A Network Model Approach to Systemic Risk in the Financial System

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Abstract

We present a network model approach to studying systemic risk for the Credit Default Swap (CDS) market. The network model of the CDS market shows how certain parameters of a network can affect the expected loss of the system relative to the initial loss caused by a default. This model also demonstrates how a clearinghouse stymies loss propagation and highlights the usefulness of important data such as counterparty exposures that are not publicly available.

Key Words: Network; Systemic Risk; CDS; Counterparty Exposures; Clearinghouse

INTRODUCTION

The 2007 Financial Crisis illustrated the severity of losses resulting from systemic risk. Top European and U.S. banks lost over $1.3 trillion on toxic assets and bad loans from 2007-2010.[2] Bank bailouts cost the U.S. government in excess of $200 billion.[3] With the bailouts being financed by the tax-paying public, the Dodd-Frank Wall Street Reform and Consumer Protection Act was passed in 2010 to address consumer protection, executive pay, and bank capital requirements. The act also expanded regulation on the shadow banking system and financial derivatives and enhanced authority of the Federal Reserve to safely wind-down systemically important institutions. As part of the Act, The Financial Stability Oversight Council and the Office of Financial Research were created.[4] Since its creation, the new Financial Stability Oversight Council has been charged with identifying and regulating threats to financial stability with systemic risk being the key focus.

Systemic risk is the risk that the failure of one significant financial institution can cause or significantly contribute to the failure of other significant financial institutions as a result of their linkages to each other.[5] Systemic risk can also be defined to include the possibility that one exogenous shock may simultaneously cause or contribute to the failure of multiple significant financial institutions in an economy.

Systemic failure can arise from four different sources: direct bilateral interbank exposures, common asset exposure among banks, net settlement systems for large payments, and imitative runs fueled by information contagion.[6] Direct bilateral exposures between institutions represent one of the most common sources of systemic risk. Failures can occur when one bank holds deposits from several other banks, and the failure in the first bank results in either distress or failure that spreads to other firms that are connected to the distressed institution. Similarly,

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[2] Reuters, Factbox – European, U.S. Bank Writedowns and Credit Losses, February 24, 2011.
[3] CNN Money, "Special Report: Bailed Out Banks," http://money.cnn.com/news/specials/storysupplement/bankbailout, November 19, 2010.
[4] The Financial Stability Oversight Committee was established by the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 to coordinate across agencies in monitoring risks and emerging threats to U.S. financial stability.
[5] ECB Workshop, "Recent Advances in Modelling Systemic Risk Using Network Analysis," January 2010.
[6] Hal Scott, "Reduction of Systemic Risk in the United States Financial System," Harvard Journal of Law & Public Policy, Vol.33, 2009.

systemic failure can occur from the counterparty exposure risk in derivative transactions. The most common and recognized of these activities are credit default swaps (CDS). Systemic risk arises from CDS when one institution fails to settle its derivative position with another institution – the end result being that both institutions fail. If the second institution fails to settle its obligations with its other counterparties, the contagion[7] of failures continues through the exposed institutions until only institutions with adequate capital remain or the system itself fails.

The severity of direct bilateral exposure failure is dependent on the degree of interconnectivity among the financial institutions involved in the derivative transactions. The lack of existing information on the degree of connectedness among the institutions remains a concern to the Financial Stability Oversight Council and other governmental regulatory bodies.

This paper proposes a network model to identify and measure the systemic risk in a financial system which may have a high degree of interconnectedness and whose failures may result in further distress or breakdowns in the system. Networks are particularly useful for modeling risk in a financial system due to their handling of contagion, resulting in either losses propagating through a financial system in crisis or the absorption of shocks in a resilient, well capitalized financial system. Network models have been applied in other areas, notably in communications, transportation, and electric power distribution. In each of these areas, some item flows from point to point through a network that involves connections between points. In the financial system there is interest in the flow of cash and credit between financial institutions. As shown in Bisias, Flood, Lo and Valavanis (2012), Chan-Lau, Espinosa, Giesecke and Sole (2009), and Bisais et al (2012), with a matrix of inter-institution exposures, a network approach can track the reverberation of a credit event throughout the system, which can help to measure which financial institution is a "hot spot".[8]

While networks have been used to model systemic risk in financial institutions since 2003, only modest research exists for systemic risk in the insurance industry. A study by the Geneva

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[7] Contagion is a mechanism describing how systemic failures can occur. It can be thought of as a "domino effect," a failure of one institution leading to failures of more institutions.

[8] Office of Financial Research Working Paper #0001, "A Survey of Systemic Risk Analytics", January 2012. http://bigdata.csail.mit.edu/sites/bigdata/files/sites/Lo%20abstract%20and%20paper%20-%20Systemic_OFR1_final.pdf

Association in 2010 suggests a reason for this lack of research.[9] The Geneva Association paper states that traditional insurance and reinsurance businesses are relatively small sources of systemic risk compared to banks and other financial institutions. The Association posits that the structure of the traditional insurance model – upfront premiums, relative lack of interconnectedness, and "substitutability"[10] -- reduces the systemic impact of the insurance industry. The group also states systemic risk does exist for two specific groups that are involved in more non-traditional activities in insurance. These two groups include firms involved in credit derivative security activities such as AIG and bond insurers such as FSA, AMBAC, and MBIA.

This research paper adds to the existing research in systemic risk by specifically applying network models to a non-traditional insurance industry that experienced disaster stemming from systemic risk during the 2007 Financial Crisis: the credit default swap (CDS) security industry.

Literature Review

Researchers have recently proposed that network models can help model the systemic risk in financial systems which display complex degrees of connectedness. Network models have been used in many fields such as communications, transportation, and utility distribution where the intricacies of the connections make optimization of the system flow analytically challenging. The application of networks to model systemic risk in financial systems has seen significant progress since the 2007 sub-prime mortgage initiated crisis. Most current research in the area of financial network models uses institution-level financial firms or banks as the nodes in the system and their bilateral exposures as the arcs or connections. Within this framework, the existing literature can be further divided by the types of data used to populate the model. Nier et al (2008), Gai (2009), and Georg (2010) use simulated data to capture insights into the network system. Castren (2009), Markose (2010), and Cont (2010) use empirical data to model their system.

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[9] Geneva Association Systemic Risk Working Group, "Systemic Risk in Insurance – An Analysis of Insurance and Financial Stability," March 2010.
[10] In this context, "substitutability" means the opposite of "Too big to fail."

Nier et al (2008) use simulated data in their network model to investigate the effect of the financial system's structure on systemic risk. In their simulated framework, banks serve as the nodes, and their interbank exposures act as the connections or the arcs in the network. The authors determine the effects of capitalization, connectivity, and concentration on contagious default in this simulated framework. They find that better capitalized banks are more resilient to contagious defaults, but the effect is non-linear. The researchers also determine that connectivity's effect on systemic risk depends on the level of connectivity. At low levels, an increase in connectivity acts as a shock transmitter, increasing the contagion effect, whereas, at sufficiently high levels, the shock absorption effect dominates, and the initial shock is spread over more and more of the bank nodes. Finally, the authors show that everything else equal, more concentrated banks are prone to larger systemic risk.

Gai and Kapadia (2009) also investigate the dual nature of connectivity in their paper. In their model, banks are again the nodes, and the interbank exposures are the arcs. Then, they assume a random (Poisson) probability that each node is linked. From this model, the authors find that the complex financial networks exhibit a "robust-yet-fragile" nature; greater connectivity helps lower the probability of contagion but increases its spread in the event that problems do occur. Furthermore, they find that illiquid markets for key financial assets compound the contagion problem, amplifying both the likelihood and the severity of the risk. Finally, they argue that credit derivatives create far-reaching inter-linkages that reduce the probability of contagion with greater use under some plausible scenarios, but the resultant exposure leads to greater financial impact in a crisis.

Georg and Poschmann (2010) continue the research in financial network models by using numerical simulations to examine the effect of a central bank in the network model of the financial system. In their model, bank nodes including a central bank are connected via their balance sheet exposures and incorporate a constant relative risk aversion utility function in determining their portfolios. The authors find that the presence of a central bank has a stabilizing effect on the financial system, and this stability effect may arise from the enhanced liquidity allocation provided by the central bank. From their model, the researchers find that systemic risk increases with credit "lumpiness," defined as fewer, large credit counterparties. The authors define two types of shocks, one resulting from the insolvency of a large bank and

resulting in contagion effects throughout the network and another in which a shock affects all the banks in a network via commonly held assets. They posit that the destabilizing effect of common shocks pose a greater threat to systemic stability than the direct contagion effect.

Castren and Kavonius (2009) use historical Euro Area Accounts data to calibrate a sector-level network model to help identify the potential key triggers to instability, to detect the contagion mechanisms in the system, and to determine the effects of leverage on a system's resistance to shock and contagion in a multi-period setting. In their model, the sectors include households, banks, non-financial corporations, insurance and pension fund companies, other financial intermediaries, general government, and the rest of the world. They extend the accounting based bilateral exposure connected network to a risk-based network by applying a contingent claims analysis approach developed by Moody's KMV. The authors find that in the 10 years since the creation of the European Monetary Union, the interlinking arcs represented by the bilateral financial accounts have grown significantly with the banking sector playing a key role in the system. They determine in their simulations that local cash-flow shocks can spread quickly via the bilateral exposures and even without the presence of defaults in the process. The authors also find that sectors with highest leverage are the most vulnerable ones to shocks.

Markose et al (2009) apply a complex agent-based computational variant of the financial network model to assess systemic risk. The authors use FDIC data and market share data of 26 banks to create a U.S. credit default swap (CDS) market-based network to investigate the consequences of the fact that the top 5 banks are responsible for 92% of the activity in the $16 trillion U.S. CDS market. Their network model uses the major banks as the main nodes in the system and incorporates a "non-U.S. bank" node to include monolines[11], hedge funds, and other insurers. The links are the bilateral obligations of the CDS. The authors argue that the implied incentives of the credit risk transfer scheme included in Basel II may have contributed to the 2007 Financial Crisis in two ways. First, the use of risk transfer mechanism allows a decrease in the actual regulatory reserve requirements which may have stopped the contagion from spreading. Second, the growth and popularity of the synthetic securitization of these risk transfers concentrates the risk among a few large dominant players. The authors determine that

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[11] Monolines in this study refer to bond insurance companies such as AMBAC, MBIA, and FSA who provided guarantees to financial assets.

the intervention of the Federal Reserve to bail out certain "too large to fail" institutions could not be averted because their large number of links to other institutions could have resulted in the failure of the whole CDS market and possibly the whole financial system. Furthermore, they identify these "super-spreaders" and propose a "system risk ratio" which quantifies how much capital is lost collectively when one of these firms fail.

Cont et al (2010) examine the financial network approach to modeling system risk in the Brazilian financial system and to measuring the systemic importance of a single institution in the system. Their model incorporates Brazilian interbank exposure data including fixed income instruments, borrowing and lending, derivatives, foreign exchange, and instruments linked to exchange-traded equity risk. The authors' stress test the model by applying correlated market shocks to the balance sheets of all the banks in the network in various default scenarios. They find that connectivity and concentration of exposures as measured by counterparty susceptibility and local network fragility are highly correlated to the systemic importance of an institution. The researchers also show that a minimum capital ratio reduces the effect of large institution defaults and that a similar effect can occur by requiring minimum capital reserves on only those systemically important firms and those who are exposed to them. Finally, they introduce a "Contagion Index" which measures the expected loss to the network triggered by the default of the institution subjected to a market shock.

Common Findings in the Network Model Literature

There seems to be some consensus in the Network Model research of systemic risk that structural parameters of a network, such as connectivity and concentration, matter as much as size when assessing the systemic importance of an institution. Size alone cannot be used to determine a firm's systemic importance. The Cont study is unique in that it studied the effect of local measures of connectivity and concentration on systemic risk. Most studies, like the Nier study, focus on aggregate measures of connectivity and concentration. The Cont study found that their

two local measures, counterparty susceptibility and local network frailty, can significantly explain default contagion.

There is some disagreement over the relationship between the connectivity of a network and contagion risk. Some authors including Babus found that greater connectivity reduces contagion risk in interbank markets, and if a certain connectivity threshold is reached, contagion risk is practically nonexistent. Gai, Georg and Nier came to different conclusions. The Gai and Georg studies found that financial networks, especially interbank networks, exhibited a "robust-yet-fragile" property. Greater connectivity of a network does help to lower the probability of contagion but actually increases its spread in the event that contagion breaks out. In the network constructed by Nier, greater connectivity led to a more resilient system after a certain connectivity threshold was reached, but for a low degree of connectivity, greater connectivity actually led to an increased contagion effect. Thus, Gai, George and Nier observed that connectivity has a contingent nature: depending on the actual level of connectivity, greater connectivity can either increase or decrease contagion risk.

Most papers focus almost exclusively on systemic risk through contagion effects, but the Georg and Cont papers argue that common asset shocks which affect all institutions of a network via commonly held assets may pose an even greater threat to systemic stability. The Cont study, in particular, shows that systemic risk is understated when common shocks are not considered.

This paper introduces a network model to characterize the systemic risk in the financial system as performed in some of the literature above. The study differs from the other papers by specifically testing the structure of the network applied to two existing financial systems: the monoline bond insurer network and the credit default swap based network. Furthermore, the paper identifies information that may not be publicly available but would be vital for regulators in monitoring systemic risk.

Credit Derivative Securities Based Network

Credit default swaps have been commonly blamed for the 2007 Financial Crisis. Nevertheless, CDS still dominate the credit derivatives market and are at the center of the global financial system.[12] The U.S., Europe, as well as other global financial institutions possess large exposures to CDS markets. The 2007 Financial Crisis underscored the challenge of measuring, monitoring and pricing credit risk.

The CDS market can be recognized as a financial network structure that connects various financial institutions through complex CDS bilateral exposures and cross holdings. Some major players in the center of the CDS market, such as AIG, have become "too interconnected to fail" since the failure of one of these institutions can bring down the entire financial system. Asymmetric and insufficient information disclosure imposes even more credit risk on financial institutions. Therefore, it is critical to develop a network model specifically for the CDS market, so that regulators or other market participants are able to identify those systemically important financial institutions, as well assess the systemic risk under a certain set of circumstances. This paper proposes a CDS network model to assist regulators in monitoring the CDS network system and identifying those "hot spots"[13] which may result in total systemic failure.

Currently, the CDS market can be viewed as a capstone in the financial system. The CDS market is a network consisting of major banks, insurance companies, hedge funds and other institutions, all connected via CDS exposure, as shown in Figure 1. The various sectors of the CDS market may be viewed as large nodes, such as the mortgage-backed securities (MBS) market or the European sovereign debt market. The arcs between those markets and the CDS market are CDS exposures that cover the underlying securities from those markets. If one market sector encounters a crisis, the loss shock can propagate to the banks and insurance companies through the exposure links.

Figure 1. CDS Market in Financial System

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[12] http://www.gailfosler.com/featured/credit-default-swaps-and-the-financial-system-an-interview-with-marti-subrahmanyam
[13] "Hot Spots" are nodes where the firm is "too big to fail"; where failure could have a devastating impact on the entire network.
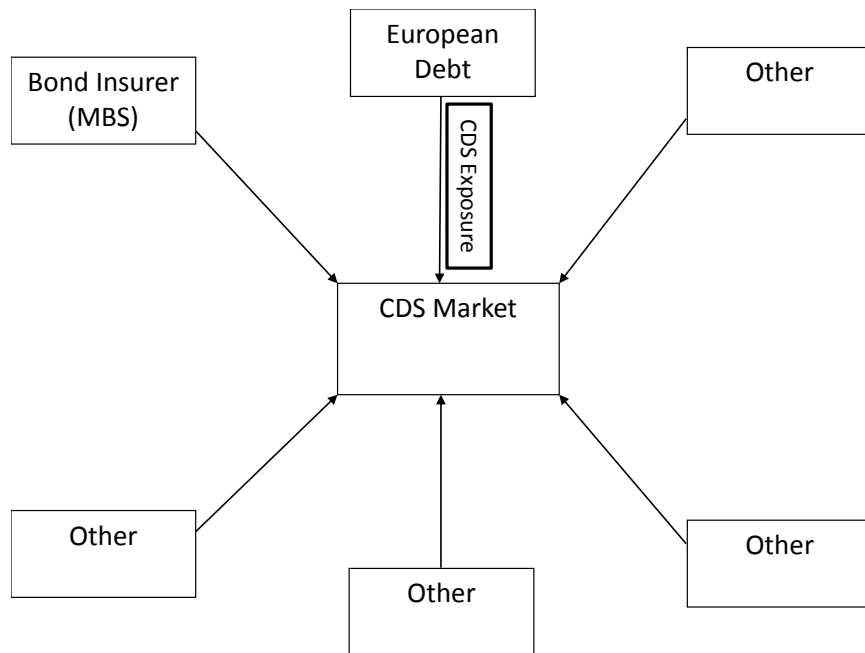
In the CDS network, the large nodes, which represent certain market sectors, contain many small nodes which are banks and other major financial institutions. Each of the smaller nodes may have exposure to more than one market sector, and each smaller node has its own balance sheet. The arcs linking different nodes are the various types of CDS exposures from different sectors.
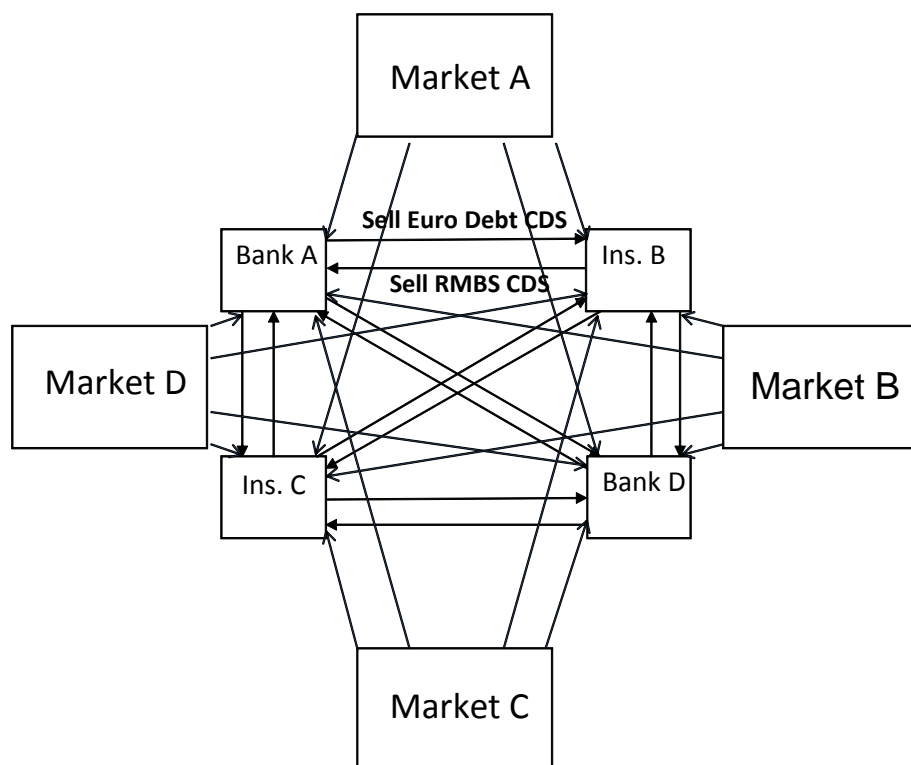
Figure 2. CDS Network Structure

Figure 2 illustrates a plausible CDS network structure. Suppose a financial institution defaults as it suffers losses exceeding a certain threshold of its core capital. If a European debt market crisis causes *Bank A* and *Insurance Company C* to become bankrupt, the losses due to their defaults can propagate to other nodes who have bought Euro Debt CDS from *Bank A* and *Insurance Company C*. Given this condition, the **Systemic Risk Ratio of a sector** is defined as the ratio of the expected final loss of the total system to the expected initial loss of a sector:

$$Sector\ Systemic\ Risk\ Ratio = E(Final\ Total\ System\ Loss)/E(Initial\ Sector\ Loss\ )$$

Similarly, the **Systemic Risk Ratio of a financial institution** is defined as the ratio of the expected final loss of the total system to the expected initial loss caused by a specific institutional default:

$$Institutional\ Systemic\ Risk\ Ratio = E(Final\ Total\ System\ Loss)/E(Initial\ Loss\ caused\ by\ a\ Default)$$

The network structure of different market sectors may vary considerably. A big CDS seller in the RMBS market may be a big CDS buyer in the European debt market. Separate modules can be established to analyze the shock from a specific market sector (e.g. European debt crisis,

sharp decline in housing prices), and to verify those "hot spots" in different market sectors. This paper proposes that the following five factors have the greatest impact on the systemic risk ratio:

- Weight of a sector in the CDS market
- Capital level
- Recovery rate (salvage ratio)
- Default criterion
- Degree of bilateral exposure within a sector

The impact of adding a national clearing house into the financial system is discussed later in the paper. This paper illustrates how a clearing house can restrain loss propagation and mitigate the systemic risk ratio.

In summary, this paper establishes a framework eligible for further development and expansion through building modules for different market sectors and collecting bilateral exposure data from banks, insurance companies, and other financial institutions. This network model aims to help regulators identify the companies that are too big or too interconnected to fail during any specific market crisis.

Network Model for CDS Market

Network Structure

CDS contracts are off balance sheet items, and therefore, "neither the SEC nor any regulator has authority over the CDS market, even to require minimal disclosure to the market."[14] Hence, there is no explicit one-to-one bilateral CDS exposure data currently available. However, for each FDIC registered bank, the gross CDS purchase or sell data can be acquired from the FDIC database.

In order to construct a network structure for the CDS market in this study, an algorithm has been developed in which a bilateral connection matrix is generated stochastically in order to simulate

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[14] "Testimony Concerning Turmoil in U.S. Credit Markets: Recent Actions Regarding Government Sponsored Entities, Investment Banks and Other Financial Institutional", http://www.sec.gov/news/testimony/2008/ts092308cc.htm

a plausible CDS network reflecting the real market.[15] The bilateral connection matrix is generated in a manner that replicates the gross buy (sell) totals for each bank, but with connections to other banks that are randomly generated portions of the totals. In this way, the larger CDS market participants tend to have more connections and larger connections in the generated bilateral connection matrix.

It is important to understand that the network model requires only one bilateral connection matrix for input in order to produce its results. However, since the authors do not have access to complete data, they generate a large number of "plausible" matrices for the input, and run the model for each one. This generates a large number of "plausible" results that can be averaged or analyzed in other ways. This stochastic element of the model process would not be required if complete data were available.

The details of the algorithm used to generate a "plausible" bilateral connection matrix are presented below.

Suppose there are N FDIC banks participating in the CDS market (Assume the gross CDS buy or sell amount is greater than zero), which are indexed as $i=1, 2,..., N$. The $N+1th$ agent represents an external node that includes all other CDS trading entities except FDIC banks and is named "Other Entities." Based on the gross CDS buy (sell) data, the market share for each bank can be obtained in the following way:

$$S_i^B = \frac{B_i}{B} : \ Bank_i \ market \ share \ on \ the \ buy \ side \ of \ CDS$$

$$S_i^S = \frac{S_i}{S} : \ Bank_i \ market \ share \ on \ the \ sell \ side \ of \ CDS$$

where,

B_i is the amount of CDS which $Bank_i$ buys.

S_i is the amount of CDS which $Bank_i$ sells.

B is the total amount of CDS bought within all banks.

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[15] This simulation of the one-to-one bilateral connections is performed as current data are not available.

S is the total amount of CDS sold within all banks.

For $Bank_i$, the number of banks from which it buys CDS is calculated:

$$N_i^B = S_i^B \cdot N^S$$

where N^S is the total number of banks that have written CDS as guarantor (i.e. the number of banks for which S(i,s)>0 .

Also, a $N \times N$ bilateral trading probability matrix X is derived from CDS market share data of N banks:

$$X = \begin{bmatrix} 0 & x_{1,2} & \dots & & x_{1,N} \\ x_{2,1} & 0 & & & . \\ & & 0 & x_{N-1,N} \\ x_{N,1} & \dots & x_{N,N-1} & 0 \end{bmatrix}$$

where $x_{i,j}$ represents the likelihood of $Bank_j$ buys CDS from $Bank_i$, equal to $S_i^S/(1 - S_j^S)$ when $i \neq j$, and is zero when $i = j$. Since the bank index is following the order from the largest to the smallest CDS market share, $x_{m,j} > x_{n,j}, \forall m < n, m \neq j \ and \ n \neq j$.

A vector of random numbers is introduced to establish the bilateral connections of a plausible network structure. For example, when establishing the bilateral connections for $Bank_j$, the number of banks it buys CDS from is represented by N_j^B. Hence, N_j^B random numbers that are uniformly distributed from 0 to 1 are generated, denoted as $r_{j,k}^B, k = 1,2,\dots,N_j^B$.

In order to determine the first counterparty of $Bank_j$, a vector of trading probabilities $y_{i,j}, i = 0, 1, \dots, N$ is obtained, where $y_{i,j} = x_{i,j}/\sum_{i=1}^{N} x_{i,j}$. The trading relationships between $Bank_j$ and other banks are noted as $I_{i,j}^B, i = 1,2,\dots,N$, and where $I_{i,j}^B = 1$ indicates that $Bank_j$ has bought CDS from $Bank_i$, whereas $I_{i,j}^B = 0$ means there is no CDS bilateral exposure between $Bank_j$ and $Bank_i$. The bank index number of the first counterparty is n^* , where $n^* = \inf\{n| \sum_{i=1}^{n} y_{i,j} > r_{j,1}^B, n = 1,2,\dots,N\}$, and the counterparty is noted as $Bank_{n^*}$. The basic idea of this algorithm is to split the total probability space into N_j^B sections that reflect the

corresponding trading probabilities, and the random number is used to anchor a bilateral connection within the total probability space and to determine the counterparty accordingly.

After the first counterparty is determined, a similar random process is performed for selecting the second one. However, the trading probability $y_{i,j}$ is modified as $y_{i,j} = x_{i,j}/\sum_{i=1}^{N} x_{i,j}, i \neq n^*$, to exclude $Bank_{n^*}$ from the bank list. Then, $r_{j,2}^{B}$ is used to determine the index number of the second counterparty. By repeating this stochastic selection procedure, N_j^{B} counterparties of $Bank_j$ are set. A stochastic bilateral connection matrix can be established by adopting a similar stochastic process for $Bank_i, i = 1,2, \dots, N$. However, when $I_{i,j}^{B} = I_{j,i}^{B} = 1$, a random number $(0 \sim 1)$ is generated. If it is less than 0.5, $I_{i,j}^{B}=0$; otherwise, $I_{j,i}^{B}=0$. In the end, a stochastic bilateral connection matrix can be written:

$$
I = \begin{bmatrix}
0 & I_{1,2}^{B} & \dots & & I_{1,N}^{B} \\
I_{2,1}^{B} & 0 & & & \cdot \\
\cdot & & 0 & & I_{N-1,N}^{B} \\
I_{N,1}^{B} & \dots & I_{N,N-1}^{B} & & 0
\end{bmatrix}
$$

Based on the stochastic bilateral connection matrix I, the matrix of CDS trading amounts is obtained:

$$
T = \begin{bmatrix}
0 & T_{1,2} & \dots & & T_{1,N} \\
T_{2,1} & 0 & & & \cdot \\
\cdot & & 0 & & T_{N-1,N} \\
T_{N,1} & \dots & T_{N,N-1} & & 0
\end{bmatrix}
$$

where $T_{i,j} = I_{i,j}^{B} \cdot B_i \cdot S_j^{S} \cdot S/B, \;\; i,j = 1,2, \dots, N$.

The upper limit for the number of banks from which $Bank_j$ can buy CDS is N_j^{B}. If $\sum_{j=1}^{N} T_{i,j} < B_i$, the unallocated CDS purchasing amount is linked to the Other Entities.

In addition, the user of the CDS network model is allowed to input predetermined CDS trading connections and trading amounts with the model simulating the rest of the network structure. Users can accordingly test the systemic risk ratios under different network structures.

Contagion Mechanism

To simplify the model, naked CDS positions are prohibited. A naked CDS position means that a bank buys CDS but does not hold the underlying debt or sells corresponding CDS to a third party.

In this paper, the primary reason that a bank buys CDS is to hedge its CDS selling position. After the selling position is fully covered, the remaining CDS long position aims to hedge the credit risk of the debt it holds. When $Bank_i$ suffers losses exceeding 20% of its Tier One Capital[16], it enters bankruptcy. If $Bank_i$ becomes bankrupt, all the CDS it has written become worthless. Suppose that $Bank_j$ has bought CDS from $Bank_i$, and therefore $Bank_j$ needs additional capital to cover the emerged credit risk due to losing the CDS coverage. It is assumed that $Bank_j$ is not able to inject sufficient capital in time, hence $Bank_j$ has to write down its capital, and the loss amount equals the notional amount of debt that CDS covered.

Within a financial network, $Bank_j$ may suffer losses caused by a specific bank default or multiple bank defaults due to a common shock. If the aggregate loss $Bank_j$ suffers becomes greater than 20% of its Tier One Capital, it defaults too. The insolvency of $Bank_j$ triggers further losses, and these losses propagate to other banks. This domino effect stops only when banks no longer become bankrupt. The ultimate loss that the system suffers may be a multiple of the initial shock.

Measure of the Systemic Risk

Company Failure

The Company Failure scenario is designed to estimate the system risk that a specific bank (noted as *Bank A*) may pose to a certain market sector. In this scenario, the initial loss to the system equals the total CDS amount that *Bank A* sells for that specific sector. Remember this is still a scenario based stress test, which means that only one sector of the CDS market fails. If any bank fails due to *Bank A*'s default, the losses spread to other banks. The system becomes stable when banks stop failing.

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[16] The 20% threshold of Tier One Capital is commonly proposed as a critical point in literature

The **Systemic Risk Ratio of a financial institution** is defined as the ratio of the expected final loss of the total system to the expected initial loss due to the institution's default:

$$Institutional\ Systemic\ Risk\ Ratio = E(Final\ Total\ System\ Loss)/E(Initial\ Loss\ caused\ by\ a\ default)$$

Sector Failure

The Sector Failure scenario is designed to assess the systemic risk associated with a market sector. If a market sector collapses and the related debt defaults, all the banks that have written CDS in this market suffer losses. The model sets the initial loss suffered by each bank equal to a proportion of the initial sector loss, where the proportion is the CDS market share of that bank. The losses start to spread if any of the banks become insolvent after suffering their initial losses.

The **Systemic Risk Ratio of a sector** is defined as the ratio of the expected final loss of the total system to the expected initial loss from a sector failure:

$$Sector\ Systemic\ Risk\ Ratio = E(Final\ Total\ System\ Loss)/E(Initial\ Sector\ Loss\ )$$

Clearing House

In this model, a clearing house is set up as an intermediate between CDS buyers and sellers. By embedding a clearing house into the financial network model, loss shocks will not spread from an insolvent bank to other parts of the system. The clearing house guarantees that CDS are still valid even though the original writer defaults. The capital that is needed to support a clearing house can be estimated subject to a certain network structure, where accurate CDS bilateral exposure data is crucial for estimation. Because bilateral exposure data is unavailable, the authors do not analyze the capital adequacy of the clearing house in this paper.

By comparing the expected final loss of the system with the expected first round loss, the effect of a clearing house's contribution to the system robustness is demonstrated.

Sensitivity Testing

There are five major factors that are incorporated into this network model including Segment Weight, Recovery Ratio, Capital Level, Default Criterion and Bilateral Exposure. When performing a sensitivity test for one specific factor, the values of the other factors are held

constant. However, since the true bilateral exposure structure is not known, only two major CDS players (JP Morgan Chase and Citibank) are chosen for investigating the impact of bilateral exposure between certain nodes on the whole CDS system. The common network structure is derived from FDIC 2008 Q4 CDS aggregate exposure data.

All the sensitivity tests are based on the Sector Failure scenario. The sensitivity test results are summarized for each of the five factors' effects on systemic risk ratio and expected system loss, with and without a clearing house. Table 1 shows a list of default values of major factors (except degree of bilateral exposure), as well as the sensitivity test range.

Table 1. The Default Value and Test Range of Four Major Factors

Factor	Default Value	Lower Level	Upper Level
Segment Weight as of total CDS market	5%	0%	50%
Capital level	100%	0%	500%
Recovery Ratio (Salvage Ratio)	50%	0%	90%
Default Criterion (as % of Tier One Capital)	20%	0%	100%

1. **Segment weight as a percentage of total CDS market**
   First, this paper examines the effect of segment weight on the systemic risk ratio and expected system loss. A higher segment weight implies that a sector represents more of the CDS market share, and therefore is more important. The failure of a dominant sector is more likely to trigger a systemic failure.

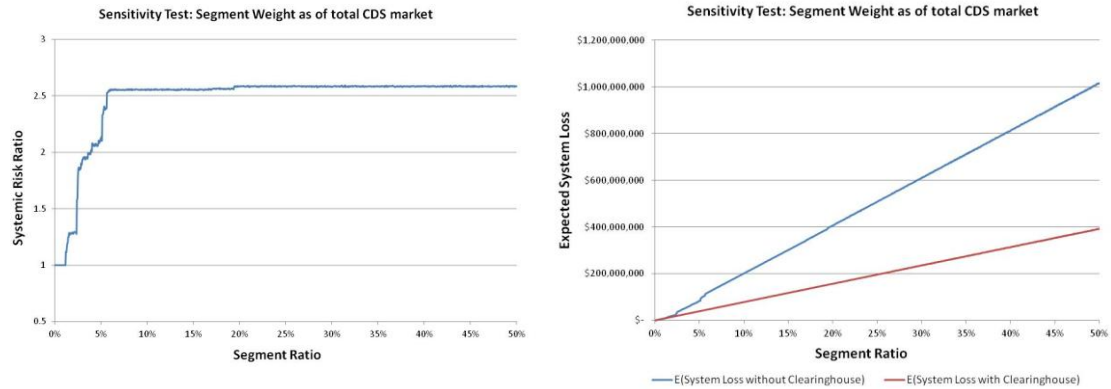**Figure 3. Impact of Segment Weight**

Figure 3 shows these results. The segment weight shows a positive but non-linear relationship with the systemic risk ratio. With all other factors held constant, the systemic risk ratio increases sharply as segment weight rises from 0% to about 8%, and then plateaus at a high level. The relationship between segment weight and expected system loss without a clearing house seems linear but shows some jumps in the lower range. In contrast, there is a clear linear relationship between segment weight and expected system loss with a clearing house. It is observed that the expected system loss with a clearing house is always smaller than without a clearing house.

2. **Recovery ratio (salvage ratio)**

In a second sensitivity test, this paper investigates the effect of the recovery ratio (salvage ratio) on the systemic risk ratio as well as the expected system loss. High recovery ratios mitigate losses from defaulting banks and bolster the system's robustness. Keeping other factors the same, recovery ratios between 0% and 90% are tested.

Figure 4. Impact of Recovery Ratio (Salvage Ratio)
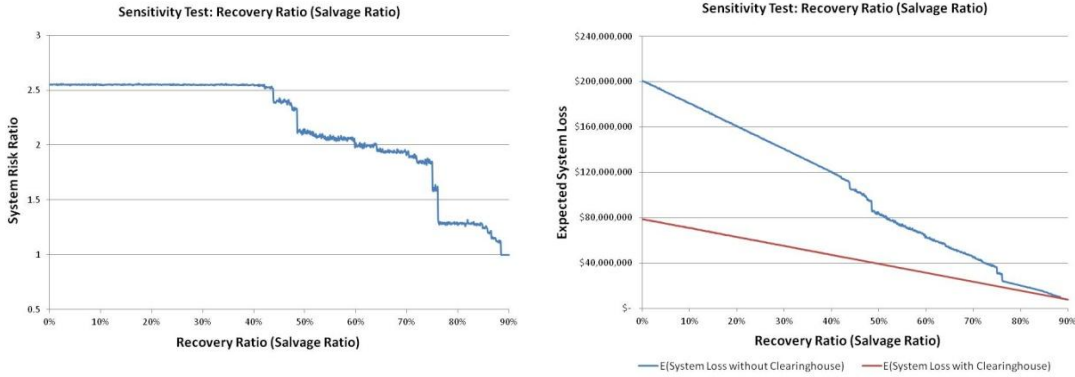
From Figure 4, it is apparent that up to a threshold of 40%, the recovery ratio does not affect the systemic risk ratio. Once the recovery ratio exceeds that threshold, the systemic risk ratio starts to decline and eventually converges to 1, which means there is no more contagion effect in the network. Figure 4 also implies an effect of the recovery ratio on the expected loss which is a mixture of linearity and jumps, but this effect is in the opposite direction of the segment weight effect.

3. **Bank capital level and default criterion**

Capital level measures capital sufficiency. Default criterion establishes the benchmark level of capital loss that a bank can bear while remaining solvent. With a fixed default criterion, higher capital levels decrease the default probability. If the capital level remains constant, a higher default criterion reduces the default probability. The sensitivity test results of banks' capital levels and default criteria (as % of Tier One Capital) in one sector are presented together because the effects of these two factors are essentially the same but on different scales.

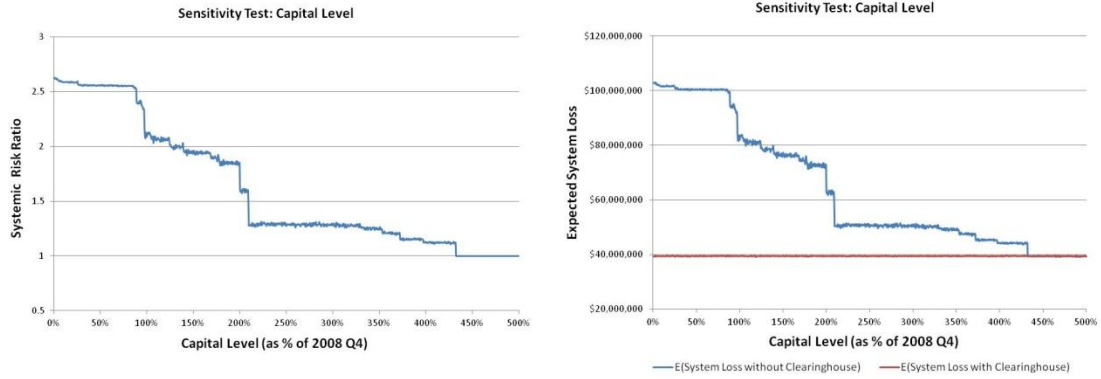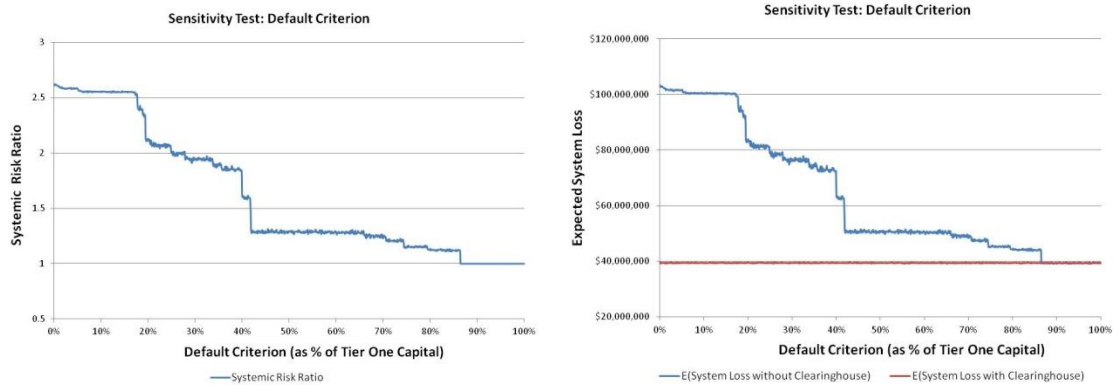**Figure 5. Impact of Capital Level**

Figures (top) – two charts titled "Sensitivity Test: Capital Level" with x-axis "Capital Level (as % of 2008 Q4)"; left y-axis "Systemic Risk Ratio", right y-axis "Expected System Loss". Legend: E(System Loss without Clearinghouse), E(System Loss with Clearinghouse).

Figure 6. Impact of Default Criterion (as % of Tier One Capital)

Figures (middle) – two charts titled "Sensitivity Test: Default Criterion" with x-axis "Default Criterion (as % of Tier One Capital)"; left y-axis "Systemic Risk Ratio", right y-axis "Expected System Loss". Legends: Systemic Risk Ratio; E(System Loss without Clearinghouse), E(System Loss with Clearinghouse).

Figures 5 and 6 indicate that capital level and default criterion have almost identical effects on the systemic risk ratio if viewed on the same horizontal axes. When these two factors increase, the systemic risk ratio gradually decreases to 1. Similarly, the impact of these two factors on the expected system loss seems to be identical. Particularly for the network with a clearing house, the expected loss is constant. This implies that the clearing house absorbs the first round losses, and thus capital level and default criterion can be viewed as independent of expected system loss.

4. **Degree of bilateral exposure**

Degree of bilateral exposure is expressed as the bilateral exposure amount, which has two opposing effects. Bilateral exposures may propagate losses to other institutions and then to the whole system, or the losses may be absorbed into the network via the bilateral exposure.

In a specific bilateral exposure sensitivity test, the authors establish a series of nominal CDS exposure amounts that JP Morgan Chase buys from Citibank, ranging from $0 to $100 million. The authors initially investigated the effect of bilateral exposure on the systemic risk ratio. From figure 7, two opposing effects can be seen over different ranges, generating a non-linear and non-monotonous curve. First, for low levels of exposure, the systemic risk ratio rises along with increases in bilateral exposure until a threshold is reached, and then it starts declining. As the exposure increases further, the systemic risk ratio rises again. But when exposure is sufficiently large, further increases in bilateral exposure decrease the systemic risk ratio.

Figure 7 also shows how the degree of bilateral exposure may affect the expected system loss, where a similar, non-linear relationship is observed in the system without a clearing house. However, when the exposure becomes sufficiently large, the expected system loss continues to rise as exposure increases, which is the opposite effect of the systemic risk ratio. This divergence implies that the systemic risk ratio may underestimate the systemic risk in some conditions. Consequently, using the systemic risk ratio is not enough to assess systemic risk. For the system with a clearing house, the system loss curve emulates a strangle[17] payoff curve.

Figure 7. Impact of bilateral exposure (JP Morgan Chase and Citibank)

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[17] A long strangle is an investment strategy implemented by buying both a call option and a put option of the same underlying security.

Sensitivity Test: Degree of Bilateral Exposure
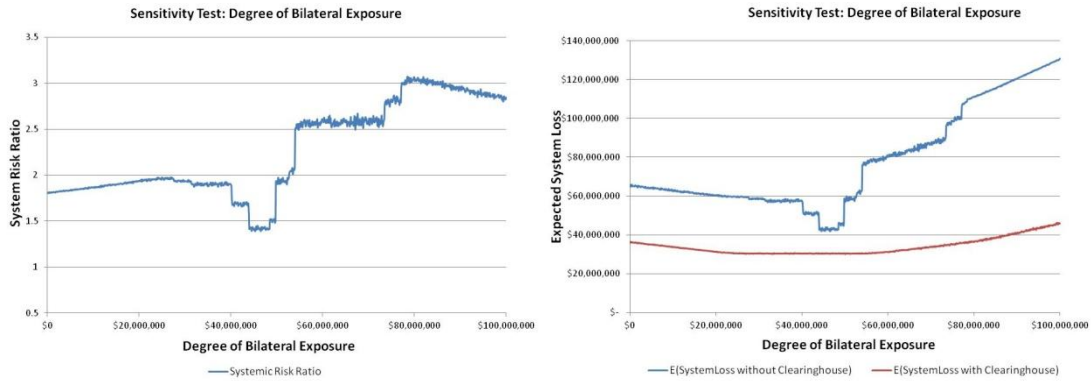
CONCLUSION

This paper applies network models to the CDS market.

The CDS network model indicated that higher segment weights, lower recovery ratios, lower capital levels and a lower default criterion resulted in higher systemic risk ratios, and these relationships were non-linear in nature. In contrast, the impact of bilateral exposure the on systemic risk ratio was more complicated, non-linear and non-monotonous.

Besides the systemic risk ratio, the other measure of systemic risk tested was the expected system loss. Under the scenarios without a clearing house, the sensitivity tests of the five factors on the expected system loss showed two general types of impacts. For segment weight and recovery ratio, the relationship was a mixture of linearity and jumps. Segment weight exhibited a positive relationship with expected system loss while recovery ratio exhibits a negative relationship. Capital level and default criterion sensitivity tests revealed negative, non-linear relationships while bilateral exposure had a more complicated, non-linear relationship with the expected system loss.

In scenarios where a clearing house was introduced to the system, the study showed that capital level and default criterion no longer affected the expected losses. Not surprisingly, the expected loss with a clearing house was always lower than the expected loss without a clearing house. This difference in expected system loss in the two scenarios was most notable when the default criterion, the capital level, or the recovery ratio was low or when the segment weight was high.

As seen in the bilateral exposure sensitivity tests, solely using the systemic risk ratio to assess systemic importance may be misleading because the expected system loss can still rise while the systemic risk ratio is declining. Thus, the authors propose incorporating both the systemic risk ratio and expected loss to assess systemic risk more comprehensively.

This study points out to the Financial Stability Oversight Committee critical data that are not available publicly or currently missing. Currently, there is no public data on one-to-one bilateral CDS exposures. Stochastic algorithm was performed to simulate the one to one exposures in the CDS market. By structuring the models so that the stochastically generated data can be replaced with data that may be obtained by the Financial Stability Oversight Committee, flexible models can be created to measure systemic risk in the financial system.

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