial Studies* 22, 5099-5131.

Table 1: Summary statistics of CDS Spreads

This table reports summary statistics on CDS spreads for 43 financial institutions from January 1, 2007 to September 9, 2008. The means, standard deviations, minimum and maximum values are based on mid-quotes. The ask-bid are differences between ask and bid prices and the normalized ask-bid is the ask-bid divided by the corresponding mid-quote.

Country	Name	Mean	Std. Dev.	Min	Max	Average Ask-bid	Average normalized ask-bid
US	Fannie Mae	32.22	21.83	6.40	87.58	2.53	0.11
US	Freddie Mac	32.09	22.06	5.25	88.15	2.74	0.12
US	Lehman Brothers	139.16	103.80	20.81	425.14	6.01	0.06
US	Bearn Sterns	114.66	96.36	20.83	727.14	5.54	0.06
US	Goldman Sachs	77.69	47.16	20.90	244.44	4.25	0.07
US	Merrill Lynch	123.28	94.52	15.63	342.19	5.47	0.07
US	Morgan Stanley	103.52	73.09	17.83	297.30	5.31	0.07
US	Bank of America	54.60	39.33	8.68	147.25	4.17	0.13
US	Wachovia	97.94	90.68	11.10	358.51	4.35	0.14
US	Citigroup	70.45	57.51	7.44	226.60	4.58	0.14
US	JP Morgan	55.72	35.23	14.49	163.83	3.73	0.09
US	Met Life	66.11	60.01	11.00	240.59	4.34	0.11
US	Safeco	43.33	26.64	17.90	135.03	4.41	0.13
US	American express	86.26	75.36	8.91	250.67	5.94	0.13
US	AIG	96.04	96.93	8.93	446.24	5.63	0.14
US	Chubb	38.72	27.42	9.86	125.92	3.65	0.13
US	Hartford	62.14	61.54	10.72	293.26	4.47	0.12
UK	Abbey	44.75	35.84	4.33	155.56	4.17	0.21
UK	Barclays	52.83	43.50	5.45	173.00	4.31	0.17
UK	HBOS	70.83	66.28	4.77	253.10	6.95	0.15
UK	HSBC	39.01	30.67	4.94	155.00	4.18	0.22
UK	Lloyds TSB	37.46	31.62	3.67	135.81	3.82	0.26
UK	RBS	52.95	43.56	4.06	204.94	4.20	0.17
UK	Standard Chartered	43.79	31.96	5.63	139.88	5.44	0.25
France	AXA	56.50	43.55	9.10	197.75	4.94	0.15
France	BNP Paribas	33.59	25.00	5.7	119.59	3.68	0.18
France	Credit Agricole	45.11	37.19	5.84	161.82	4.64	0.17
France	Societe Generale	42.53	34.73	6.01	148.60	4.28	0.20
Germany	Allianz	41.10	29.25	6.04	133.02	4.33	0.18
Germany	Commerzbank	49.39	34.58	8.16	164.50	4.69	0.15
Germany	HVB	42.62	30.69	6.17	144.81	4.53	0.19
Germany	Deutsche Bank	47.49	32.20	9.82	155.13	4.54	0.14
Germany	Dresdner Bank	49.83	39.84	5.48	167.85	4.77	0.20
Germany	Hannover Rueckversicherung	41.64	29.57	8.50	143.93	4.34	0.16
Italy	Banco Monte Dei Paschi	44.31	32.69	6.13	158.07	7.37	0.17
Italy	UniCredit SpA	43.03	29.26	7.48	151.42	4.07	0.14
Netherlands	ABN AMRO	48.39	39.32	5.53	189.22	4.18	0.16
Netherlands	ING	44.84	39.80	4.62	177.49	4.22	0.21
Netherlands	Rabobank	28.86	24.47	3.00	99.83	3.52	0.26
Switzerland	Credit Suisse	52.24	37.72	9.86	186.26	4.42	0.12
Switzerland	UBS	53.97	48.12	4.55	225.25	4.73	0.2
Spain	Banco Santander	45.39	33.66	7.62	152.39	4.34	0.16
Portugal	Banco Commercial Portugues	48.58	34.99	8.15	157.21	4.48	0.15

Table 2: Cluster Analysis

This table reports 4 clusters of 43 largest financial institutions based on a hierarchical cluster analysis. The average linkage method is used to measure the distance between cluster pairs and the cubic cluster criterion (CCC) is used to choose the number of clusters.

Cluster 1 (US GSEs)	Cluster 2 (US Banks)	Cluster 3 (US Insurances)	Cluster 4 (EU Financial Institutions)
Fannie Mae	Lehman Brothers	Met Life	Abbey
Freddie Mac	Bearn Sterns	Safeco	Barclays
	Goldman Sachs	American express	HBOS
	Merrill Lynch	AIG	HSBC
	Morgan Stanley	Chubb	Lloyds TSB
	Bank of America	Hartford	RBS
	Wachovia		Standard Chartered
	Citigroup		AXA
	JP Morgan		BNP Paribas
			Credit Agricole
			Societe Generale
			Allianz
			Commerzbank
			HVB
			Deutsche Bank
			Dresdner Bank
			Hannover Rueckversicherung
			Banco Monte Dei Paschi
			UniCredit SpA
			ABN AMRO
			ING
			Rabobank
			Credit Suisse
			UBS
			Banco Santader
			Banco Commercial Portugues

Table 3: Principal Component Analysis

This table reports the cumulative fractions of the total variation explained by the first few principal components in each cluster. The clusters are defined as in Table 2. The cumulative fractions are computed as the ratio between the sum of the first few largest eigenvalues divided by the sum of all eigenvalues.

	Cluster 1 (US GSEs)	Cluster 2 (US Banks)	Cluster 3 (US Insurances)	Cluster 4 (EU Financial Institutions)
1st factor	90.04%	62.56%	66.13%	70.82%
First 2 factors	100%	72.32%	80.23%	80.17%
First 3 factors		79.24%	89.44%	82.50%
First 4 factors		85.27%	94.14%	84.52%
First 5 factors		89.54%	97.49%	86.49%

**Table 4: Forecast error variance decomposition results (percentage)
among US GSEs and the other three clusters**

Day	Fannie Mae	Freddie Mac	US Banks	US Insurances	EU financial institution
Variance of Fannie Mae explained by shocks to the five CDS spreads					
0	93.7	0.0	5.7	0.4	0.2
1	84.7	8.1	5.1	0.7	1.4
2	81.0	10.9	4.9	1.0	2.2
10	76.2	11.0	5.1	1.7	6.1
30	76.1	11.0	5.1	1.7	6.1
Variance of Freddie Mac explained by shocks to the five CDS spreads					
0	47.7	45.9	2.9	3.4	0.1
1	48.9	44.2	3.3	2.6	0.9
2	47.0	41.5	3.8	3.6	4.1
10	43.9	38.0	3.9	3.9	10.3
30	43.9	38.0	4.0	3.9	10.3
Variance of US banks explained by shocks to the five CDS spreads					
0	0.0	0.0	90.1	6.3	3.7
1	0.0	0.4	86.3	8.3	5.0
2	0.3	0.3	84.4	8.1	6.9
10	0.9	0.8	81.4	8.9	8.0
30	0.9	0.8	81.3	8.9	8.1
Variance of US insurances explained by shocks to the five CDS spreads					
0	0.0	0.0	0.0	100.0	0.0
1	0.0	0.6	0.0	99.4	0.0
2	0.0	0.9	0.2	97.6	1.2
10	0.2	1.0	1.1	86.3	11.5
30	0.2	1.0	1.1	86.2	11.5
Variance of EU financial institutions explained by shocks to the five CDS spreads					
0	0.0	0.0	0.0	0.0	100.0
1	0.1	0.1	0.5	0.9	98.3
2	0.3	0.4	2.3	1.8	95.4
10	1.3	0.5	3.9	1.9	92.4
30	1.3	0.5	3.9	1.9	92.4

Note: The variance decomposition is based on the directed graph on innovations given in Figure 1.

**Table 5: Forecast error variance decomposition results (percentage)
for US banks and first principle components of other groups**

Days	US GSEs	US Insurances	EU financial Institutions	Lehman Brothers	Bear Sterns	Goldman Sachs	Merrill Lynch	Morgan Stanley	Wachovia	Citi-group	JP Morgan	Bank of America
Variance of US GSEs explained by the shocks of the 12 CDS spreads												
0	90.1	4.6	0.0	2.4	0.4	2.1	0.2	0.3	0.0	0.0	0.0	0.0
1	83.6	4.5	0.0	3.0	0.5	3.5	0.2	1.9	0.7	1.9	0.2	0.1
2	76.2	4.3	1.7	3.8	1.3	4.6	0.6	2.7	0.6	3.3	1.0	0.1
30	67.6	4.1	5.7	3.6	1.9	5.3	0.9	4.1	2.0	3.1	1.2	0.4
Variance of US insurances explained by the shocks of the 12 CDS spreads												
0	0.0	100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.3	96.8	0.0	0.1	0.0	0.0	0.0	0.0	0.4	0.5	1.8	0.0
2	0.4	91.3	0.4	0.1	2.6	0.0	0.5	0.3	0.5	0.6	3.4	0.1
30	0.5	77.3	7.0	0.5	4.2	1.5	1.0	1.1	2.1	0.9	3.3	0.8
Variance of EU financial institutions explained by the shocks of the 12 CDS spreads												
0	0.0	0.0	100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.8	94.5	0.1	0.1	1.1	0.2	1.6	0.1	0.5	0.7	0.4
2	0.1	1.4	85.8	0.6	0.1	3.6	0.2	5.0	0.2	0.7	0.8	1.5
30	0.3	1.9	77.1	1.8	0.9	7.0	0.9	5.9	0.4	0.7	1.0	2.3
Variance of Lehman Brothers explained by the shocks of the 12 CDS spreads												
0	0.0	10.7	0.0	80.9	0.7	0.0	0.1	7.8	0.0	0.0	0.0	0.0
1	0.5	10.1	0.0	77.2	0.7	0.2	0.4	8.0	0.2	0.2	1.3	1.5
2	0.9	9.9	1.1	71.8	0.6	1.2	0.9	7.5	0.3	0.3	2.3	3.4
30	0.9	9.0	3.5	67.6	0.7	2.6	1.4	7.5	0.3	0.4	2.5	3.8
Variance of Bear Sterns explained by the shocks of the 12 CDS spreads												
0	0.0	4.1	0.0	31.1	61.8	0.0	0.1	2.9	0.0	0.0	0.0	0.0
1	0.4	6.2	0.6	32.6	54.2	0.0	0.1	2.4	0.4	0.0	1.7	1.5
2	0.4	6.3	2.9	30.9	50.7	0.2	0.1	2.4	0.6	0.1	2.9	2.6
30	0.6	6.3	4.5	28.7	46.4	2.4	1.2	3.2	0.6	0.6	2.7	3.0

Table 5 (Continued)

Days	US GSEs	US Insurances	EU financial Institutions	Lehman Brothers	Bear Sterns	Goldman Sachs	Merrill Lynch	Morgan Stanley	Wachovia	Citi- group	JP Morgan	Bank of America
Variance of Goldman Sachs explained by the shocks of the 12 CDS spreads												
0	0.0	5.6	0.0	42.2	7.0	37.2	3.5	4.6	0.0	0.0	0.0	0.0
1	0.3	6.6	0.0	39.5	6.7	33.1	2.2	6.5	0.2	1.1	1.2	2.8
2	0.4	6.3	0.5	36.7	6.2	31.3	3.0	6.5	0.2	1.6	2.5	4.8
30	0.5	6.2	1.6	35.4	5.9	30.7	3.1	6.7	0.4	1.7	3.3	4.8
Variance of Merrill Lynch explained by the shocks of the 12 CDS spreads												
0	0.0	2.8	0.0	20.8	0.4	0.0	76.5	4.7	0.0	0.0	0.0	0.0
1	0.0	4.0	0.5	25.7	0.3	0.8	54.8	8.2	0.0	1.0	1.9	2.8
2	0.1	3.6	1.0	21.6	0.3	2.5	52.7	7.5	0.0	1.8	3.7	5.3
30	0.2	3.8	1.3	20.5	0.7	3.6	51.0	7.4	0.3	2.0	4.0	5.5
Variance of Morgan Stanley explained by the shocks of the 12 CDS spreads												
0	0.0	0.7	0.0	4.8	7.0	0.0	0.7	86.9	0.0	0.0	0.0	0.0
1	0.7	3.7	0.2	7.0	7.5	0.1	1.0	76.6	0.9	0.0	2.0	0.1
2	1.0	4.9	1.7	7.5	6.9	0.3	0.9	70.8	0.9	0.1	4.4	0.9
30	1.0	5.6	2.3	7.5	6.7	0.9	1.6	67.5	0.9	0.2	4.5	1.4
Variance of Wachovia explained by the shocks of the 12 CDS spreads												
0	0.0	3.5	0.0	26.4	3.8	1.9	0.2	2.6	61.7	0.0	0.0	0.0
1	0.3	2.3	0.0	26.8	6.0	6.5	0.2	4.1	50.7	0.1	0.3	2.9
2	1.1	2.3	0.1	24.6	5.8	6.9	0.8	3.8	45.9	0.2	0.6	8.2
30	1.4	2.1	0.5	22.4	5.4	9.8	1.0	3.9	43.7	0.5	1.1	8.4
Variance of Citigroup explained by the shocks of the 12 CDS spreads												
0	1.4	1.6	0.0	8.5	1.0	0.0	0.1	6.4	3.1	54.2	0.0	23.9
1	2.8	1.2	1.7	11.1	0.8	0.2	0.4	11.7	2.7	42.5	0.3	24.8
2	3.4	2.9	3.0	11.8	1.1	0.3	0.8	11.3	2.6	38.3	1.1	23.6
30	3.5	4.6	3.5	11.8	1.1	0.8	1.2	10.9	3.1	35.8	1.4	22.3

Table 5 (Continued)

Days	US GSEs	US Insurances	EU financial Institutions	Lehman Brothers	Bear Sterns	Goldman Sachs	Merrill Lynch	Morgan Stanley	Wachovia	Citi- group	JP Morgan	Bank of America
Variance of J.P. Morgan explained by the shocks of the 12 CDS spreads												
0	1.0	1.8	0.0	10.3	2.7	4.6	0.7	9.7	0.1	1.6	50.3	17.4
1	1.4	2.4	2.9	9.7	2.5	3.4	0.5	12.9	0.1	1.9	34.8	27.8
2	2.0	2.5	4.5	10.5	2.9	4.3	0.8	12.5	0.1	1.7	32.3	25.9
30	2.4	3.4	4.7	10.0	3.2	8.5	1.5	12.2	0.1	1.6	28.9	23.8
Variance of Bank of America explained by the shocks of the 12 CDS spreads												
0	4.8	0.6	0.0	1.3	1.1	0.1	0.2	11.1	0.0	0.0	0.0	80.9
1	4.9	0.7	0.9	5.0	1.4	0.1	0.8	12.4	0.0	0.3	0.5	73.3
2	4.7	3.0	1.9	6.9	2.2	0.2	1.7	11.1	0.0	0.6	2.5	65.2
30	5.0	4.2	2.8	7.1	2.2	1.9	1.9	10.8	0.5	0.7	3.1	60.1

Note: The variance decomposition is based on the directed graph on innovations given in Figure 2. The values are the averages of two different assumed edges for the only undirected edge between Morgan Stanley and Merrill Lynch.

**Table 6: Forecast error variance decomposition results (percentage)
for US insurance companies and first principle components of other groups**

Days	US GSEs	US Banks	EU financial Institutions	American Express	AIG	Chubb	Met Life	Hartford	Safeco
Variance of US GSEs explained by shocks to the nine CDS spreads									
0	80.6	0.0	0.9	0.7	1.3	9.4	0.0	0.0	7.0
1	76.3	0.2	2.1	2.6	2.2	8.4	0.1	0.0	8.0
2	71.3	1.1	5.0	3.1	2.8	8.0	0.2	0.9	7.6
30	64.3	1.3	8.5	3.5	4.1	7.9	0.5	2.7	7.1
Variance of US Banks explained by shocks to the nine CDS spreads									
0	0.0	65.4	0.0	1.4	12.6	9.0	4.5	0.0	7.0
1	0.4	59.1	0.3	1.6	14.3	9.6	5.1	0.0	9.5
2	0.5	57.6	2.7	1.8	13.9	9.3	4.9	0.1	9.2
30	0.8	52.3	5.2	2.9	13.5	10.1	4.9	0.3	9.9
Variance of EU financial institutions explained by shocks to the nine CDS spreads									
0	0.0	0.0	100	0.0	0.0	0.0	0.0	0.0	0.0
1	0.1	0.1	96.9	0.0	2.0	0.1	0.2	0.3	0.3
2	0.4	0.9	93.8	0.0	2.9	0.2	0.3	0.7	0.9
30	1.2	2.4	87.9	0.3	3.1	1.3	0.9	2.2	0.8
Variance of American Express explained by shocks to the nine CDS spreads									
0	0.0	0.0	2.4	79.3	4.1	3.9	0.3	2.2	7.7
1	0.0	0.3	8.1	72.6	5.3	5.6	0.5	1.5	6.0
2	0.0	0.3	12.9	68.9	4.9	5.1	0.5	1.4	6.1
30	1.0	0.7	14.3	64.6	4.9	6.0	0.8	1.5	6.3
Variance of AIG explained by shocks to the nine CDS spreads									
0	0.0	0.0	0.0	0.0	76.7	13.8	0.0	0.0	9.5
1	0.0	0.0	2.5	1.2	71.6	14.9	0.6	0.1	9.1
2	0.1	0.2	10.7	2.5	63.2	14.1	0.8	0.2	8.1
30	1.6	0.8	16.4	2.4	54.7	15.0	1.0	0.3	7.8

Table 6 (Continued)

Days	US GSEs	US Banks	EU financial Institutions	American Express	AIG	Chubb	Met Life	Hartford	Safeco
Variance of Chubb explained by shocks to the nine CDS spreads									
0	0.0	0.0	0.0	0.0	0.0	59.4	0.0	0.0	40.6
1	0.4	0.2	0.2	0.9	0.6	55.0	0.4	0.0	42.3
2	0.6	0.2	3.3	1.2	1.4	52.7	0.4	0.2	40.1
30	0.8	0.5	13.6	1.4	1.9	46.7	1.0	0.5	33.5
Variance of Met Life explained by shocks to the nine CDS spreads									
0	0.0	0.0	0.0	0.0	3.5	28.9	47.8	0.0	19.8
1	0.0	0.2	0.4	0.2	6.4	26.4	41.8	0.3	24.4
2	0.0	0.2	6.3	0.4	6.7	24.0	38.4	1.4	22.6
30	0.4	1.0	14.9	0.6	6.4	21.9	34.1	1.9	18.9
Variance of Hartford explained by shocks to the nine CDS spreads									
0	0.0	0.0	0.0	0.0	0.3	16.7	3.6	25.9	53.6
1	0.4	0.0	0.3	0.8	1.7	16.9	5.9	21.7	52.3
2	0.4	0.0	3.1	0.8	3.4	16.1	5.7	20.6	49.9
30	0.8	0.3	12.1	1.4	3.3	15.8	6.8	18.1	41.3
Variance of Safeco explained by shocks to the nine CDS spreads									
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100
1	1.4	0.1	0.0	0.1	0.5	0.3	0.7	0.2	96.7
2	1.8	0.1	0.6	0.7	1.3	0.7	0.9	0.8	93.1
30	1.8	0.4	5.8	2.0	1.4	1.7	2.1	2.0	82.8

Note: The variance decomposition is based on the directed graph on innovations given in Figure 3.

Table 7: I-index

This table reports I-index (importance index from the perspective of interconnectedness) for 43 financial institutions based on their contemporaneous causal patterns. Assigned to be 3, the prime senders of credit risk information are those who send out at least two more shocks than what they receive. Assigned to be 0, the prime receivers of credit risk information are institutions which receive at least two more shocks than what they spread out. The exchange centers of credit risk information are assigned to be 2. They intensively receive from at least 2 financial institutions and then transfer credit risk information to at least 2 others. The institutions other than the above three categories are assigned to be 1.

Country	Name	I-index
US	Fannie Mae	1
US	Freddie Mac	1
US	Lehman Brothers	3
US	Bearn Sterns	2
US	Goldman Sachs	2
US	Merrill Lynch	1
US	Morgan Stanley	3
US	Bank of America	2
US	Wachovia	0
US	Citigroup	0
US	JP Morgan	0
US	Met Life	2
US	Safeco	3
US	American express	1
US	AIG	3
US	Chubb	3
US	Hartford	0
UK	Abbey	1
UK	Barclays	2
UK	HBOS	1
UK	HSBC	1
UK	Lloyds TSB	1
UK	RBS	2
UK	Standard Chartered	1
France	AXA	1
France	BNP Paribas	3
France	Credit Agricole	1
France	Societe Generale	1
Germany	Allianz	1
Germany	Commerzbank	2
Germany	HVB	2
Germany	Deutsche Bank	0
Germany	Dresdner Bank	3
Germany	Hannover Rueckversicherung	1
Italy	Banco Monte Dei Paschi	1
Italy	UniCredit SpA	1
Netherlands	ABN AMRO	0
Netherlands	ING	0
Netherlands	Rabobank	0
Switzerland	Credit Suisse	1
Switzerland	UBS	3
Spain	Banco Santander	1
Portugal	Banco Commercial Portugues	1

Table 8: Estimation results of the OLS regressions with a single instrument

This table reports results from OLS regressions where dependent variables are out I-index in Table 8 on a single instrument. G-index is the Gompers-Ishii-Metrick (2003) measure of managerial entrenchment. E-index is the Bebchuk, Cohen and Ferrell (2009) measure of entrenchment. Board size is the total number of directors in the firm. % independent director is the percentage of out directors who have no significant connection with the firm. The coefficient estimates in each simple regression are reported with *, **, *** denoting significance at 10%, 5%, and 1% respectively. The t-statistics reported in parentheses below are based on robust errors adjusted for heteroskedasticity. “Nobs” is the numbers of observations used in each simple regression. Adjusted R-squares are also reported for each simple regression.

	2006			2007			2008		
	estimate	nobs	Adj-R ²	estimate	nobs	Adj-R ²	estimate	nobs	Adj-R ²
Log market value (million USD)	-0.47 (-1.11)	39	0.5%	-0.50 (-1.25)	39	1.2%	-0.10 (-0.25)	35	-2.8%
Total debt/ Total asset	0.01 (1.58)	39	4.6%	0.01 (0.92)	39	-0.2%	0.01 (0.77)	36	-1.4%
Short-term debt/ Total asset	2.00** (2.29)	39	10.8%	1.87* (1.89)	39	7.1%	1.09 (1.02)	36	0.4%
Total debt/ common equity	0.05** (2.43)	39	12.9%	0.04* (1.78)	39	6.7%	0.03* (1.91)	35	8.1%
Short-term debt/ common equity	0.08*** (3.32)	39	19.8%	0.06*** (2.61)	39	14.4%	0.04* (1.80)	35	6.1%
G-index	0.11 (1.10)	17	-1.4%						
E-index	0.000 (0.00)	15	-7.7%	0.10 (0.54)	16	-5.4%			
Board size	-0.07 (-1.23)	17	0.6%						
% independent director	-0.48 (-0.85)	17	-5%						
Average Ask-bid				0.28 (1.09)	43	-0.5%	0.11 (1.21)	43	1.3%
Average normalized Ask-bid				-2.27 (-1.31)	43	0.9%	-7.76 (-0.64)	43	-1.2%
Write-down (billion USD)				0.02 (0.82)	32	-1.2%	-0.004 (-0.46)	32	-2.6%
% of write down / total asset				0.23 (0.71)	29	-1.9%	0.08 (0.77)	29	-1.6%
% of write down /market value				0.01 (0.68)	29	-1.7%	0.001 (1.05)	28	-2.7%

Figure 1 Contemporaneous causal flow patterns among US GSEs and other clusters

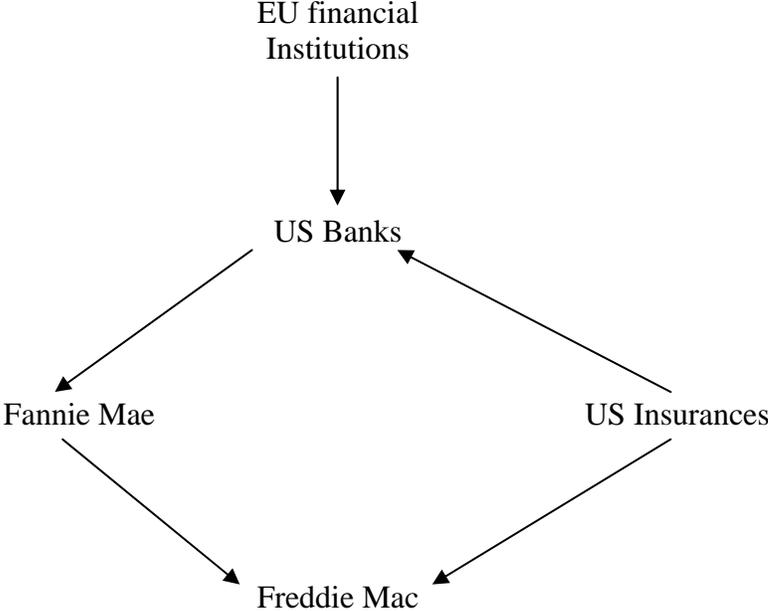


Figure 2 Contemporaneous causal flow patterns among US banks as well as other clusters

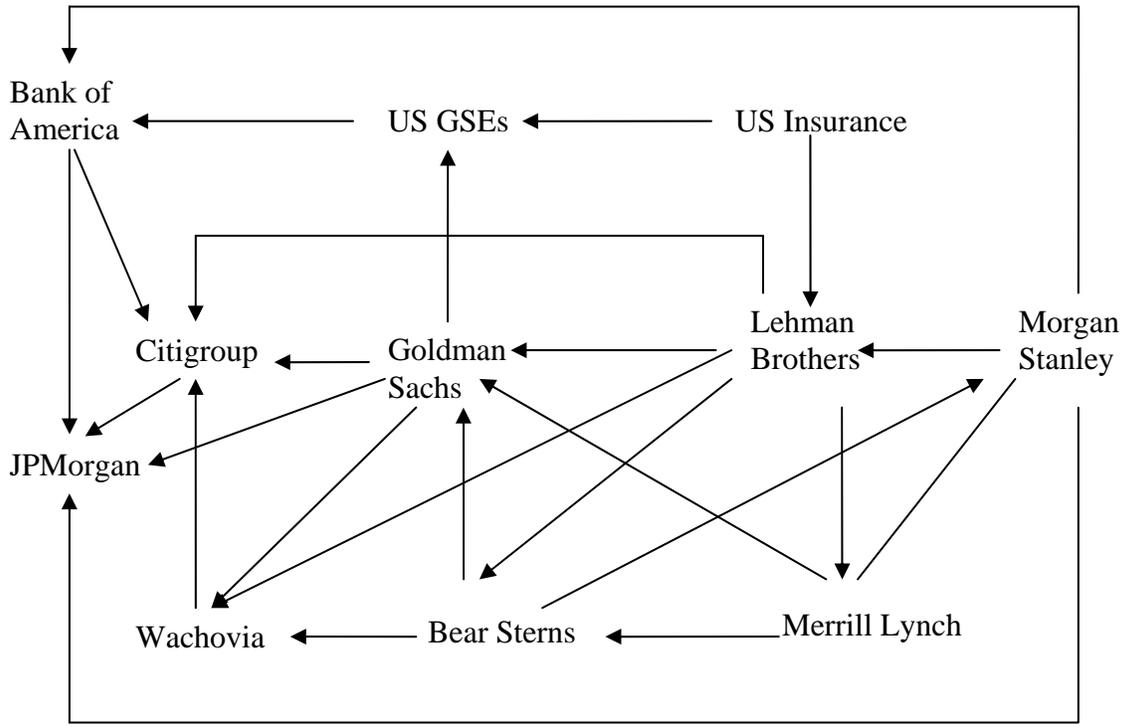


Figure 3 Contemporaneous causal flow patterns among US insurance companies as well as other clusters

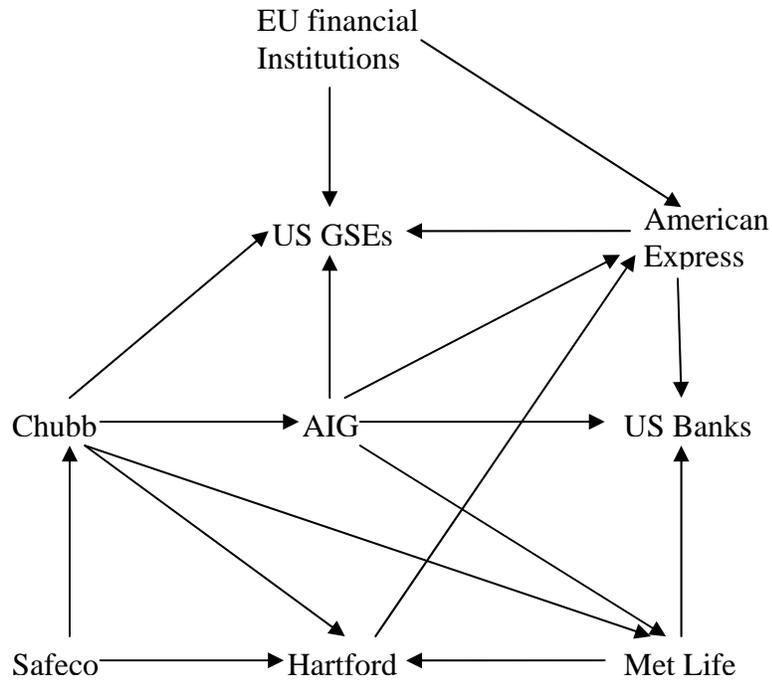


Figure 4 Contemporaneous casual flow patterns among European financial institutions as well as other clusters

