Systemic Risk and Topological Fragility of CDS Networks: 2004Q1-2007Q4

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Abstract

This paper uses FDIC call report data to calibrate the financial network of CDS obligations. It shows how, given the maladaptation of banks to perverse incentives of the Joint Agencies Rule 66 (Federal Regulation 56914 and 59622) and Basel II Credit Risk Transfer (CRT) frameworks, regulatory policy might actually have unintentionally intensified systemic risk and instability as the use of CDS contracts increased. In particular, the paper shows that, in the years following the introduction of Basel II, the topological complexion of the CDS market was progressively altered as the entrenchment of regulations resulted in a growing degree of clustering and concentration of CDS obligations amongst a few large banks. Moreover, it shows that inadequately accounting for contingent payments under credit derivatives contracts due to the assumed transfer of risk under CRT can ultimately result in the undercapitalisation of banks where market conditions imply that contracts are not easily replaced upon the failure of trade counterparties.

key discussion point - Financial networks, Financial contagion, Network topology, Basel II, Credit risk transfer, Credit default swaps (CDS), Regulatory policy monitoring, Systemic risk

1 Introduction

Markose et al., (2012) illustrated the manner in which the dynamics of perverse incentives that arise from the credit risk mitigation based regulatory frameworks introduced under the January 1, 2002 Joint Agencies Rule 66 (Federal Regulation 56914 and 59622) and crystallised within Basel II (hereon in both

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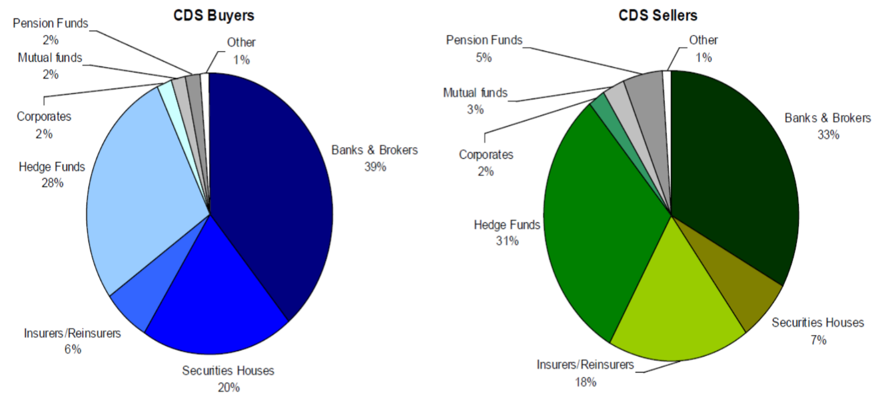
Figure 1: CDS Buy and Sell Side Market Participation by Counterparty Type 2006Q4



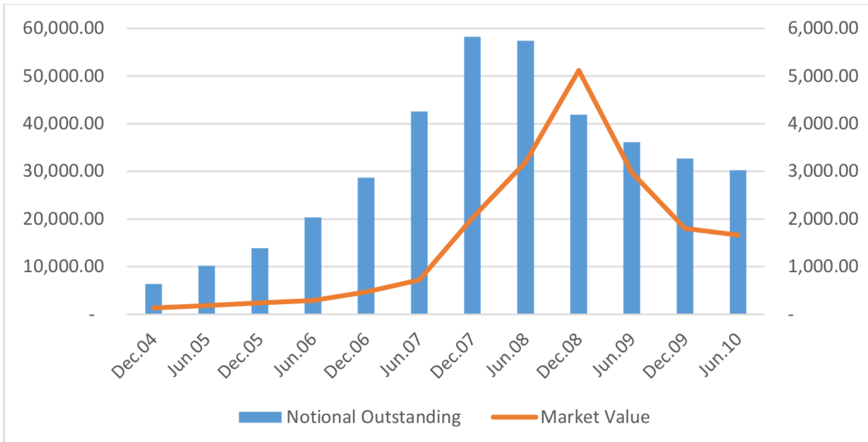
Source: British Bankers Association

will be referred to as Basel II) could result in the rapid accumulation of residential mortgage-backed securities (RMBSs) holding and credit default swap (CDS) exposures on bank balance sheets. It was stipulated that banks' very act of adhering to the rules on credit risk transfer (CRT) that underpinned the Basel II regulatory regime gave rise to the use of credit derivatives to insure against the default risk on reference RMBS assets that dominated the financial landscape between 2002 and 2007.[1] Regulations ensured that banks became the leading buyers and sellers of credit protection within this market, which at its peak stood at US$58tn, and they have, consequently, become vulnerable (Figures 1 and 2).

This vulnerability has arisen due to the structural weaknesses of the CDS market and the issues of poor regulatory policy design highlighted in the previous paper. Representing over 98% of the market for credit derivatives, CDS contracts have

[1]The CDS market consisting of banks and non-bank financial intermediaries has since 2008, evolved into an information source, guiding market expectations on the default probability of the reference entity.

Figure 2: CDS Total Notional Outstanding 2006Q4 to 2010Q2 (US$ Billions)



Notes: (1) Notional Outstanding (right hand axis) are the sum of CDS contracts bought (or equivalently sold) for all contracts in aggregate on a per-trade basis. For example, a transaction of US$10m notional between buyer and seller of protection is reported as one contract for US$10m gross notional, as opposed to two contracts for $20 million notional. (2) Market Value (left hand axis) is the sum of the net protection bought by net buyers (or equivalently net protection sold by net sellers) and represents the maximum possible net funds transfers between net sellers of protection and net buyers of protection that could be required upon the occurrence of a credit event.

played an inimitable, pervasive, and ruinous role in the global financial crisis of 2007-2008 that originated from the US subprime crisis and quickly evolved into an epidemic that resulted in the European sovereign debt crisis. This paper is concerned with modelling the specific weakness stemming from the large concentration of trading activity amongst small numbers of key participants in the CDS market.

Without exception, the growth of financial innovation enabling private sector liquidity and leverage creation collateralised by pro-cyclically sensitive assets (i.e. those assets, such as RMBSs that banks used as collateral through ABCP conduits in the repo market and that lose value during economic downtowns) were a central fixture of the 2007-2008 crisis. As noted in the previous paper, regulators sought to tighten rules that led banks to take risky assets off their balance sheets by employing measures and rules that encouraged banks to hold assets on their balance sheets. This took the form of the central role of CDSs in

CRT and synthetic securitisation under Basel II.[2] his new regulatory treatment of CRT accelerated the leverage process and ultimately increased the connectivity between depository institutions and unregulated non-depository financial intermediaries and the wider derivatives markets. American International Group (AIG), for instance, sold protection of approximately $1.8tn notional of CDSs, guaranteeing payment in the case of defaults or other credit events on mortgage-backed securities. Whilst the majority of these CDS contracts required AIG to post collateral as the credit quality of the referenced securities (or AIG's own credit rating) deteriorated, AIG was not required to post any initial margins on these contracts, because this was deemed unnecessary given AIG's triple-A rating. As the subprime crisis worsened, AIG faced margin calls that it could not meet. To avert bankruptcy and a wider risk of global financial meltdown, the Federal Reserve and the Treasury injected tens of billions of dollars into AIG, which in turn went to its derivatives counterparties (see Office of the Special Inspector General for the Troubled Asset Relief Program [SIGTARP], Factors Affecting Efforts to Limit Payments to AIG Counterparties, November 17, 2009).

The degree to which the CRT framework of the 2002 and 2004 regulations were structurally unstable is akin to banks and other net protection buyers of CDSs purchasing insurance from the passengers on the Titanic. The demise and subsequent absorption of Merrill Lynch, at the time the biggest underwriter of collateralised debt obligations (CDOs), by Bank of America was, for example, the result of ratings. downgrades of multiple bond insurers such as ACA Capital

[2]Under the 1988 Basel Accord, banks were required to hold 8% in regulatory capital charges against their default risky assets. With a risk weighting of 50% this meant that banks would hold 4% capital against residential mortgage loans. Under the 2002 Joint Agencies Rule 66 and the 2004 Basel Accord, the same residential mortgage loan could become subject to as little as a 1.6% capital charge through CRT under synthetic securitisation. ECB (2009) points out that in its 2007 filing to the SEC, AIG FP, the hedge fund arm of American International Group (AIG), categorically eluded to providing CDS guarantees to European banks in order for these banks to reduce their regulatory capital requirements.

Holdings Inc., which suffered a 12 notch fall to CCC in its debt rating, making over US$2.6bn in default protection acquired by Merrill worthless.[3]

By encouraging CRT through the use of CDSs, regulators who wanted to foster an economically effective means by which banks could diversify away credit risks from balance sheet exposures by passing them unto triple-A rated institutions better placed to manage them created systemically unsustainable outcomes. Darby (1994), Persuad (2002), Lucas et al. (2007), and Gibson (2007) have argued that inappropriate structural form and a high degree of concentration can scupper any benefits perceivable from CRT. That CRT enables banks to make significant regulatory capital savings and expand short-term assets, could automatically improve their balance sheet diversification at the macro level was not a sustainable presumption on the part of regulators. The whole was not the some of its parts. As seen in the 2007-2008 crisis, in which contractual obligations were amongst the same subset of banks, the initial diversification eroded away as the network of obligations became highly connected; this concentration then bred systemic risk and a system too interconnected to fail (TITF). Moreover, despite their intention to push banks towards using CDSs to manage balance sheet risks and the accessibility of the data to regulators, no analysis was undertaken to identify or measure the extent to which growing the structural concentration of CDS contracts could lead to systemic risk. This paper shows that the series of contractual obligations could have been constructed and the topological fragility of the financial network defined. Moreover, because the purpose of this thesis is to highlight the use of agent- based computational economics (ACE) in the design and testing of policy, the analysis will focus on the macro level, rather than the systemic risk of individual entities.

The focus of the analysis is on the US CDS market and considers only the

[3]The reader is referred to the Bloomberg News article of January 17, 2008 ―Merrill Lynch Plans to Write Off ACA Bond Insurance (Update1)‖ at http://www.bloomberg.com/apps/news?pid =newsarchive&sid=abJ54xMm7k4Y.

banks that participated in the CDS market and for which balance sheet data are available through the FDIC. During the period 2004-2008, between 26 and 38 banks actively engaged in the CDS market. Of these, 5 banks in 2006 (JP-Morgan, Citibank, Bank of America, HSBC, and Wachovia) accounted for 95% of the gross notional in CDS sales. By 2007 this market share had increased to 97%. To visually capture the nature of the network of contractual obligations with such a high concentration of CDS sales associated with these 5 banks, the analysis herein utilises the network model that Markose et al. (2010) devised. Because the primary objective here is to see if and how ACE models could have been used in the ex post assessment of policy and, at the very least, to pick up the early warning signs of potential systemic risks, the analysis also looks back to the credit derivatives market structure prior to the full inception of the Basel II rules in 2004 and will compare this against market conditions during the US housing bubble of 2006 and also at the height of the subprime crisis of 2007.

Furthermore, the analysis is carried out on a worst-case-scenario basis. It is therefore implicitly assumed in the use of gross notional data on CDS, that without a central repository for full examination of all bilateral trade information, at the height of panic during crisis situations, the replacement of lost credit guarantees upon the failure of a trade counterparty is not readily feasible. This does not, however, negate the use of bilateral offsets during trade and collateral settlement. For the purpose of this analysis, it is simply assumed that full market look-through is not readily available from an operational perspective to properly reassign contracts amongst surviving banks during high intensity moments as in financial crises. This assumption is later relaxed and the two sets of results are compared.

The paper identifies the extent to which banks' CDS exposures were highly concentrated to the point that the failure of highly connected banks could trigger an extreme socialised loss of capital that would see similarly connected banks collapse. Section 2 is an overview of the structure of CDS trades and the systemic risk that arises from them given practices such as trade offsetting.[4] Section 3 reviews the economic literature on financial networks and the empirical research methodology under a graph theoretic framework. Section 4 discusses the FDIC data used in modelling. Section 5 reviews the simulation results using two distinct network topologies and measures of credit derivatives exposures. The final section presents concluding remarks to the paper.

2 Credit Default Swaps and their Potential for Systemic Risk

2.1 Structural Inconsistency of CDS Contracts

CDSs are bilateral credit derivatives contracts that fall into one of two primary classes of trade based on their underlying: single name CDSs and CDS indices. Single- name CDSs are contracts typically specified over a 5-year period in which payoffs are linked to a credit event such as default, restructuring of debt, or bankruptcy of the underlying corporate or sovereign entity. The credit event in turn triggers a payment by the protection seller. CDS index trades, on the other hand, reference an underlying index/basket of entities and trade cash flows are associated with credit events on individual constituents of the underlying index; these events are similar to those on single name trades.

Both single-name and CDS index contracts have tended to be bilaterally and privately negotiated, and respective parties to any given trade are bound to the contract until the trade maturity date. In both instances the protection buyer

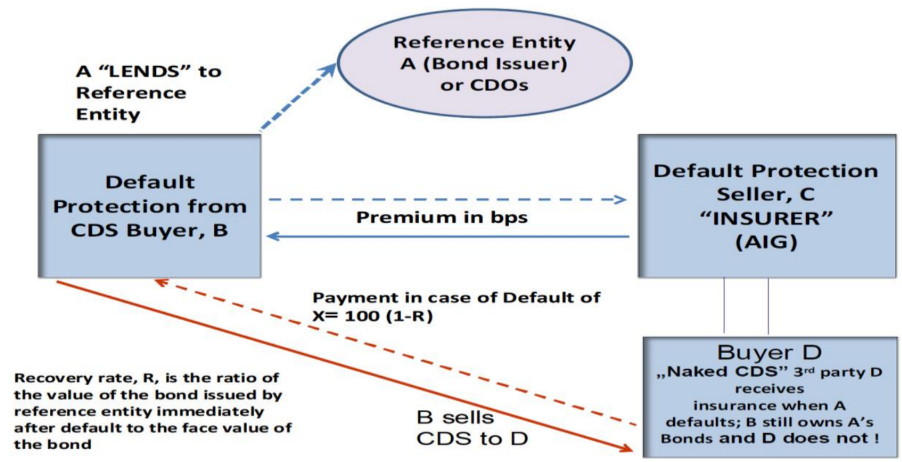
[4]In a trade offset, counterparties close out positions by entering new trades of the same value in the opposite direction to that they wish to close out. So for instance a US$10 protection selling position could be closed out by taking an offsetting trade position to buy US$10 of credit protection on the same reference entity as the original trade.

makes ongoing periodic premium payments that are dictated by daily fluctuations in the credit spread on the underlying credit exposure to the protection seller until the credit event. Credit spreads function as a measure of the credit worthiness and, more specifically, the probability of default and recovery value of the reference assets. Spreads are quoted as a percentage of the CDS gross notional at the start of the contract or inception of the CDS index. High spreads indicate increasing market expectations of default with a jump to default spike at the point of the credit event while, low spreads are suggestive of lower default risk. This link between CDS spreads and the probability of default has an interesting impact on CDS protection sellers also. When a protection seller faces increasing credit spreads on CDS contracts for which it is the reference entity, it will struggle to raise liquidity and thus increase its likelihood of insolvency. As Duffie et al. (2010) illustrate in citing the Bear Stearns collapse, the loss of liquidity could be triggered by a run on the collateral posted by the protection seller. This raises the issue of counterparty credit risk and underscores the importance of the gross notional value of exposures.

The potential also exists for bear raids and speculative naked CDS positions (see Figure 3).[5] In Figure 3 the naked CDS position is held by D, which buys CDS protection from B against a default by A, though D does not, in fact, have any direct credit exposure to A. Consequently, it could be in D's interests to instigate a sequence of events, such as the short selling of debt issued by A that would lead to the demise of A. If C is under-collateralised, the default in A might also cause C to fail.

[5] A naked CDS position is one in which the protection buy does not hold a physical exposure to the reference entity for which it is buying protection. Instead, it is speculating on the eventual default of that reference entity to either gain on cash settlement at default or by offsetting the position at a higher spread. Consequently CDS exposures are not one-for-one matches to the underlying obligation but can also substantially exceed the notional value of the underlying debt. Protection buyers thus become empty creditors indifferent to and in some cases benefiting the default of the CDS underlying (Hu and Black, 2008; Yavorsky, 2009).

Figure 3: Bear Raid and Naked CDS



Source: Markose et al. (2010, pp. 16).

CDS markets can therefore be seen as highly self-reflexive. In fact, the ECB (2009) reports that an increasing correlation between (CDS) counterparties and (CDS) reference entities has recently taken on a new dimension in those countries whose banking sector has been supported by public authorities (p. 25). This in turn has exposed sovereigns to increased CDS spreads as they engaged in national bank-rescue packages. As Figure 3 shows, empty creditors could buy protection against these governments, short their debt, and trigger a sovereign debt crisis due to their national bank rescue packages. This cyclicality in the association of gross notional exposures of a counterparty or its creditors/sponsors to the credit quality of the underlying is also referred to as wrong way risk and is difficult to model using traditional methods for pricing CDSs.

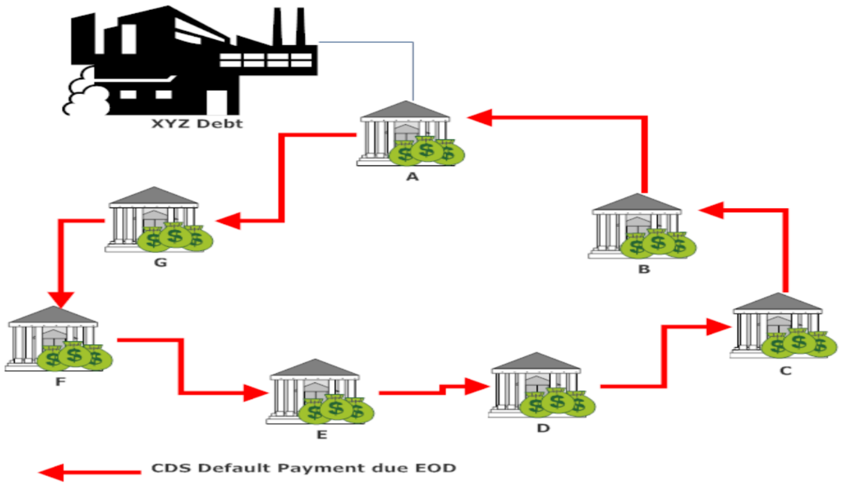
2.2 CDS Chain Settlement Risk and Systemic Risk

A further and possibly the most esoteric risk that leads to systemic failure in the CDS market sterns from a settlement-failure cascade and/or related counterparty abstraction. This arises when a party to a trade is unable to deliver in the short term during a default event, causing other market participants to cease outgoing payments. This was the case during the impactful Freddy Mac and Fannie Mae defaults.

In a highly stylised explanation, consider, as shown in Figure 4 some financial intermediary, A, that has exposures to some reference entity, XYZ Debt. A wishes to mitigate its balance sheet credit risk exposure to XYZ Debt and reduce regulatory capital charges on this asset, so it buys CDS credit protection from B. B, now exposed to XYZ Debt's default risk, seeks to hedge this risk and buys protection from C. C initially holds this net exposure, but then decides to offset and buys protection from D, which offsets the exposure with E, E with F and F with G. Now assuming that G, after the passage of time, wishes to offset this exposure and credit spreads have moved such that A receive a basis spread income from selling protection to G relative to what it pays to B, then A will sell protection to G and thus enable G to offset its exposure to XYZ Debt.

For expositional simplicity, now assume a default event of XYZ Debt that requires the delivery of US$10million in cash or securities within three business days of the default notification. If all of the CDS counterparties that have carried out their various bilateral counterparty risk analysis conclude that their counterparties will fail to pay with a probability of 0.01%, then each of the seven banks could assume a crude counterparty exposure risk of US$10million x 0.01% = US$1,000. However, because of the exposure settlement chain, A in reality faces the risk of the default of not just B, but also C or any other bank in the chain. Thus, the true exposure of A in the chain is 6 approximately US$6,000 (i.e. $US\$10m \times \left[1-(1-0.01\%)^6\right]$). This risk increases as the chain length increases and the systemic risk exposure at default may even exceed the value of

Figure 4: CDS Offsetting: Default Payment Settlement Chain



Notes: The settlement chain starts with bank A buying for example US$10m in credit protection against a default in XYZ Debt from bank B. Bank B then offsets its exposure with A by purchasing credit protection from bank C against XYZ. Bank C latter offsets this exposure with protection purchases from bank D, which likewise buys credit protection from E. This chain continues with bank A selling protection to bank G against the XYZ exposure. Assuming a 0.01% probability that each CDS counterparty fails to pay in the event of XYZ Debt's default, then bank A faces a counterparty exposure risk of US$10m x (1-(1-0.01%)) 6 or US$6,000.

the underlying exposure to XYZ Debt. The localised offsetting of risk common in the interdealer market means the chain is only as strong as its weakest link. Any one of the counterparties' default or refusal to pay will potentially result in a cascading sequence of defaults by others in the chain should they not be sufficiently collateralised to meet payment obligations.

3 Empirical Methodology

3.1 Overview of Multi-Agent Networks

The representation of linkages between agents, be they from the physical sciences, computer sciences, or social sciences and economics, through the mathematics of network analysis or graph theorem is a longstanding tradition in the literature (Barabasi and Albert, 1999; Jackson, 2005; Jackson and Watts, 2002;

Montayo and Sole, 2001; Newman, 2003; Watts, 1999; Watts and Strogatz, 1998). With specific regard to systemic risk in financial networks, Allen and Gale (2001) study the behaviour of the banking system in response to contagion under different network topologies. Allen and Gale and Nier et al. (2007) both argue that sparse networks are less stable than fully connected networks. However, it should be noted that these studies ignore the forced or even strategic behaviour that arises from a failure. For example, a bank that witnesses the loss of CDS cover that it purchased for balance sheet and regulatory capital management will have to shift that exposure elsewhere or repatriate the credit risk and increase its risk capital. By so doing, it may find it is locking in mark-to-market losses as the value of underlying assets decline.

Diamond and Dybvig (1983) use shocks induced by the random exchange of interbank deposits to show that complete networks or a complete structure of claims with greater connectivity between banks improve the financial system's resilience to contagion. Using shocks caused by deposit drawdowns, in which depositors withdraw funds out of fear that the banks will fail due to losses in the interbank market, Freixas et al. (2000) arrive at a similar conclusion. Both studies stipulate that the ability to transfer losses from the failure of any given bank to the portfolios of other banks improves the stability of the network. Increasing network density, the degree of connectivity between individual nodes, has been shown to enhance the stability of financial networks (Dasgupta, 2004; Leitner, 2005; Vivier-Lirimont, 2004). Leitner also shows that allowing internal bailouts improves stability insofar as agents are willing to bail out other agents to prevent wider systemic meltdowns.

Numerous empirical studies have extended the body of theoretical work to measure the resilience of a number of interbank lending markets to systemic risk. Sheldon and Maurer (1998), using maximised entropy to draw out the connections between banks, study the Swiss interbank market. Other interbank markets covered in the literature include the US Fed-funds market (Furfine, 2003); the German interbank market (Memmel and Stein, 2008; Upper and Worms, 2004); the UK market (Well, 2004); the market in Belgium (Degryse and Nguyen, 2004); the Dutch interbank market (Van Lelyveld and Liedrop, 2004); the Italian interbank market (Iori et al., 2005) and the Portuguese interbank lending market (Cocco et al., 2009). More recently, this body of research has been extended to use actual CDS notional data for 26 FDIC insured banks (Markose et al., 2010) and CDS spread data on the largest 43-46 North American and European institutions (Eichengreen et al., 2009; Yang and Zhou, 2010) to identify the extent of interconnectedness in the CDS market. In addition, Yenilmez and Saltoglu (2011) suggest the use of entropy measures as a basis for determining the systemic significance of financial institutions. On the other hand, Markose (2012a) and Markose et al. (2011, 2012b) propose the use of centrality measures in defining a systemic risk tax on super spreaders.

A common feature of these studies has been the characterisation of the financial networks as dense localised clusters with short paths lengths between nodes or agents. Barabasi and Albert (1999) note that these small-world networks show node connectivity, which is highly skewed with fat tails or follows power law distributions. Barabasi and Albert use preferential attachment to obtain the power law statistics by setting node sizes as a function of their existing size or connectivity. In this paper, two network topological constructions of the CDS network are considered: (a) a market share based small-world network[6] and (b) a random graph based network, which randomly draws connections between

[6] A small-world network is a graph in which the majority of nodes are not direct neighbors of one another, but may be reached from every other by a small number of steps. More precisely, a small- world network is defined as a network where the typical distance L (the number of required steps) between two randomly selected nodes grows proportionally to the logarithm of the number of nodes (N) in the network. That is:
$L \propto Log(N)$.

nodes subject to the condition that the total contractual obligations of the banks are consistent with the empirical data.

Furthermore, when considering the market for CDS and appropriate empirical data used in constructing the network of contractual obligations, it is important to note that although the International Swaps and Derivatives Association (ISDA) cautions about the use of gross notional amounts as a measure of risk,[7] the use of gross positive and negative fair value amounts depend on the normal functioning of markets. The normal functioning of markets, by definition, requires that contracts can be exchanged in a current transaction between willing parties, other than in a forced or liquidation sales (Board of Governors of the Federal Reserve System, 2004; International Bank for Reconstruction and Development, 2011, ISDA, 2012; Office of the Comptroller of the Currency, 2012). However, this does not necessarily account for the loss of guarantees in the event of the failure of a guarantor under market-crisis circumstances. O'Kane and Turnbull (2003) distinguish between the transfer of funds in the event of credit events and business-as-usual mark-to-market valuation of CDS contracts. Fair value accounting rules under the International Accounting Standards Board's IAS 39 and its successor the International Financial Reporting Standards Foundation's IFRS 9, simply stipulate that assets be valued at the current cost of replacing existing positions in those assets either using available market prices or an approved valuation model where no market price is readily available. Consequently, fair value accounting for CDS exposures as O'Kane and Turnbull illustrate need only account for ongoing transfers on the premium leg and not the contingent payment of the underlying face value of protection bought or

[7] See "Understanding Notional Amount" on the ISDA CDS Marketplace Market Overview site http://www.isdacdsmarketplace.com/market_overview/understanding_notional_amount (accessed July 2014).

sold. Thus, in an environment in which contracts are not easily replaced, the failure of a protection seller potentially exposes the beneficiary to higher capital charges against the previously insured credit exposures.

Notwithstanding, Pozen (2009), in citing SEC (2008, Exhibit II.4: Percentage of Assets Measured at Fair Value by Industry – As of First Quarter-End), notes that as of the end of 2008Q1, only 31% of bank assets where accounted for on a fair value basis, with the remainder accounted for at historical cost. Furthermore, Avdjiev et al. (2011) illustrate a duality in the reporting of CDS exposures as part of the measure of ―guarantees extended‖ by BIS supervised banks. The authors indicate that BIS consolidated banking statistics entries will generally entail a bank reporting buy-side CDS exposures at gross notional, if that bank holds the underlying security. However, when the bank does not own the underlying security, it is required to report the positive fair value of CDS protection purchased as derivatives exposures against its counterparty. Mindful of this dualism in reporting and the impact of different market conditions on the credit risk exposure of banks, the analysis in this paper uses both gross notional and gross fair value measurements.

3.2 Graph Theoretic Framework for the Multi-Agent CDS Network

As noted, graph theory has proved to be a useful tool to describe contractual relationships within financial networks. Under the graph theoretic framework, a graph $G_t\left(V,E\right)$with N vertices and M edges at time t is comprised of a set of unordered nodes, $V\left(G\right) = \{n_1, n_2, n_3, \ldots, n_{N-1}, n_N\}$ and edges $E\left(G\right) = \{e_1, e_2, e_3, \ldots, e_{M-1}, e_M\}$. If there is an edge $e \in E$ connecting adjacent or neighbour nodes i and j , then e is incident to nodes i and j , which are the endpoints or endvertices of e. Denoting such an edge as $e\left(\overrightarrow{i,j}\right)$indicates that e is a directed edge that transfers a flow from the source i to the sink j. Conversely, $e\left(\overleftarrow{i,j}\right)$ represents a flow from j to i, whilst $e\left(\overleftarrow{i,i}\right)$ represents a flow from i to itself and is called a *loop*; $e\left(\overleftrightarrow{i,j}\right)$ is a multiple edge connecting nodes i and j. A graph consisting of directed edges is referred to as a *directed graph* (digraph), which can be simple if it has no loops or multiple edges, or as a *directed multigraph* if it consists of loops and/or multiple edges. Furthermore, directed edges imply that the order of the nodes matter, and the endpoints are thus ordered pairs. This is in contrast to an undirected graph, which is defined in terms of unordered pairs of nodes where the edge connecting j to i is that same as the edge connecting i to j. Moreover, when each edge has a weight w_{ij}—which may be used to signify the strength or effectiveness of connections between nodes i and j —greater than one, the graph is referred to as a *weighted graph*.

Graphs can also be represented in the mathematical form of a matrix. Thus graph $G_t\left(V, E\right)$can be described as a square N x N adjacency matrix A whose entries $a_{ij}\left(i, j = 1, 2, 3, ..., N-1, N\right)$ are binary observations set to 1 if an edge exists that connects nodes i and j , or 0 otherwise. There are many ways in which to specify the entries of the adjacency matrix and ultimately construct the graph. This can be accomplished using empirical data in which the relationship between nodes is known or by selecting both the nodes and edges between nodes either using known behavioural facts about relationships or a random process. This latter case is referred to as a *random graph*, and such a graph reflects the probability distribution with which it was created.

3.3 Key Network Statistical Measures

The local and global structures of graphs have been characterised by a number of statistical measures, including node degree, the clustering coefficient, path length, density, centrality, and so on. The degree k_i of a node i refers to the number of edges incident to the node and is specified as:

$$k_i = \sum_{j \in V} a_{j,i} \tag{1}$$

and

$$k_i = \sum_{i \in V} k_i \tag{2}$$

is the total degree across all nodes in the graph. The average degree across all nodes in the graph is a measure of the extent to which the graph is connected. Diestel (2005) details methods of identifying connected components of a graph. The density—the extent to which nodes in the network are linked relative to all possible linkages in a complete graph—of the graph can thus be expressed as

$$\Phi^G = \frac{K}{N\,(N-1)} \tag{3}$$

Note that because nodes in a directed graph potentially having multiple ingoing and outgoing edges, it is also possible to define in-degree (k_i^+) and out-degree (k_i^-) distributions for the graph. In a weighted graph, the degree of the each node may be represented in terms of the sum of all neighbouring edge weights; that is, the node strength

$$s_i = \sum_{j \in V} a_{j,i} w_{j,i} \tag{4}$$

The significance of a node within a graph is also captured by its local clustering coefficient. Watts and Strogatz (1998) introduced this measure to determine how close a node's neighbours are to being a clique.[8] That is, the extent to which a subset of nodes, connected to some given node in the graph, are connected. The clustering coefficient measures the tendency for nodes to cluster together in a graph. With respect to weighted graphs, Barrat et al. (2004) specify the local clustering coefficient as

$$c_i = \frac{1}{k_i\left(k_i - 1\right)} \sum_{j,m \in \Xi_i} \frac{1}{\overline{w_i}} \frac{w_{ij} + w_{im}}{2} a_{ij} a_{im} a_{jm} \tag{5}$$

where $\overline{w_i} = \frac{s_i}{k_i} = \sum\limits_{j \in N} \frac{w_{ij}}{k_i}$ is the average weight of edges incident to node i (hence $j, m \in \Xi_i$). It should be noted, however, that a number of variations can be used to compute the clustering coefficient (Rubinov and Sporns, 2010), none of which provide a single general-purpose measure to characterise clustering in weighted complex networks (Saramäki et al., 2007). Nevertheless, the global clustering coefficient is given as

$$C = \frac{1}{N} \sum_{i=1} c_i \tag{6}$$

or in a random graph

$$C^{\Gamma} = p \tag{7}$$

where p is the independent probability of drawing any of the M edges between any two selected nodes.

A further closely related measure assesses the dynamical properties behind net-

[8]A clique of a graph G is a complete subgraph of G. The largest possible clique within G is typically referred to as a maximum clique (Diestel, 2005; Harary, 1994; Watts and Strogatz, 1998).

work interactions. This measure has arisen from research into the stability of interactions within ecosystems. Indeed, the notion of stability—defined as the presence of one or more equilibrium points or limit cycles at which the system remains for at least one complete cycle after recovery when it faces a disturbing force, or to which it returns if perturbed by the force (Connell and Sousa, 1983, p. 790)—has long been the focus of much debate. In the field of ecology, for example, research has considered the relationship between the complexity or diversity of ecological systems and the stability of such systems (Connell and Sousa, 1983; Levin and D'Antonio, 1999).

One of the measures at the centre of this debate is the May-Wigner network stability model (Hastings, 1982; May, 1972, 1973, 1974; Wigner, 1957), which defines the criteria for the probable stability or instability of a system of N linear ordinary differential equations with random coefficients fixed in time, as N increases to infinity.

The May-Wigner network stability condition

$$\sqrt{N\Phi\sigma^2} < 1 \tag{8}$$

is specified across three parameters

- N, the size of the network in terms of the total number of nodes;
- Φ, the density of edge connectivity within the network; and
- σ, the average strength of interactions between the various vertices, which can be approximated as

$$\sigma = \sqrt{\frac{\sum_{i \neq j = 1} \left(a_{ij} - \overline{X}\right)^2}{N-1}} \tag{9}$$

where $\overline{X} = \frac{\sum\limits_{i \neq j=1} a_{ij}}{N}$ is the average connection between nodes. Note that in the May- Wigner model, as it pertains to random graphs, the values of a_{ij} are typically drawn from a statistical distribution with a zero mean and a standard deviation, σ (see, Buckley and Bullock 2007; Buckley et al., 2005; Cohen and Newman, 1985; Ulanowicz, 2001).

The May-Wigner condition shows that the more complex the system of interactions captured in a graph becomes as either N or the network connectivity increases, the more susceptible it becomes to destabilising shocks (May, 1972, 1974). However, the literature has questioned the generality of these results. Counter examples to the May-Wigner conclusions include, but are not limited to, the introduction of features such as trophic levels or hierarchical structures of interaction through spatial blocks (McMurtrie, 1975), tree structures (Hogg, et al., 1989), and multi-patch scaling of boreal forests (Jentsh, et al., 2000). Kao (2010) detailed the cascading of causality between tiers in hieratical structures. The underpinning assumption—that interaction coefficients between spices can usually be described as a random variable fixed in time—behind May's (1972, 1974) conclusions has further been proven false in its generality (Cohen and Newman, 1995).

Sinha (2005) and Sinha and Sinha (2006) nevertheless have shown the universality of the May-Wigner theorem. To this end, Sinha and Sinha posit that instability in one section of a network need not affect other elements of the same network. Thus, even when complexity results in an unstable network (as the May- Wigner theorem states), a non-equilibrium steady state can still exist so that the surviving fraction of the network is able to remain stationary. Instability can result in the extinction of the proportion of species, but will not eliminate all species (Sinha and Sinha, 2006). Consequently, in systems such as financial networks with broker-dealer interactions, connected sets of peripheral nodes should exist so that the cascading contagion effect from the failure of a highly connected node to those that are connected to it at diminishing degrees in the hierarchical structure declines at the peripheries of the network.

In this instance, rather than simply measuring network stability at a global level using the May-Wigner statistic, the centrality of nodes becomes an important measure of network stability. One such centrality measure is the eigenvector centrality, which assigns relative centrality scores to all nodes in a network. The eigenvector centrality scores are defined for nodes in a network based on their systemic significance. The assignment of these scores also relies on the principle that connections to high-scoring nodes contribute more to the score of the node being considered rather than to connections the node has with low-scoring nodes. The eigenvector centrality score for each node, i, in the graph $G_t\left(V,E\right)$ with N vertices captured in the adjacency matrix, $A=\left(a_{ij},t\right)^N$ where at time t, $\left(a_{ij},t\right)=1$ for $i\neq j$ if node i and j are connected, and $\left(a_{ij},t\right)=0$, otherwise is given by the function[9]

$$v_i=\frac{1}{\lambda}\sum_{j\in\Xi_i}v_j=\frac{1}{\lambda}\sum_{j\in N}A_{ij}v_j \tag{10}$$

where Ξ_i, is the set of neighbours of i and λ, is a constant and is the largest real part of the dominant eigenvalue, λ_{max} of matrix A and its associated eigenvector. Equation 10 essentially states that because the connection of node i to nodes that are themselves important makes the node itself more central, the eigenvector centrality of node i is proportional to the average centrality of nodes incident to node i. Rearranging and rewriting 10 in vector notation yields

$$Av=\lambda_{max}v \tag{11}$$

[9]Note $i\neq j$ must hold because it is assumed that there are no self-loops in the graph.

where v is the vector of centralities $v = \{v_1, v_2, \ldots, v_N\}$ and each v_i element of the vector represents the centrality value of the corresponding node. The largest centrality value therefore conveys the node most central to the network. It is noteworthy that despite the multiplicity of eigenvalues, λ, for which an eigenvector solution exists, according the Perron-Frobenius theorem (Meyer, 2000, Chapter 8) the requirement that all elements of the eigenvector of a non-negative matrix A be positive is satisfied only by the dominant eigenvalue λ_{max}. This makes v the principal eigenvector of the adjacency matrix A.

3.4 Topological Construction of the US CDS Network

Representing the CDS market as a network of contractual obligations between participating banks entails mapping the bilateral contracts between any pair of banks. Nevertheless, because of the lack of individual contract–level data, the construction of the CDS network work will attempt to fill out the elements of the associated adjacency matrix using (a) financial institution market shares and (b) a random mapping of contractual obligations between institutions. In both constructions the vertices of the graphs represent financial institutions, and the edges between the nodes represent the bilateral obligations between any two financial institutions.

3.4.1 Topological Construction of the US CDS Network

The initial topological construction of the US CDS network is undertaken using the relative market shares of banks. In constructing the market share – based US CDS network, the assumption is made that there exists at least two factors in financial markets with bilateral trading that create persistent trading relationships, which in turn result in a small world network structure. The first of these factors is, as noted previously, the presence of broker-dealer relationships. The second factor stems from apparent frictions that can result in multi-tiered and discriminatory trading among classes of agents in financial markets. In the literature on asset price determination, these frictions have been documented as including exogenous trading costs (Acharya and Pederson, 2005), endogenous search and bargaining related frictions (Duffie et al., 2005, 2007), and trading delays and inefficiencies arising from agents' bargaining through intermediaries (Gale and Kariv, 2007; Gofman, 2011; Goyal and Vega- Redondo, 2007).

The small-world CDS network is constructed so as to ensure that banks with an empirically large share of buy and sell side exposures receive preference in assigning and weighting contractual linkages. Consequently, the probability of a contract and, thus, an edge existing between banks i and j (where i is the protection seller and j is the protection buyer) will depend on bank i's sell-side market share and j's buy-side market share. Moreover, this market share-based preference in contractual attachments implies that the distribution of directed edges across banks will exhibit a power-law distribution whereby fewer nodes account for a greater number of directed edges.[10] In this instance the resulting network is a member of the multiple classes of scale-free networks.[11]

On this basis, the following adjacency matrix can be defined:

[10]In its most basic form, a power-law distribution is of the form:
$p(x = d; z) = \frac{d^{-z}}{\zeta(z)}$
where $z > 1$ is the power-law parameter and the Rietmann zeta function that acts as a normalising constant is given as $\zeta(z) = \sum_{i=1}^{\infty} \frac{1}{i^z}$. Reed and Hughes (2002) and Clauset et al. (2009) provide a detailed review and real-world applications of power-law distributions.

[11]Amaral, Barthélémy, Stanley (2000) conducted an empirical review of scale-free networks and other classes of small-world networks.

$$
\frac{\left[\begin{array}{ccccc} 0 & a_{ij}w_{ij} & \cdots & \cdots & a_{iN}w_{iN} \\ a_{ji}w_{ji} & 0 & \cdots & \cdots & a_{jN}w_{jN} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ \vdots & \cdots & \cdots & 0 & \vdots \\ a_{Ni}w_{Ni} & a_{Nj}w_{Nj} & \cdots & \cdots & 0 \end{array}\right] \Bigg| \sum_{j\neq i=1}^{N} a_{ij}w_{ij} = \begin{cases} Gr_i \\ Gr_j \\ \vdots \\ \vdots \\ Gr_N \end{cases}}{\sum_{j\neq i=1}^{N} a_{ji}w_{ji} = \{Br_i, Br_j, \cdots, \cdots, Br_N\}} \tag{12}
$$

with the conditions that individual sell-side exposures satisfy

$$
\sum_{j\in \Xi_i^{Gr}} S_j^{Br} Gr_i \leq Gr_i \tag{13}
$$

and individual buy-side exposures satisfy

$$
\sum_{j\in \Xi_i^{Br}} S_j^{Gr} Br_i \leq Br_i \tag{14}
$$

where across the rows of the matrix, $a_{ij}w_{ij} = S_i^{Gr} Br_j$, and along the columns of the matrix, $a_{ji}w_{ji} = S_j^{Gr} Br_i$ for

$S_i^{Gr} = \frac{Gr_i}{\sum_{i=1}^{N} Gr_i}$, the CDS sell-side market share of bank i,

$S_i^{Br} = \frac{Br_i}{\sum_{i=1}^{N} Br_i}$, the CDS buy-side market share of bank i,

Gr_i, the gross notional/negative fair value of contracts for which bank$i$ is guarantor and

Gr_i, the gross notional/positive fair value of contracts for which bank$i$ is beneficiary.

Any residual exposure is sold to or purchased by an external entity, the N^{th} agent. Note that the zeroes along the diagonal indicate that all contractual obligations are made to other agents (see Upper 2007). Banks do not engage in such practices as inter-book or internal trading or any other form of transfer pricing that would mean a bank could have CDS obligations to itself.

3.4.2 Topological Construction of the US CDS Network

The random graph implementation of the US CDS market is based on the Erdős-Rényi (ER) model, which generally refers to any of two related models that Erdős and Rényi (1959, 1960 and 1961) and Gilbert (1959) introduced for the construction of random graphs. Considering a set of random graphs, Γ, with elements $\Gamma_z(\tilde{n}, M)$ that are random graphs consisting of $\tilde{n}$ nodes and a possible M edges, there are $\tilde{n}(\tilde{n}-1)/2$ possible edges with which to connect pairs of nodes. Selecting some subset of these edges produces the random graph $\Gamma_z(\tilde{n}, M)$, which is one of the possible $2^{\tilde{n}(\tilde{n}-1)/2}$ constituents of Γ.

In the Erdős and Rényi (1959) or $G(\tilde{n}, M)$ model each graph $\Gamma_z(\tilde{n}, M)$ of the possible $\left(\begin{array}{c}\left(\begin{array}{c}\tilde{n}\\2\end{array}\right)\\M\end{array}\right)$ graphs is chosen uniformly at random. The Gilbert (1959) or $G(\tilde{n}, p)$ model, on the other hand, choses each graph $\Gamma_z(\tilde{n}, M)$ randomly by drawing edges between pairs of nodes according to some common probability p or by deleting edges between pairs of nodes according to the probability $q = 1 - p$. Erdős and Rényi, (1960, 1961) have shown that both approaches are equivalent. Nevertheless, to maintain a similar level of connectivity to that under the market-share US CDS network topology, the random graph implementation of the US CDS Network follows the Gilbert (1959) model with

$$p = \Phi^{MSN} = \frac{K^{MSN}}{N(N-1)} \tag{15}$$

where K^{MSN} is the total number of directed edges in the market-share network and it is assumed that $N = \tilde{n}$. Each sell-side bank i is accordingly paired with a buy-side bank j with the probability p.

In like manner to the market share–based US CDS market network, the random graph implementation of the US CDS market network is represented in the form of an adjacency matrix. Again, the a_{ij} are binary values that indicate the existence of a contractual obligation between banks i and j. These connections are initially selected as undirected edges, which are then transformed into two directed edges assigned a uniformly distributed probability weighting

$$p\left(e\left(\overrightarrow{i,j}\right)\right) \sim U\left(0,1\right) \tag{16}$$

Consequently, the weighted elements of the random graph adjacency matrix are given by the fraction of total protection sold by all banks as a proportion of the probability weighting of edge $e\left(\overrightarrow{i,j}\right)$ to the total probability weighting off all edges in the random graph. That is,

$$a_{ji}w_{ji} = \frac{p\left(e\left(\overrightarrow{i,j}\right)\right)}{\sum_{i=1}^{N} p\left(e\left(\overrightarrow{i,j}\right)\right)} \sum_{i=1}^{N} Gr_i \tag{17}$$

Moreover, to ensure consistency in the construction of the randomly generated graph over repeated simulation runs, an arbitrary seed value is used. The use of a seed value is consistent with other implementations of the ER model for generating random graphs. For example, the Los Alamos National Laboratory NetworkX Python language software package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks utilises an optional integer seed value as part of the construction of the erdos_renyi_graph(n, p, seed, directed) method.

3.5 Topological Construction of the US CDS Network

Given the topological construction of the US CDS market network, further analysis is conducted to quantitatively capture the systemic impact of the failure of each of the financial institutions within the network. This is accomplished with the sequential round-by-round algorithm that Furfine (2003) described. Starting with the failure of the trigger bank, assuming contractual tear ups and some recovery rate, γ, on the trigger bank's liabilities, subsequent banks j in the first round of contagion, are assumed to fail if their direct bilateral net loss from CDS exposures to the trigger bank exceeds some percentage threshold, ε, of the bank's of Tier 1 Capital. In keeping with the topologically constructed adjacency matrix, the financial failure condition is given by

$$(\gamma a_{ij} w_{ij} - a_{ji} w_{ji}) > \varepsilon \Pi_j \tag{18}$$

where $j \in D^Q$ is the set of defaulting banks at round Q of the contagion process.

It follows from this that in later rounds of contagion associated with the trigger bank's demise, further banks will subsequently fail if the total bilateral losses for a bank $m \notin D^Q$that has not failed at round Q, defined as the sum of their losses suffered through contractual linkages with both the trigger bank and those banks that failed in preceding rounds, exceeds bank m's sustainable loss. That is,

$$\left[(\gamma a_{ij} w_{ij} - a_{ji} w_{ji}) + \sum_{j \in D^Q} (\gamma a_{jm} w_{jm} - a_{mj} w_{mj}) \right] > \varepsilon \Pi_j \tag{19}$$

Put more generally, for each subsequent iteration, Q, such that m remains solvent until Q, default occurs if losses due to direct exposures to the set of defaulted banks and the trigger bank exceeds bank m's remaining sustainable loss. That is,

$$\left[(\gamma a_{im} w_{im} - a_{mi} w_{mi}) + \sum_{j \in \bigcup\limits_{r=1}^{Q-1} D^r} (\gamma a_{jm} w_{jm} - a_{mj} w_{mj})\right] > \varepsilon \Pi_m \qquad (20)$$

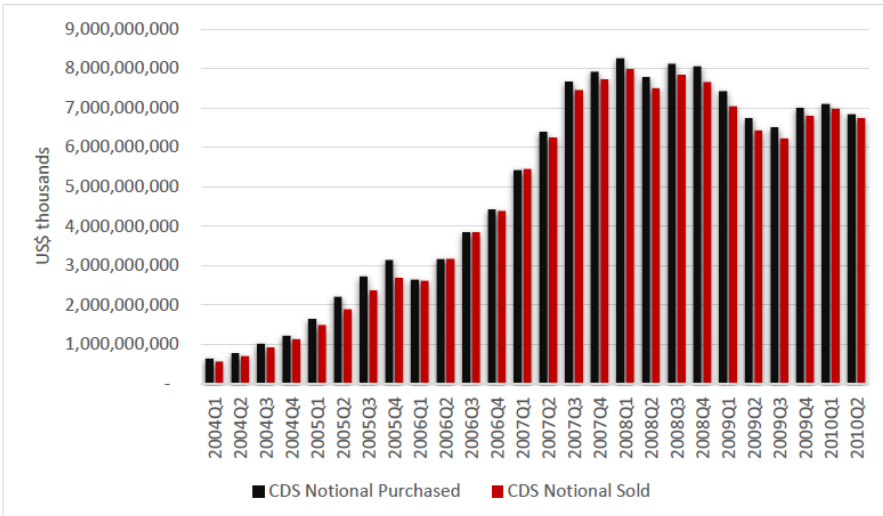
where $m \notin \left\{\bigcup D^1, \bigcup D^2, \ldots, \bigcup D^{Q-1}\right\}$and $\bigcup\limits_{r=1}^{Q-1} D^r$ is the set of defaulting banks between rounds 1 and $Q-1$ inclusive. The contagion process ends where there are either no surviving banks or none of those that have survived fail at round $Q+1$.

4 Data

The data are taken from the BIS data repository and the FDIC for the three time periods 2004Q1, 2006Q4 and 2007Q4. The FDIC data are publically available and can be found in the quarterly thrift and call reports that each FDIC-insured bank in the US submits. The BIS data provide a semi-annual overview of the global derivatives markets. The BIS data are used as a basis of inferring the buy and sell exposures of monolines such as insurance companies. Specifically, for the three time periods, monoline buy and sell side exposures are derived based on their global market share as of 2006Q4 and the fraction of the total CDS exposures globally accounted for by the participating US banks in the analysis periods.

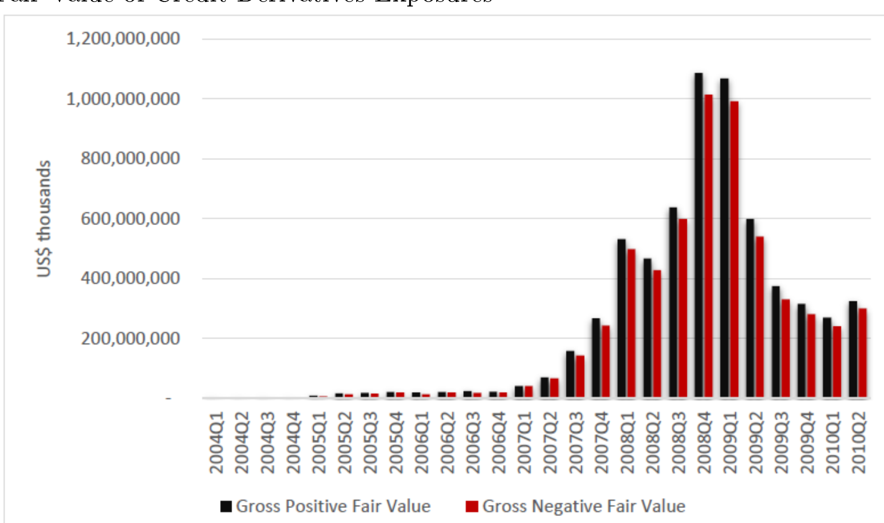
Figures 5 to 9 chart the CDS participation as well as Tier 1 capital data from the FDIC reports. As Figure 5 shows, the period between 2004Q3 and 2007Q4

Figure 5: FDIC Insured Banks CDS Market Participation: Gross Notional CDS Credit Protection Bought and Sold



Note: The data are taken from the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969).

Figure 6: FDIC Insured Banks Credit Derivatives Market Participation: Gross Fair Value of Credit Derivatives Exposures



Note: The data are taken from the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7b.1 "Credit derivatives: Gross fair values" (RC-codes: Gross negative fair value, RCONC220; Gross positive fair value, RCONC221).

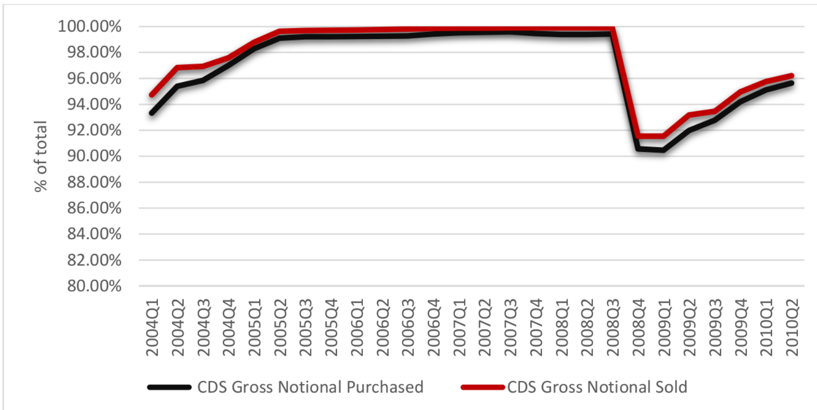
witnessed a significant rise in the use of credit derivatives and, in particular, CDS by the FDIC-insured banks. Much of this growth occurred between 2006Q1 and 2007Q4, at the height of the subprime mortgage bubble. By 2008Q1 CDS gross notional outstanding buy and sell side positions had peaked at US$8.26tn and US$7.98tn respectively before progressively declining until 2009Q2.

Over the same period gross notional positive and gross notional negative fair values, which respectively represent the maximum possible net derivatives receivables and derivatives payables between net sellers of protection and net buyers of protection that could be required upon the occurrence of a credit event, also increase, peaking at US$1.08tn and US$1.01tn. However, unlike the exposures at gross notional, exposures at fair value witness two periods of sharp increases between 2007Q2 to 2008Q1 and 2008Q2 to 2008Q4. Note that with gross notional exposures having peaked by 2008Q1, the second period of sharp growth in gross fair value stems in part from the very high credit spreads and potential of uncancelled liabilities or unhedged exposures at gross notional level during the financial crisis of 2008-2009 following the subprime mortgage crisis of 2006-2007.

At individual bank level, the pool of banks reporting gross notional exposures is, in some cases, larger than those reporting at gross fair value. This is in part a result of the mark-to-market nature of the fair value amounts versus the historical value nature of gross notional amounts. For instance, in 2004Q1 Morgan Stanley reported US$0.01bn in gross notional sales of CDS protection. However, at gross fair value, either the bank deemed that these positions had no discernable market value, or they were simply not reported at fair value.

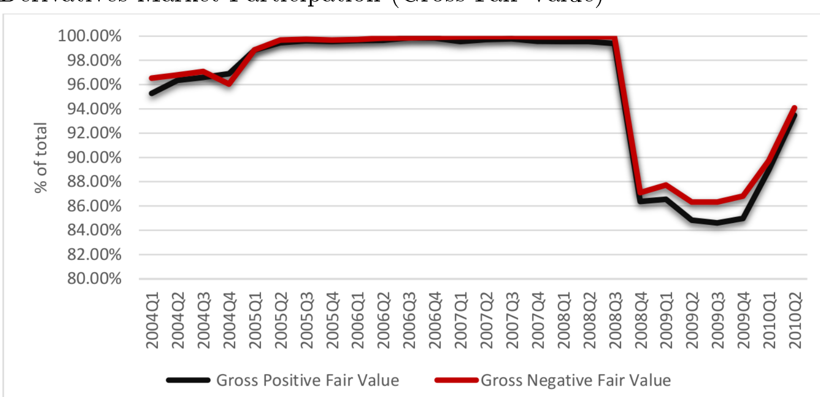
Moreover, the data show that the Top 5 US banks according to total gross notional participation in the CDS market between 2004 and 2007 (Bank of America, Citibank, HSBC, JPMorgan and Wachovia) consistently accounted

Figure 7: Top 5 Banks as Percentage of Total FDIC Insured Banks CDS Market Participation (Gross Notional)



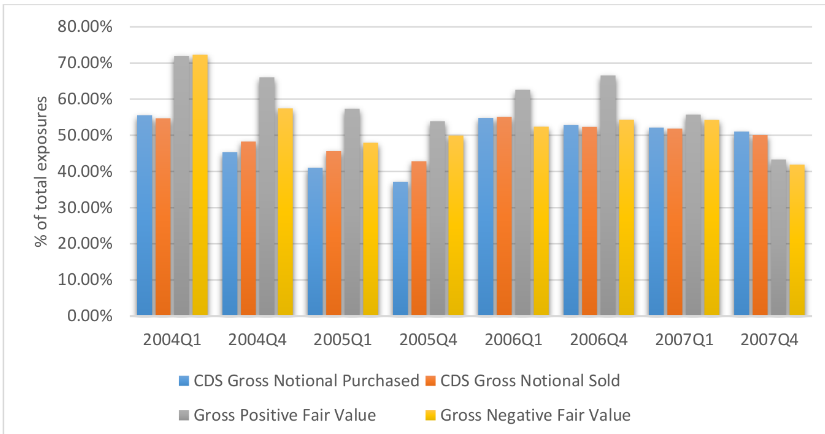
Note: (1) Top 5 refers to the five FDIC-insured US banks with the largest gross notional in CDS contracts between 2004Q1 and 2007Q4 as reported in the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969). These banks are Bank of America, Citibank, HSBC, JPMorgan and Wachovia. (2) The trend in the data from 2008Q4 onwards is accounted for by a substantial expansion of exposures reported by Goldman Sachs.

Figure 8: Top 5 Banks as Percentage of Total FDIC Insured Banks Credit Derivatives Market Participation (Gross Fair Value)



Note: (1) Top 5 refers to the five FDIC-insured US banks with the largest gross notional in CDS contracts between 2004Q1 and 2007Q4 as reported in the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969). These banks are, Bank of America, Citibank, HSBC, JPMorgan, and Wachovia. (2) This chart is based on data listed in item 7b.1 "Credit derivatives: Gross fair values" (RC-codes: Gross negative fair value, RCONC220; Gross positive fair value, RCONC221). (3) The trend in the data from 2008Q4 onwards is accounted for by a substantial expansion of exposures reported by Goldman Sachs.

Figure 9: Credit Derivatives Exposures of JPMorgan Chase as a Proportion of Total Credit Derivatives Exposures of the Top 5 FDIC Insured Banks (2004Q1 to 2007Q4)



Note: (1) Top 5 refers to the five FDIC-insured US banks with the largest gross notional in CDS contracts between 2004Q1 and 2007Q4 as reported in the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969). These banks are Bank of America, Citibank, HSBC, JPMorgan, and Wachovia. (2) Gross fair value data are taken as listed in item 7b.1 "Credit derivatives: Gross fair values" (RC-codes: Gross negative fair value, RCONC220; Gross positive fair value, RCONC221).

for over 92% and averaged 99% of the FDIC-insured US banks' buy and sell CDS exposures in terms of both gross notional and gross fair values. Of these, JPMorgan Chase consistently ranked as having the largest credit derivatives exposures in terms of both CDS gross notional and credit derivatives gross fair values. Indeed, between 2004Q1 and 2007Q4 JPMorgan had expanded its CDS gross notional exposures on both buy and sell sides from US$330.06bn and US$292.79bn to US$4.02tn and US$3.86tn respectively. Likewise JPMorgan's credit derivatives gross positive fair value rose from US$2.94bn to US$115.15bn, whilst credit derivatives exposures reported at gross negative fair value grew from US$1.71bn to US$101.76bn.

It is worth noting that between 2004Q1 and 2007Q4 JPMorgan accounted for over 42% of the credit derivatives market participation by the Top 5 FDIC-insured US banks. Reported at gross notional, JPMorgan averaged 50% of both buy and sell side exposures of the Top 5. At gross fair value, the bank's exposures progressively declined from 72% of the total exposure of the top five in 2004Q1; however, as of year-end 2007, both the gross positive and gross negative fair value exposures of JPMorgan still averaged 43% of the credit derivatives exposures of the Top 5 banks.

With regards to the Tier 1 capital holdings, the data show that FDIC-insured US banks continued to expand their capital base. However, the increase in capital holdings is betrayed by information gleaned from a comparison of this capital with sell-side credit derivatives exposures. In particular, gross negative fair value exposures increase sharply as a proportion of Tier 1 capital. Having started as low as under 1% of Tier 1 capital, credit derivatives measured at gross negative fair value as a proportion of Tier 1 capital began to spiral upwards from 2004Q4, reaching as much as 190% of Tier 1 capital by 2008Q4. Looking only at the period between 2004Q4 and 2007Q4, Table 1 breaks down this growth in the relative size of gross negative fair value exposures compared to Tier 1 capital. Table 6.1 shows that the primary drivers for the observed rise in credit derivatives measured at gross negative fair value as a proportion of Tier 1 capital were the Top 5 banks. Certainly, for the non-Top 5 banks, credit derivatives exposures measured at gross negative fair value accounted for only 0.12% of Tier 1 capital as of year-end 2007. By contrast, having accounted for 1.13% of Tier 1 capital at the end of 2004, credit derivatives exposures of the Top 5 US banks measured at gross negative fair value had come to represent a staggering 85% of their Tier 1 capital by 2007Q4.

Table 1: Credit Derivatives Exposures and Tier 1 Capital 2004Q to 2007Q4 (US$ billions)

Banks	Call Report Item	2004Q4	2005Q4	2006Q4	2007Q4
Top 5 Banks	Tier 1 capital	175.84	213.61	248.02	285.96
	CDS gross notional purchased	1,183.03	3,116.53	4,392.48	7,877.14
	CDS gross notional sold	1,099.97	2,673.45	4,382.76	7,715.06
	Gross positive fair value	3.47	21.56	22.45	266.05
	Gross negative fair value	1.99	19.15	18.88	243.19
	Gross negative fair value as percentage of capital	1.13%	8.96%	7.61%	85.04%
Other Banks	Tier 1 capital	116.15	116.61	133.19	133.88
	CDS gross notional purchased	36.59	24.40	25.41	41.93
	CDS gross notional sold	22.47	2.25	2.31	3.77
	Gross positive fair value	0.11	0.10	0.04	1.15
	Gross negative fair value	0.08	0.06	0.02	0.16
	Gross negative fair value as percentage of capital	0.07%	0.05%	0.02%	0.12%
All Banks	Tier 1 capital	341.66	383.14	440.85	482.36
	CDS gross notional purchased	1,219.62	3,140.94	4,417.89	7,919.07
	CDS gross notional sold	1,127.11	2,681.08	4,389.02	7,723.03
	Gross positive fair value	3.58	21.65	22.49	267.20
	Gross negative fair value	2.07	19.21	18.90	243.35
	Gross negative fair value as percentage of capital	0.61%	5.01%	4.29%	50.45%

Note: (1) Top 5 refers to the five FDIC-insured US banks with the largest gross notional in CDS contracts between 2004Q1 and 2007Q4 as reported in the FDIC Call Report Schedule RC-L – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969). These banks are Bank of America, Citibank, HSBC, JPMorgan, and Wachovia. (2) Gross fair value data are taken as listed in item 7b.1 "Credit derivatives: Gross fair values" (RC-codes: Gross negative fair value, RCONC220; Gross positive fair value, RCONC221). (3) Tier 1 Capital data are taken as reported in the FDIC Call Report Schedule RC-R – Derivatives and Off-Balance Sheet Items Item 7a.1 "Credit derivatives: Notional amounts, Credit default swaps" (RC-codes: Guarantor, RCFDC968/RCONC968; Beneficiary, RCFDC969/RCONC969).

It should nevertheless be noted that under normal market conditions and where legally enforceable bilateral netting agreements exist, exposures with negative fair values can be used to offset contracts with positive fair values. The resulting net current credit exposure (NCCE)—the greater of the sum of all mark-to-market values (both positive and negative) of the individual transactions subject to bilateral netting agreement or zero—across all counterparties will therefore influence the amount of capital held. This is because regulators such as the OCC utilise the NCCE as a primary metric when they evaluate the credit risk associated with banks' derivatives exposures.

5 Results

Experiments are conducted with both gross notional and gross fair values. The former are used to identify potential losses when the failure of the trigger bank results in unmet contractual obligations on the reference entity on which the CDS protection is taken, and those obligations cannot be transferred. Gross fair values are used to signify the losses incurred on credit derivatives when a counterparty fails to meet market value cash flow obligations; however, CDS contracts can be easily replaced. Furthermore, experiments are conducted assuming 0% and 50% recovery rates on failed banks' contractual liabilities. Because the objective of this research is to determine whether regulatory rules that encourage the use of credit derivatives had an influence on the structure of this market over time, snapshots of the US CDS network described in section 3 above are assessed at three distinct periods, 2004Q4, 2006Q4 and 2007Q4.

5.1 Network Characteristics

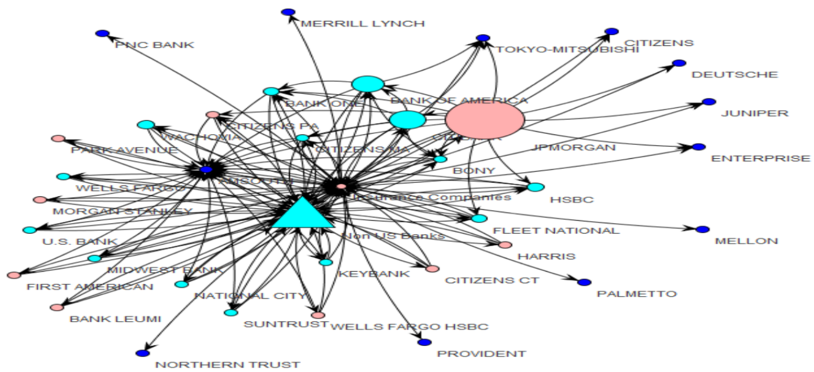
The US CDS networks under the market share and random graph topological constructs for each of the three periods using both gross notional and gross fair values are visually depicted in Figures 6.10 and 6.13 using a spatial radial tree layout—a means of locating nodes on a graph such that the root node is placed at the center of the graph and the child-nodes are located in a circular fashion around the root. In all four figures, banks that operate exclusively as CDS buyers are represented by the vertices coloured in dark blue. Net CDS buyers are identified by the light blue nodes. Exclusive CDS protection sellers are represented in dark red, and net protection sellers are highlighted in light pink. Net neutral entities—that is, those with equal buy and sell side exposures—are marked white, whereas the black nodes depict the defaulted banks. Grey nodes represent banks that, although solvent, are unconnected to other banks in the network.

Furthermore, banks and insurance companies are represented as the circular nodes, whereas the outside entity or non-US bank entity used to capture all residual buy and sell side exposures is depicted as the triangular node. FDIC-insured US banks are further identified by their empirical market share. Consequently, the size of the node representing each participating bank is correlated to the relative market share of that bank's buy and sell side exposures.

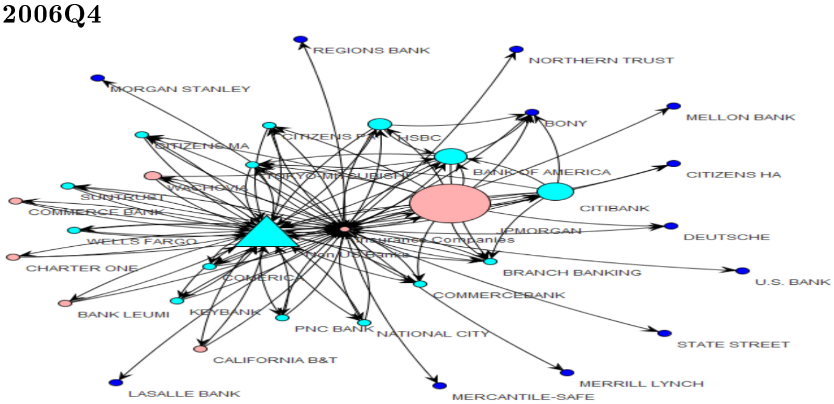
Note that under the market-share construction of the US CDS network, using gross notional values, JPMorgan is a net protection seller in all three periods. By contrast, using gross fair values, JPMorgan is a net protection buyer during 2004Q1, butit becomes a net protection seller in 2006Q4 and 2007Q4. Furthermore, unlike the market-share construction, which is governed by the empirical data, the random graph construction merely takes the aggregated sell-side exposures and randomly distributes them between the banks. Consequently, protection buyers such as Merrill Lynch in 2004Q1 under the empirical data – derived market-share network become protection sellers. Similarly, protections sellers such as JPMorgan in the 2006Q4 market-share network become protection buyers under the random graph construction of the US CDS network. Finally, the insurance companies appear as the root node in the market- share networks as a result of the approximation from the global CDS market data.

Figure 10: Market Share Constructed CDS Network (CDS Gross Notional) 2004Q1, 2006Q4 and 2007Q4

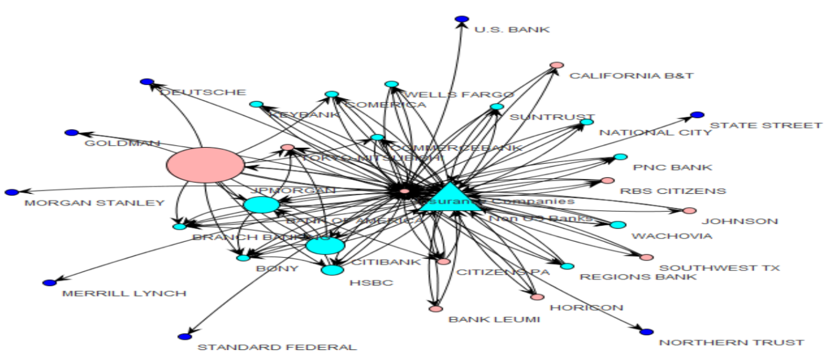
2004Q1



2006Q4



2007Q4

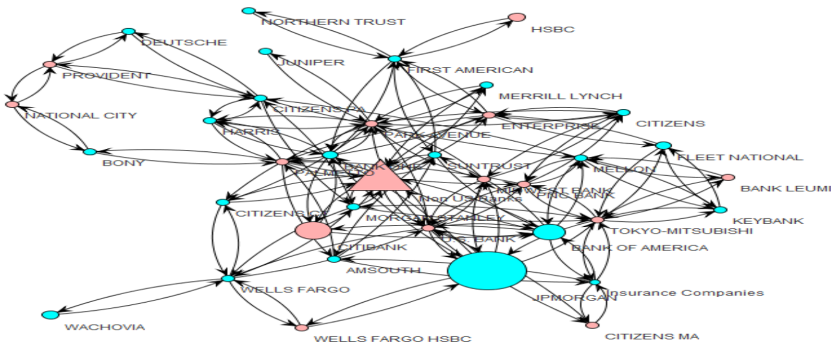


Key: *Pure Protection Seller* *Net Protection Seller* *Pure Protection Buyer* *Net Protection Buyer* *Defaulted*

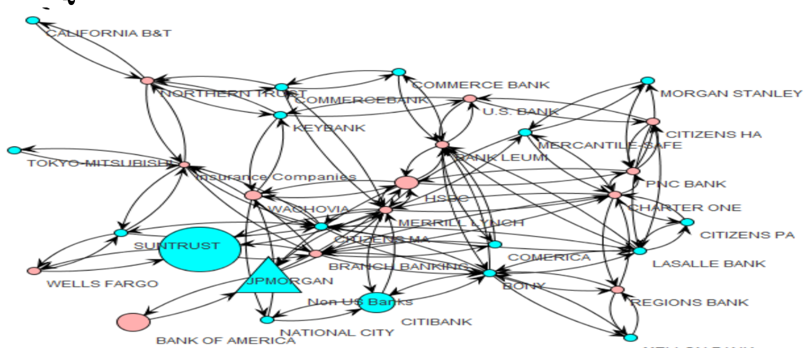
Notes: (1) The empirically constructed market share CDS network (gross notional) for US banks and non-US bank financial intermediaries (the triangle): Using the spatial radial tree layout (top: 2004Q1; middle: 2006Q4; bottom: 2007Q4). (2) Weights are assigned according to empirically observed CDS market share on both buy and sell side. (3) Node sizes are determined by empirical market-share data.

Figure 11: Erdős-Rényi Random Graph Construction of the US CDS Network (CDS Gross Notional) 2004Q1, 2006Q4 and 2007Q4

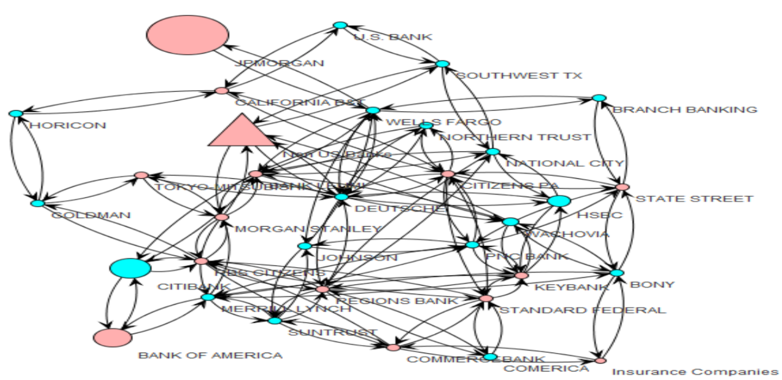
2004Q1



2006Q4



2007Q4

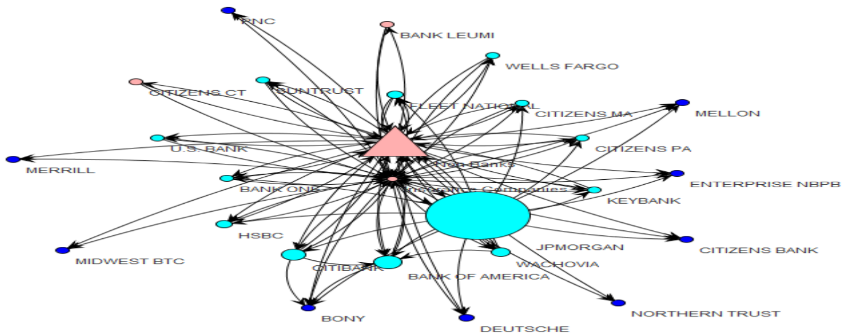


Key: *Pure Protection Seller* *Net Protection Seller* *Pure Protection Buyer* *Net Protection Buyer* *Defaulted*

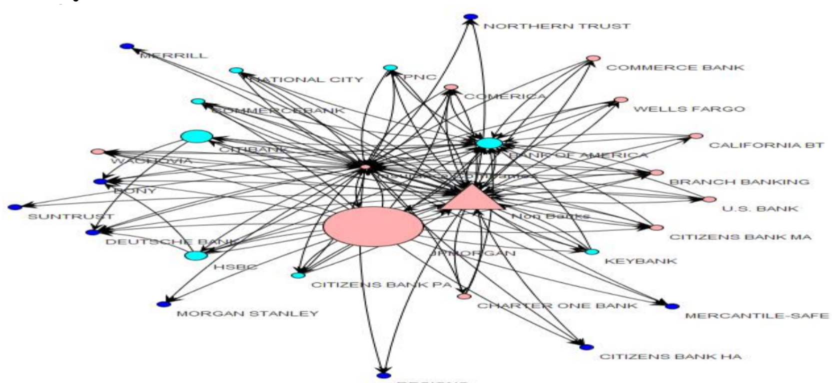
Notes: (1) The Erdős-Rényi random graph CDS network (gross notional) for insured US banks, insurance companies, and non-US bank or outside entity (the triangle): Using the spatial radial tree layout (top: 2004Q1; middle: 2006Q4; bottom: 2007Q4). (2) Weights are assigned according to a uniform random distribution (with a seed value of 77) of the total empirically observed CDS gross notional sold. (3) Node sizes are determined by empirical market-share data.

Figure 12: Market Share Constructed CDS Network (Credit Derivatives Gross Fair Value) 2004Q1, 2006Q4 and 2007Q4

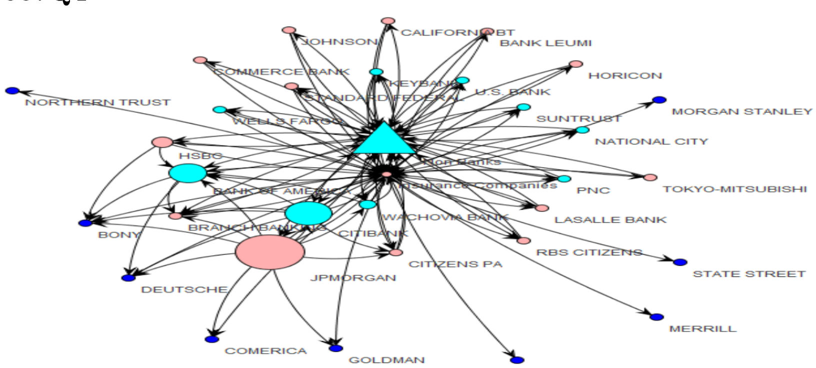
2004Q1



2006Q4



2007Q4

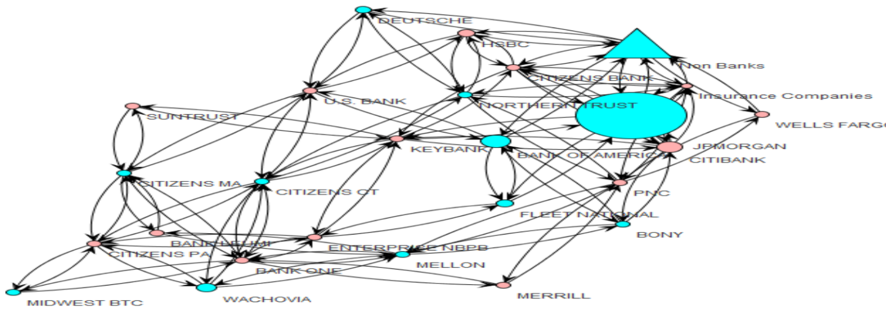


Key: *Pure Protection Seller* *Net Protection Seller* *Pure Protection Buyer* *Net Protection Buyer* *Defaulted*

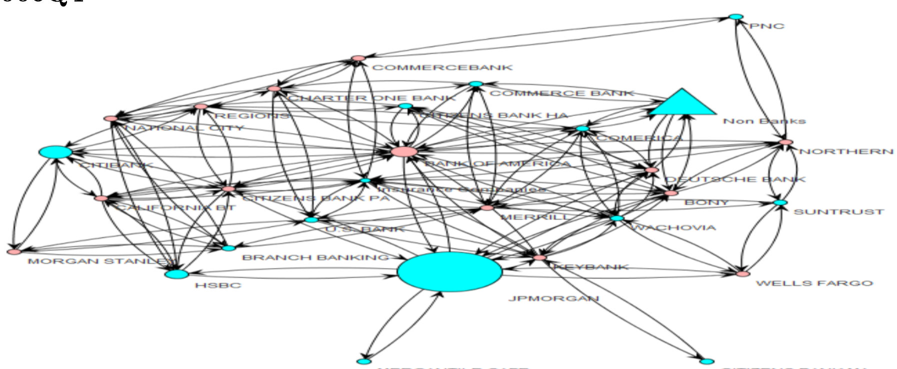
Notes: (1) The empirically constructed market share CDS network (gross notional) for US banks and non-US bank financial intermediaries (the triangle): Using the spatial radial tree layout (top: 2004Q1; middle: 2006Q4; bottom: 2007Q4). (2) Weights are assigned according to empirically observed credit derivatives gross fair value market share (positive and negative). (3) Node sizes are determined by empirical market-share data.

Figure 13: Erdős-Rényi Random Graph Construction of the US CDS Network (Credit Derivatives Gross Fair Value) 2004Q1, 2006Q4 and 2007Q4

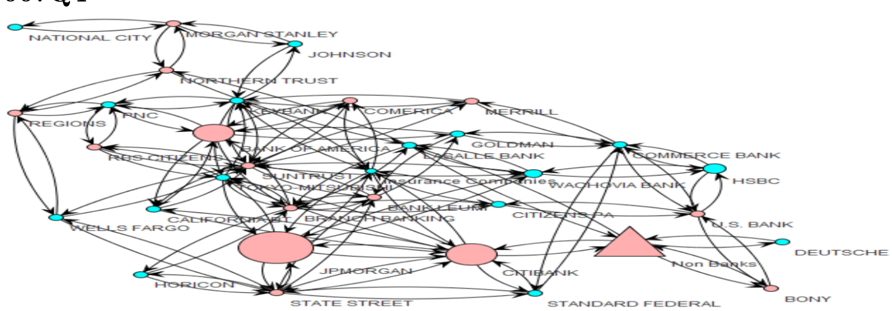
2004Q1



2006Q4



2007Q4



Key: Pure Protection Seller Net Protection Seller Pure Protection Buyer Net Protection Buyer Defaulted

Notes: (1) The Erdős-Rényi random graph CDS network (gross notional) for insured US banks, insurance companies, and non-US bank or outside entity (the triangle): Using the spatial radial tree layout (top: 2004Q1; middle: 2006Q4; bottom: 2007Q4). (2) Weights are assigned according to a uniform random distribution (with a seed value of 77) of the total empirically observed credit derivatives gross negative fair value. (3) Node sizes are determined by empirical market- share data.

The results reflected in Tables 2 to 7 are derived from simulating the failure of each entity in the US CDS network. The results from the gross notional value based network assuming 0% recovery are listed in Tables 2 and 3 for the market-share network and random graph, respectively. In Table 4 the simulated results from the empirical market share–derived network are collated, assuming 50% recovery on contractual liabilities of the defaulting bank. Similarly, Tables 5 lists simulation results based on the gross fair value constructed market-share network under the assumption of 0% recovery rates. Tables 6 and 7, conversely, assume a 50% recovery rate on liabilities at gross fair value for both empirical market share and random graph topological constructions of the US CDS network.

The results from the simulations are as follows: Firstly, with respect to the market-share networks, the positive skewness of between 2.9 and 3.3 combined with the large positive kurtosis (leptokurtic) measuring between 7.97 and 11.76, depending on the trading data used, indicates that the degree distribution has a high peakedness relative to the normal distribution and that the mass of the distribution is concentrated on the left tail (i.e., longer right tail). This is consistent with the existence power laws reported in small-world networks in which, as in this instance, a few banks have a large number of buy-side and sell-side connections to other banks. Moreover, given a critical value of 0.1 as prescribed by Clauset et al (2009, p.3 and 17), the test statistic listed in the tables indicate that there is statistically significant evidence that the possibility of power laws in the CDS network data cannot be rejected. Thus, persistent trading relationships such as broker-dealer relationships and discriminatory trading among a few large players imply a hierarchical structure. By contrast, the recorded moderate kurtosis and skewness under the ER random graph constructed US CDS networks are consistent with the probability distribution used to derive contractual obligations among the banks. Certainly, under the 2004Q1 US CDS network constructed as a random graph, the skewness of -0.2 to 0.79 and kurtosis of -0.38 to 1.24 suggest a degree distribution with a shape fairly similar to a uniform distribution. Consequently, there is limited evidence of hierarchical structures in trading relationships in the construction of the US CDS network as an ER random graph.

The second observation from the simulations across all three time periods is that the clustering coefficient is larger in the market-share construction of the US CDS network than in the ER random graph network topology. This difference is significantly higher when data that pertain to the gross fair value of credit derivatives exposures are used. Furthermore, although the market-share networks exhibit greater clustering, the progression of this clustering over time differs depending on the data used to construct the US CDS network. Measuring exposures at gross notional suggests that the clustering coefficient increased year-on-year (the clustering coefficient of 0.21 witnessed in the 2004Q1 simulation compared to 0.23 and 0.24 in 2006Q4 and 2007Q4, respectively) as regulations fostering the escalating use of CDS became entrenched. Conversely, when exposures are measured at gross fair value, the clustering coefficient was to observed spike to 0.50 in 2006Q4; however, in both 2004Q4 and 2007Q4 the clustering coefficient was 0.26.

The variance-to-mean ratios, which characterise the distribution of contractual obligations between the agents in terms of how dispersed or clustered these contractual obligations are compared to a standard statistical model, do, however, suggest a large degree of clustering. Moreover, this clustering with regard to the market-share network topology is relatively greater in 2006Q4 and 2007Q4 using the gross fair value of exposures. This is not as clear when the gross notional

Table 2: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Notional based Market Share Network)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.55	5.36	3.33	11.76	8.10	0.22	30.23	0.24	0.141	-112.87	-1389.22	25.19%	10.03%
	Out-Degrees (CDS Sellers)	3.55	6.06	2.98	9.49	10.36								
2006Q4	In-Degrees (CDS Buyers)	3.29	4.62	3.26	11.46	6.49	0.20	27.09	0.23	0.177	-65.31	-797.50	15.36%	10.2%
	Out-Degrees (CDS Sellers)	3.29	6.08	3.06	10.52	11.21								
2004Q1	In-Degrees (CDS Buyers)	3.84	6.09	2.90	7.97	9.66	0.21	31.42	0.21	0.047	-14.58	-82.27	4.87%%	7.60%
	Out-Degrees (CDS Sellers)	3.84	6.14	2.96	9.68	9.81								

Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 0\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})$ % of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

Table 3: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Notional based Erdős-Rényi Random Graph Network with a Seed Value of 77)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.81	1.46	0.21	-0.71	0.56	0.24	8.23	0.01	0.332	-1215.44	-10866.77	271.21%	78.47%
	Out-Degrees (CDS Sellers)	3.81	1.46	0.21	-0.71	0.56								
2006Q4	In-Degrees (CDS Buyers)	3.29	1.87	0.49	-0.02	1.08	0.20	9.83	0.02	0.168	-654.03	-4323.00	153.85%	55.2%
	Out-Degrees (CDS Sellers)	3.29	1.87	0.49	-0.02	1.08								
2004Q1	In-Degrees (CDS Buyers)	3.89	2.17	0.79	0.38	1.21	0.22	11.66	0.04	0.232	-54.70	-387.28	18.29%	35.75%
	Out-Degrees (CDS Sellers)	3.89	2.17	0.79	0.38	1.21								

Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 0\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})\,\%$ of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

Table 4: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Notional based Market Share Network Assuming 50% Recovery)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.29	5.18	3.53	12.28	8.21	0.22	30.23	0.24	0.141	-63.60	-1389.20	14.19%	10.03%
	Out-Degrees (CDS Sellers)	3.29	5.84	3.21	10.38	10.38								
2006Q4	In-Degrees (CDS Buyers)	3.07	4.48	3.46	11.99	6.59	0.20	27.09	0.23	0.177	-38.88	-736.64	9.15%	9.40%
	Out-Degrees (CDS Sellers)	3.07	5.84	3.29	11.29	11.17								
2004Q1	In-Degrees (CDS Buyers)	3.59	5.88	3.06	8.28	9.68	0.21	31.42	0.21	0.047	-12.19	-81.34	4.08%	7.50%
	Out-Degrees (CDS Sellers)	3.59	5.92	3.13	10.09	9.77								

Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 50\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})$ % of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

Table 5: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Fair Value based Market Share Network)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.42	5.13	3.32	11.70	7.70	0.21	28.40	0.26	0.207	-18.80	-37.02	4.20%	8.13%
	Out-Degrees (CDS Sellers)	3.42	5.79	2.98	9.68	9.79								
2006Q4	In-Degrees (CDS Buyers)	4.35	5.11	2.38	5.08	6.00	0.31	32.85	0.50	0.069	-14.16	-1.98	3.67%	5.15%
	Out-Degrees (CDS Sellers)	4.35	6.75	2.57	6.93	10.48								
2004Q1	In-Degrees (CDS Buyers)	3.69	3.67	2.85	8.59	3.64	0.30	27.45	0.26	0.323	-10.17	-0.32	4.01%	4.00%
	Out-Degrees (CDS Sellers)	3.69	6.60	2.44	5.75	11.81								

Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 0\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})\,\%$ of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

Table 6: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Fair Value based Erdős-Rényi Random Graph Network with a Seed Value of 77 Assuming 50% Recovery Network)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.82	1.59	0.57	0.35	0.66	0.24	8.90	0.01	0.371	-17.38	-58.87	3.88%	12.87%
	Out-Degrees (CDS Sellers)	3.82	1.59	0.57	0.35	0.66								
2006Q4	In-Degrees (CDS Buyers)	5.10	2.31	0.99	3.59	1.05	0.36	15.02	0.04	0.017	-14.02	-3.68	3.63%	12.87%
	Out-Degrees (CDS Sellers)	5.10	2.31	0.99	3.59	1.05								
2004Q1	In-Degrees (CDS Buyers)	4.31	1.54	-0.21	-1.24	0.55	0.35	9.21	0.03	0.000	-10.17	-0.65	4.02%	10.10%
	Out-Degrees (CDS Sellers)	4.31	1.54	-0.21	-1.24	0.55								

Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 50\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})\,\%$ of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

Table 7: Systemic Risk Simulation Results and Network Statistics for 2004Q1, 2006Q4 and 2007Q4 (Gross Fair Value based Market Share Network Assuming 50% Recovery)

		Mean	Standard Deviation	Skew	Kurtosis	Variance to Mean Ratio	Connectivity	May-Wigner Stability	Weighted Clustering Coefficient	Power-Law p-value	Average Total Capital Loss (US$ Billions)	Average Total Loss of CDS Gross Notional (US$ Billions)	Average Loss of Total Core Capital (%)	Average Loss of CDS Cover (%)
2007Q4	In-Degrees (CDS Buyers)	3.42	5.13	3.32	11.70	7.70	0.21	28.40	0.26	0.207	-15.60	-18.62	3.48%	4.10%
	Out-Degrees (CDS Sellers)	3.42	5.79	2.98	9.68	9.79								
2006Q4	In-Degrees (CDS Buyers)	4.35	5.11	2.38	5.08	6.00	0.31	32.85	0.50	0.069	-13.91	-1.73	3.60%	4.50%
	Out-Degrees (CDS Sellers)	4.35	6.75	2.57	6.93	10.48								
2004Q1	In-Degrees (CDS Buyers)	3.69	3.67	2.85	8.59	3.64	0.30	27.45	0.26	0.323	-10.15	-1.73	4.01%	4.00%
	Out-Degrees (CDS Sellers)	3.69	6.60	2.44	5.75	11.81								

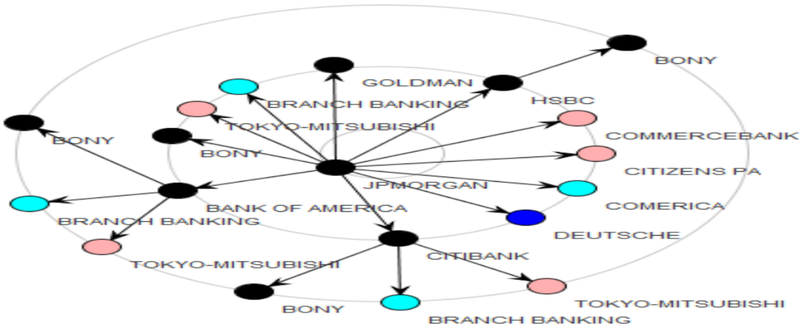
Notes: (1) The statistics recorded in the table are the average across all banks based on the simulated default or failure of each of the banks participating in the CDS network in the specified time period. (2) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital and a recovery rate on defaulting bank liabilities$\gamma = 50\%$. (3) All network statistics are reported at contagion round$Q = 0$, whereas contagion effects are reported at contagion round $Q = 10$, (4) Each snapshot of the US CDS network consists of the following number $(N = \tilde{n})\,\%$ of entities: 2004Q1, $N = 37$; 2006Q4, $N = 34$; 2007Q4, $N = 33$ (5) Power-Law p-values are derived from the sum of in and out degrees associated with each bank and computed using the on the Peter Bloem Java Package implementation of Clauset et al. (2009) for discrete data and critical value of 0.1 and 10000 trials (https://github.com/Data2Semantics/powerlaws/)

value of exposures are used. Although the degree of clustering in relation to protection selling does increases between 2004Q1 and 2007Q4, there is a decline on the protection buying side. The ER random graph network topology, by contrast, with variance-to-mean ratios ranging from 0.55 to 1.21, shows little evidence of clustering using either gross notional or gross fair values.

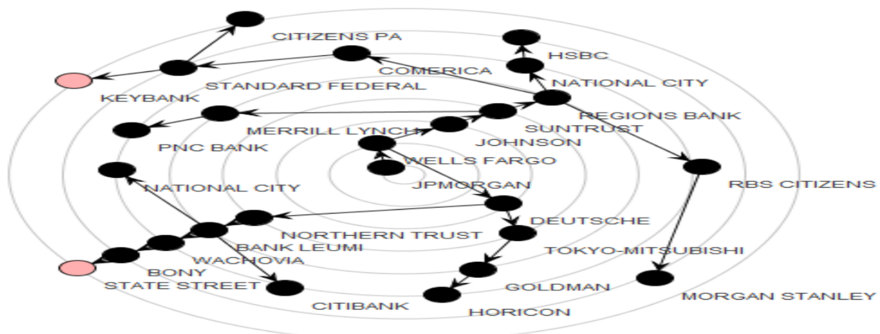
Finally, the last four columns of Tables 2 to 7 relate to the systemwide average losses of core capital and protection cover for the entire network upon the triggered failure of each of the financial entities, assuming a sustainable loss threshold of $\varepsilon = 20\%$ and liability recovery rates of $\gamma = 0\%$ and $\gamma = 50\%$. Comparing the topological constructions, the ER random graph framework results in more widespread losses across the simulated US CDS network. Measuring exposures at gross notional shows that the random graph gives rise to Tier 1 capital losses of approximately 18.29% of the available capital in 2004Q1 prior to the simulated defaults, compared to the 4.87% under the market-share network topology. This dissimilarity is even more prominent as losses increase over time, so that by 2007Q4 the defaults simulated in the random graph generate losses, on average, over 10 times as large as those under the market-share network. Underpinning this is the clustering of exposures between a few large entities in market-share network compared to the more dispersed sharing of exposures under the ER random graph. Comparing the contagion flow of the most devastating FDIC-insured bank default in the simulated 2007Q4 market share network, JPMorgan, to the impact of the same bank under the ER random graph constructed networks, it is clear that the contagion chain extends farther under the random graph (Figure 14). Whereas, losses are limited to the highly interconnected first tier of banks under the market-share network in the random graph, defaults cascade down to the more peripheral banks such as Citizens Bank of Pennsylvania.

Figure 14: Impact of the Failure of JPMorgan: Market Share vs Erdős-Rényi Random Graph Constructed US CDS Network (2007Q4 Gross Notional Amounts)

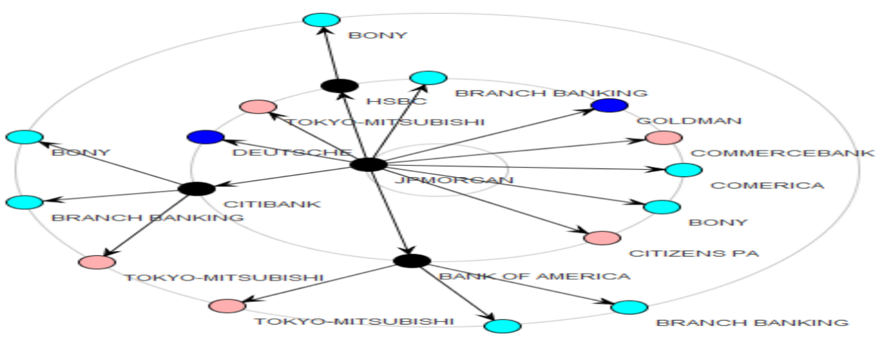
2007Q4: Market Share with 0% Recovery



2007Q4: Erdős-Rényi Random Graph with 0% Recovery



2007Q4: Market Share with 50% Recovery



Key: *Pure Protection Seller* *Net Protection Seller* *Pure Protection Buyer* *Net Protection Buyer* *Defaulted*

Notes: (1) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital. (2) The recovery rate on defaulting bank liabilities is $\gamma = 0\%$ for top and middle contagion chains and $\gamma = 50\%$ for bottom contagion chain. (3) The rings represent the contagion round. The final round is the point at which the network stabilises following the failure of the trigger bank.

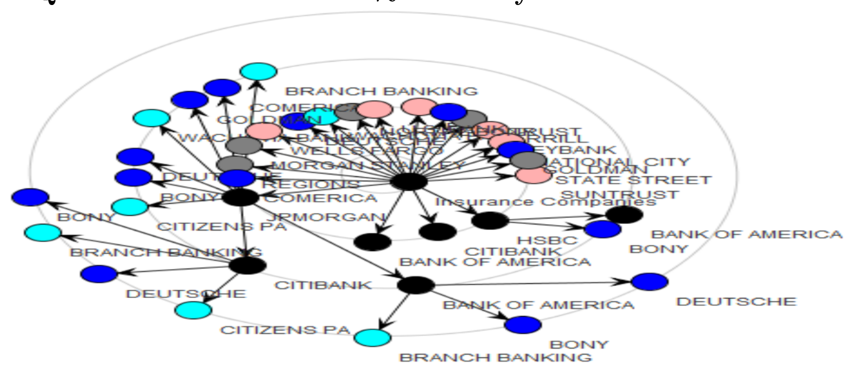
More specifically, Figure 14 shows that under the market-share construction with exposures measured at gross notional assuming 0% recovery, the failure of JPMorgan results in the demise of Bank of America, Citibank, and HSBC, which are unable to cover their combined loss of US$1.66tn with their sustainable loss threshold of 20% of their available Tier 1 capital. The collapse of these three banks has a combined impact of bringing down Bank of New York (BONY) before the contagion chain terminates. To neutralise this chain of losses, a suggested injection of US$1.7tn in core capital would have been required.

By contrast, under the ER random graph the contagion chain is much more devastating. Starting with the failure of Wells Fargo due to the loss of its randomly allocated US$121.65bn in gross notional exposures to JPMorgan, it proceeds to bring down Deutsche Bank and SunTrust. The cascading of losses continues for an additional four rounds, with a total of 23 banks defaulting. The simulation suggests an additional US$1.47tn in Tier 1 capital would be required to prevent the failures.

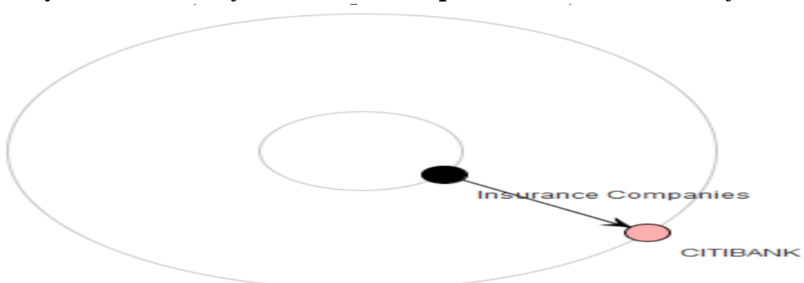
It is worth noting that assuming a recovery rate of 50% on defaulting banks' liabilities significantly reduces the amount of depleted Tier 1 capital from the average failure. Indeed, based on gross notional exposures under the market-share US CDS market network, 2007Q4 core capital losses drop from 25.19% to 14.19% and from 15.36% to 9.15% for 2006Q4. There is, however, only a 0.79% impact of a 50% recovery rate on 2004Q1 gross notional exposures compared to the 0% recovery rate scenario. This would suggest that banks relying on CDS protection became progressively undercapitalised. Indeed, the bottom panel of Figure 14 shows that, even with a 50% recovery rate, the simulated 2007Q4 failure of JPMorgan still results in the demise of Bank of America, Citibank and HSBC. It is estimated that this contagion chain would require an additional US$910.29bn in order to counteract.

Figure 15: Impact of the Failure of the Monoline: Market Share vs Erdős- Rényi Random Graph Constructed US CDS Network (2007Q4 Gross Fair Value)

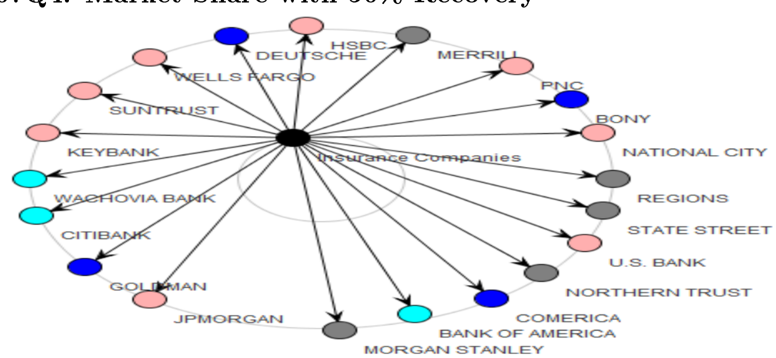
2007Q4: Market Share with 0% Recovery



2007Q4: Erdős-Rényi Random Graph with 50% Recovery



2007Q4: Market Share with 50% Recovery



Key: *Pure Protection Seller* *Net Protection Seller* *Pure Protection Buyer* *Net Protection Buyer* *Defaulted* *Unconnected*

Notes: (1) Simulations assume a sustainable loss threshold $\varepsilon = 20\%$ of Tier 1 capital. (2) The recovery rate on defaulting bank liabilities is $\gamma = 0\%$ for top and middle contagion chains and $\gamma = 50\%$ for bottom contagion chain. (3) The rings represent the contagion round. The final round is the point at which the network stabilises following the failure of the trigger bank.

Accounting for credit exposures at gross fair value, the simulations suggest that the US CDS market retained at the same level of stability in 2007Q4 as it did in 2004Q1. Recorded losses under the market-share network, on average, did not exceed 4.20%, and assuming a 50% recovery rate, simulated losses declined from the 4.01% recorded for 2004Q1 to 3.48% in 2007Q4. The simulations further show that although the ER random graph US CDS market network topology results in a greater number of defaults than the market-share network does, on a bank-by-bank basis, only where a recovery rate of 0% is assumed will the market-share network exhibit cascading defaults. Moreover, this result only occurs in 2006Q4, when Wachovia is the trigger bank, and in 2007Q4 in the case of JPMorgan and the monoline (Figure 15).

Accordingly, when risk capital is aligned with mark-to-market valuation of credit derivatives exposures, the simulation results indicate that, on average, FDIC-insured banks were more than adequately capitalised to withstand losses from the failure of participants in the CDS market. Indeed, simulated defaults, assuming 50% recovery under both market-share and ER random graph network topologies, yield almost identical results with respect to the erosion of Tier 1 capital. This is in spite of the larger losses CDS cash flow, of 9.58% to 12.87%, in the settlement chain under the ER random graph.

Whilst the abovementioned has focused on recovery rates of 50% and 0%, it is worth noting that by increasing recovery rates progressively from 0% to 60%, core capital losses generally tended to decrease in a linear and consistent fashion across all trigger banks. The loss in CDS cover nevertheless was observed to be dependent on whether the defaulting bank was a net protection buyer or net protection seller. For net protection buyers such as Bank of America, defaults tended to result in a constant loss of CDS cover regardless of the assumed recovery rate. Triggered failures of net protection sellers however, gave rise to a stepped process of losses in CDS cover. Declining loss of CDS cover was nevertheless only showed a material impact of US$29.78bn in 2004Q4 shifting from a 50% recovery rate to a 60% recovery rate assuming the failure of JPMorgan. For both 2006Q4 and 2007Q4 the impact of shifting from an assumed 0% recovery rate to 60% recovery rate was less than US$2bn or approximately 0.02% of total initial CDS cover.

5.2 Systemic Risk and the Role of Banks and Monolines

Tangential to the abovementioned is the assessment of the evolution of the role that market participants played over time; specifically, the extent to which certain institutions potentially evolve to play a more central role within the US CDS market. Listed in Table 8 are the eigenvector centrality scores of the top 5 ranking banks, the monoline, and others. Centrality scores are given for both gross notional and gross fair value based market-share networks over the three periods.

With exposures measured at gross notional outstanding, Table 8 shows that, on average, the centrality scores increased between 2004Q1 and 2007Q4. Interestingly, the observations suggest that, with a 2004Q1 centrality score of 0.296 and a 2007Q4 centrality score of 0.297, monolines relative to other entities remained at the same level of importance within the US CDS market. By contrast, where the credit risk associated with credit derivatives exposures are accounted for at gross fair value, monolines' centrality is observed to decline. Having as a sector been ranked as the third most important entity within the network, the monolines become the fifth most central participant in the US CDS market by 2007Q4.

Table 8: Systemic Significance of CDS Market Participants under the Market Share Based Network Topology 2004Q1, 2006Q4 and 2007Q4

	Gross Notional Outstanding			Gross Fair Value		
Banks	**2004Q1**	**2006Q4**	**2007Q4**	**2004Q1**	**2006Q4**	**2007Q4**
Bank of America N.A.	0.188	0.273	0.315	0.100	0.195	0.312
Citibank N.A.	0.312	0.286	0.286	0.137	0.249	0.396
HSBC Bank USA	0.08	0.143	0.121	0.121	0.135	0.104
JPMorgan Chase Bank	0.608	0.633	0.607	0.570	0.602	0.524
Wachovia Bank N.A.	0.066	0.050	0.039	0.025	0.040	0.056
Others	0.003	0.0001	0.0001	0.002	0.0001	0.0000
Monolines	0.296	0.295	0.297	0.288	0.300	0.295
Non-US Bank Outside Entity	0.629	0.590	0.589	0.749	0.655	0.609
Network Average	0.061	0.066	0.068	0.074	0.075	0.070

Note: (1) Eigenvectors centrality scores are computed in Mathworks MatLab 2012b as the singular value decomposition normalised roots of the characteristic polynomial of the weighted adjacency matrices. (2) Selection of the Top 5 listed banks is based on their ranking across all three periods and both gross notional and gross fair value datasets. (3) As the source and destination of residual buy and sell-side exposures, eigenvector centrality scores of the non-US bank outside entity are high by construction.

The results further indicate that although the peripheral institutions had little if any significance to the US CDS market, banks such as Bank of America, Citibank, and HSBC became increasingly more important. Bank of America, for example, having had the fifth highest eigenvector centrality score of 0.188 in 2004Q1, progressively became the third most important entity within US CDS market by 2007Q4, with a centrality score of 0.315 based on the gross notional amount outstanding. Although Citibank became significantly less central in respect to gross notion outstanding exposures, both it and HSBC witnessed increased centrality rankings by 2007Q4 using gross fair value data.

Furthermore, it is noteworthy that, by construction, the non-US bank outside entity is expected to have the highest centrality ranking because of its representation as the remaining market segment and its role as the source and destination of all residual exposures. However, as the results show, by 2006Q4, JPMorgan had surpassed non-US bank outside entity where contractual obligations are measured in terms of the gross notional amount outstanding. This particularly illustrates the evolving systemic significance of the failure of JPMorgan and the resulting capital injections required to prevent those financial institutions to which it is heavily connected from collapsing, having lost the credit protection they had acquired from JPMorgan.

6 Conclusion

Using data on FDIC-insured US banks, this chapter assessed the ability of regulators to determine the ex post evolution of systemic risk associated with the use of CDS and, more generally, credit derivatives following the introduction of regulatory rules under Basel II and the Joint Agencies Rule 66 (Federal Regulation 56914 and 59622), which encouraged synthetic securitisation. Because of the lack of contract-level data, a network of contractual obligations between banks was constructed by using market share and a random graph network topology. Furthermore, because of the intrinsic nature of CDS contracts as guarantees against the face value of referenced credit exposures as well as accounting rules that stipulate exposures must be reported at fair value or mark-to-market basis, the analysis used both gross notional outstanding and gross fair value measures of bank exposures. The latter were treated as the guide to capital requirements under normal-functioning market conditions where contracts are easily replaced without loss as defined under fair value accounting rules such as IAS 39 and IFRS 9. Gross notional outstanding, on the other hand, was used to signify the loss of credit protection under abnormal circumstances such as a financial crisis; where normal market conditions as defined by international accounting rules does not apply, and contracts are not easily replaced. Under these circumstances, the failure of a CDS counterparty results in not only the termination of payments under the premium leg of transactions, but also the loss of credit protection and the requirement to raise additional risk capital from the repatriation of the underlying credit risk.

Contagion chains under both network topologies and measures of bilateral contractual obligations were compared assuming 0% and 50% recovery rates on liabilities. The random graph topology resulted in the widespread decimation of the US CDS market, where 0% recovery rates are assumed both at gross notional and gross fair value. By contrast, under the assumption of 50% recovery and normal trading conditions, capital losses remained on average well below the assumed sustainable loss of 20% of Tier 1 capital. Indeed, stress testing showed that in general banks were adequately capitalised to weather losses from credit derivatives counterparty failures under normal market conditions. Conversely, at the height of a market crisis in which bilateral exposures are not easily replaced and the face value of reference exposures are repatriated, the results showed that even assuming a 50% recovery rate in 2007Q4 leads to unsustainable losses requiring, on average, a minimum of 14% more Tier 1 capital than was available. Moreover, the additional Tier 1 capital required to, on average, ameliorate market immunity to failures of participating institutions progressively increase over time. Interestingly, average capital injections to maintain market stability in 2004Q1 were similar (between 4% and 5%) under the market-share based network topology whether contractual obligations were measured at gross fair value or gross notional outstanding.

Consequently, it is clear that, although CRT clauses in the Basel II regulations assumed that on-balance sheet credit risk can be transferred away and capital requirements calculated according to ongoing credit derivatives counterparty exposures, the resulting risk capital became increasingly insufficient to protect banks against the repatriation of risk once counterparties failed. Conforming with Pozen's (2009) statement, the bailout of banks and transfer of so-called toxic assets that underlie credit derivatives exposures to governments can at best be attributed only to fair value accounting insofar as it drove the determination of risk capital rather than the fundamentals of the transactions. The results further suggest that regulators would have been able to monitor and identify the evolution of systemic risk, systemically important institutions, and the escalating capital inadequacy had a crisis market been the basis of measuring the credit risk from credit derivatives.

However, it is important to caution that the abovementioned results are driven by the available data and market segment upon which the analysis is focused. It is thus expected that a larger data pool and extended market reach into other interbank interactions in the repo markets and markets for other derivatives products, as can be captured in a directed hypergraph analysis, would enrich the results.[12] Nevertheless, with appropriate analysis and use of database-driven multi-agent computational models such as the one presented here, regulators can potentially identified systemic implications of the policy measures that they implement, and corrective measures can be assessed and introduced much sooner without the requirement for taxpayer bailouts.

The design and implementation of regulatory policy is a complex and an ongoing undertaking with agents whose actions not only impact other agents, but also the environment within which they operate. The analysis presented here

[12]Directed hypergraphs are much like standard directed graphs. However, whereas standard arcs connect a single tail node to a single head node, hyperarcs/hyperedges connect a set of tail nodes to a set of head nodes. In this regard a small number of banks may participate in other markets which the majority of those in the CDS may not directly operate in but the majority become subject to spill-overs from failures arising from exposures of the minority in those markets.

has highlighted the oversimplification of Currie's (2005) regulatory policy design beliefs of that regulators can define models to which banks would adhere and from which policy makers would gain the desired social welfare outcomes. As illustrated here, when underlying risk is not fully captured in capital requirements, the very act of banks' adhere to regulatory policy can, in fact, propagate far-reaching systemic failures.

Finally, it is worth noting that the network models assessed here were based on bilateral contracts between counterparties. From a policy efficacy perspective, and in view of recent efforts towards the centralised clearing of CDS and other OTC derivatives under the July 21, 2010 Dodd–Frank Wall Street Reform and Consumer Protection Act (Pub.L. 111-203, H.R. 4173; commonly referred to as Dodd-Frank) and the August 16, 2012 Regulation 648/2012 or European Markets Infrastructure Regulation (EMIR), it would be interesting to compare these results with those that would be derived from a model in which the ultimate counterparty was a central clearing counterparty (CCP). In such a study, bilateral contracts between individual firms would contain ―Give Up‖ clauses permitting an executing broker to enter trade positions with the CCP on behalf of the individual firms.[13] In addition to the topological network analysis of the CCP model, the study could use network flow models to assess the potential for gaming of CCP rules and determine capital requirements to counter the impact of failures of individual institutions as well as the CCP.

[13]Further reading on this line of study would include but not limited to Acharya and Bisin, 2011; Bank of Canada, 2011; Bech and Atalay, 2008; Beyeler et al., 2007; BIS, 2010; Bliss and Papathanassiou, 2006; Bliss and Steigerwald, 2006; Duffie et al, 2010; Fleming et al., 2010; Galbiati and Soramaki, 2012; Gregory, 2010; Iori et al., 2008; Kern et al., 2011; Litan, 2010; Wetherit et al., 2008; Wilkins and Woodman 2010

References

1. Acharya, V.V., & Pedersen, L.H. (2005). Asset Pricing with Liquidity Risk. Journal of Financial Economics, 77(2), 375-410.

2. Albert, R and Barabási, A-L. (1999), Emergence of scaling in random networks Science 286 509-512

3. Albert, R and Barabási, A-L. (2002). Statistical mechanics of complex networks. Reviews of Modern Physics. 74 (1): 47–97.

4. Albert, R., Jeong H., & Barabási, A. (1999). The Diameter of the World Wide Web. Arxiv preprint cond-mat/9907038.

5. Allen, F. & Gale, D. (200). Financial Contagion. Journal of Political Economy, 108(1), 1–33.

6. Amaral, L. A. N., A. Scala, Barthélémy, M., & H. E. Stanley (2000). Classes of Small-World Networks. Proceedings of the National Academy of Sciences, 97(21), 11149–11152

7. Bech, M. L., & Atalay, E. (2008). The Topology of the Federal Funds Market. Working Paper Series 986, European Central Bank.

8. Beyeler, W, Bech, M, Glass, R & Soramäki, K. (2006). Congestion and Cascades In Payment Systems. Federal Reserve Bank of New York Staff Reports No. 259 BIS. (2010). Strengthening Repo clearing and Settlement Arrangements. CH-4002 Basel, Switzerland Bank for International Settlements.

9. Bliss, R., & Papathanassiou, C. (2006). Derivatives Clearing, Central Counterparties and Novation: The Economic Implications. Paper presented at a Symposium held by the European Central Bank and the Federal Reserve Bank of Chicago, Issues Related to Central Counterparty Clearing

10. Bliss, R.R., & Steigerwald, R. S. (2006). Derivatives Clearing and Settlement: A Comparison of Central Counterparties And Alternative Structures. Journal of Economic Perspectives, 4Q(2006), 22-29

11. Buckley, C. L., & Bullock, S. (2007). Sensitivity and Stability: A Signal Propagation Sweet Spot in a Sheet of Recurrent Centre Crossing Neurons. BioSystems, 94(1-2), 2-9.

12. Buckley, C. L., Bullock, S., & Cohen, N (2005). Timescale and Stability in Adaptive Behaviour. Capcarrere, et al. (Eds.) Advances in Artificial Life: 8th European Conference, ECAL 2005, Canterbury, UK, September 5-9, 2005 Proceedings. Lecture Notes in Computer Science 3630, 292-301. Springer-Verlag Berlin Heidelberg.

13. Clauset, A., Shalizi, C.R., & Newman, M.E.J. (2009). Power-Law Distributions in Empirical Data. SIAM Review, 51(4), 661-703.

14. Cocco, J., Gomes, F., & Martins, N. (2009). Lending Relationships in the Interbank Market. Journal of Financial Intermediation, 18(1), 24-48.

15. Cohen, J.E., & Newman, C.M. (1985). When Will a Large Complex System Be Stable? Journal of Theoretical Biology, 113(1985), 153-156.

16. Connell, J.H., & W.P. Sousa., (1983). On the Evidence Needed to Judge Ecological Stability or Persistence. American Naturalist 121(6), 789-824.

17. Currie C. (2005). Towards a General Theory of Financial Regulation: Predicting, Measuring and Preventing financial Crises. UTS Working Paper No. 142, University of Technology, Sydney

18. Dasgupta, A. (2004). Financial Contagion yhrough Capital Connections: A Model of the Origin and Spread of Bank Panics. Journal of European Economic Association, 2(6), 1049-1084.

19. Degryse, H., & Nguyen, G. (2007). Interbank Exposures: An Empirical Examination of Systemic Risk in the Belgian Banking System. International Journal of Central Banking, 3(2),951-979.

20. Diamond, D.V., & Dybvig, P. (1983). Bank Runs, Deposit Insurance, and Liquidity. Journal of Political Economy, 91(3), 401-19. Diestel, R (2005). Graph Theory. (3 rd Edition). Springer-Verlag Heidelberg, New York.

21. Duffie, D., Li, A and Lubke, T. (2010). Policy Perspectives on OTC Derivatives Market Infrastructure, Federal Reserve Bank of New York Staff Report no. 424.

22. Duffie, D., N. Garleanu, and L.H. Pedersen, (2005). Over-the-Counter Markets. Econometrica 73(6), 1815-1847.

23. Duffie, D., N. Garleanu, and L.H. Pedersen, (2007). Valuation in Over-the-Counter Markets. Review of Financial Studies, 20(5), 1865-1900.

24. ECB. (2009). Credit Default Swaps and Counterparty Risk. Report. European Central Bank.

25. ECB. (2010). Recent Advances in Modeling Systemic Risk Using Network Analysis. European Central Bank.

26. Eichengreen, B., Mody, A., Nedeljkovic, M., & Sarno, L. (2009). How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads. National Bureau of Economic Research Working Paper No. 14904. doi: 10.3386/w14904

27. Erdős, P.; A. Rényi (1961). On the evolution of random graphs. Bulletin of the International Statistical Institute 38(4),343–347.

28. Erdős, P.; Rényi, A. (1959). On Random Graphs. I. Publicationes Mathematicae 6: 290–297.

29. Erdős, Paul; A. Rényi (1960). On the evolution of random graphs. Publications of the Mathematical Institute of the Hungarian Academy of Sciences 5: 17–61.

30. Fleming, M. J., Hrung, W. B., & Keane, F. M. (2010). Repo Market Effects of the Term Securities Lending Facility. Federal Reserve Bank of New York Staff report no. 426.

31. Fontaine, J.S., Perez-Saiz, H., & Slive, J. (2011). Optimum Structure of a Central Counterparty. Bank of Canada Working Paper October 2011

32. Freixas, X., Parigi, B.M., & Rochet, J.C. (2000). Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking 32(3), 611–38.

33. Furfine, C.H. (2003). Interbank Exposures: Quantifying the Risk of Contagion" Journal of Money, Credit and Banking, 35(1), 111–28.

34. Galbiati, M., & Soramäki, K. (2012). Clearing Networks" Journal of Economic Behavior & Organization 83(3), 609-626.

35. Gale, D., & Kariv, S. (2007). Financial Networks. American Economic Review, 97(2), 99-103.

36. Gilbert, E. N. (1959). Random Graphs. Annals of Mathematical Statistics, 30(4), 1141–1144.

37. Gofman, M., (2011). A Network-Based Analysis of Over-the-Counter Markets. working paper University of Wisconsin.

38. Goyal, S., & F. Vega-Rodondo, (2007). Structural Holes in Social Networks. Journal of Economic Theory 137(1), 460-492.

39. Gregory, J. (2010a). Pros and Cons of Central Counterparty Clearing. Presentation on the Impact of Regulatory Reform on Clearing and Settling OTC Derivatives, 5 February 2010.

40. Gregory, J. (2010b). Counterparty Credit Risk: The New Challenge for Global Financial Markets. Wiley Finance.

41. Hastings, H. M. (1982). The May-Wigner Stability Theorem for Connected Matrices. Bulletin of the American Mathematical Society, 7(2), 387-388.

42. Hogg, T., Huberman, B. A., & McGlade, J. M. (1989). The Stability of Ecosystems. Proceedings of the Royal Society of London. Series B, Biological Sciences 237(1286), 43-51.

43. Hu, H. T. C., & Black, B. (2008). Equity and Debt Decoupling and Empty Voting II: Importance and Extensions. University of Pennsylvania Law Review, 156(3), 625-739.

44. Iori G., de Masi, G., Precup, O., Gabbi, G., & Caldarelli, G. (2008). A Network Analysis Of The Italian Overnight Money Market. Journal of Economic Dynamics and Control, 32(1), 259-278.

45. Jackson, M.O. (2005). Allocation Rules for Network Games. Games and Economic Behaviour, 51(1), 128-154.

46. Jackson, M.O., & Watts, A. (2002). The Evolution of Social and Economic Networks. Journal of Economic Theory, 106(2), 256-295.

47. Kao, R. (2010). Networks and Models with Heterogeneous Population Structure in Epidemiology in Estrada, E., Fox, M., Higham, D.J. & Oppo, G-L. (Ed.). Network Science (pp. 51-84). Springer-Verlag, London.

48. Leitner, Y. (2005). Financial Networks: Contagion, Commitment, and Private Sector Bailouts. Journal of Finance, 60(6), 2925-2953.

49. Levine, J. M., & D'Antonio, C. M. (1999). Elton Revisited: A Review of Evidence Linking Diversity and Invasibility. Oikos 87(1) 15-26. doi: 10.2307/3546992

50. Litan, R.E. (2010). The Derivatives Dealers Club and Derivatives Markets Reform: A Guide for Policy Makers, Citizens and Other Interested Parties. Initiative on Business and Public Policy at Brookings.

51. Markose, S. M. (2011). Multi-Agent Financial Network Analyses for Systemic Risk Management Post 2007 Financial Crisis: A New Complexity Perspective for G10 and BRICs. Talk given at the Reserve Bank of India Financial Stability Division, 22-23 August 2010.

52. Markose, S. M. (2012). Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-spreader Tax. IMF Discussion Papers.

53. Markose, S. M., Bewaji, O., & Giansante, S. (2012a). Multi-Agent Financial Network. (MAFN) Model of US Collateralized Debt Obligations. (CDO): Regulatory Capital Arbitrage, Negative CDS Carry Trade and Systemic Risk Analysis. Alexandrova-Kabadjova, B., Martinez-Jaramillo, S., Garcia-Almanza, A.L., & Tsang, E. (Ed.) Simulation in Computational Finance and Economics: Tools and Emerging Applications, (pp. 225-254). IGI Global.

54. Markose, S. M., Giansante, S., & Shaghaghi, A. R. (2012b). Too Interconnected to Fail: Financial Network of US CDS Market Topological Fragility and Systemic Risk. Journal of Economic Behavior & Organization, 83(3) 627–646.

55. Markose, S. M., Giansante, S., Gatkowski, M., & Shaghagi, A.R. (2010). Too Interconnected To Fail: Financial Contagion and Systemic Risk in Network Model of CDS and Other Credit Enhancement Obligations of US Banks. Discussion Paper 683. Economics Department, University of Essex.

56. May, R. (1972). Will A Large Complex System Be Stable? Nature. 238: 413–414. May, R. (1973). Qualitative Stability in Model Ecosystems. Ecology. 54(3), 413–414. May, R. (1974). Stability and Complexity in Model Ecosystems (2nd ed). Princeton University Press.

57. McMurtrie R.E., (1975). Determinants of Stability of Large Randomly Connected Systems. Journal of Theoretical Biology 50: 1-11.

58. Memmel, C., & Stein, I. (2008). Contagion in the German Interbank Market.

59. Meyer, C.D. (2000). Matrix Analysis and Applied Linear Algebra. Chapter 8 Volume 1. SAIM.

60. Nier, E. Yang J., Yorulmazer T., & Alentorn, A. (2007). Network Models and Financial Stability. Journal of Economics Dynamics and Control, 31(6) 2033-60.

61. O'Kane, D., and Turnbull, S. (2003) Valuation of Credit Default Swaps, Lehman Brothers Fixed Income Quantitative Credit Research, April 2003

62. Reed, W.J., & Hughes, B.D. (2002). From Gene Families and Genera to Incomes and Internet File Sizes: Why Power Laws are so Common in Nature. Physical Review E. 66(2002) 067103.

63. Rubinov, M., & Sporns, O. (2010). Complex Network Measures of Brain Connectivity: Uses and Interpretations. NeuroImage; 52(3) 1059-1069.

64. Saramäki, J., Kivelä, M., Onnela, J-P., Kaski, K., & Kertész, J. (2007). Generalizations of the Clustering Coefficient to Weighted Complex Networks. Physical Review E: Statistical, Nonlinear, and Soft Matter Physics. 75(2) 027105-1 to 027105-4.

65. Sheldon, G., & Maurer. M. (1998). Interbank Lending and Systemic Risk: An Empirical Analysis For Switzerland. Swiss Journal of Economics and Statistics 134(4) 685-704.

66. Sinha, S. (2005). Complexity vs. Stability in Small-World Networks. Physica A. (Amsterdam) 346: 147–153.

67. Sinha, S., & Sinha, S. (2006). Robust Emergent Activity in Dynamical Networks. Physics Review E Stat. Nonlinear Soft Matter Physics, 74: 066177.

68. Upper, C and Worms, A. (2004). Estimating Bilateral Exposures in the German Interbank Market: Is There a Danger of Contagion?" European Economic Review, 48(4), 827-849.

69. Upper, C. (2007). Using Counterfactual Simulations to Assess the Danger of Contagion in Interbank Markets. BIS Working Papers 234, Monetary and Economic Department of the Bank for International Settlements, CH-4002 Basel, Switzerland.

70. van Lelyveld, I., & Liedrop, F. (2004). Interbank Contagion in the Dutch Banking Sector. Netherlands Central Bank, Research Department in its series DNB Working Paper.

71. Vivier-Lirimont, S. (2004). Interbanking Networks: Towards a Small Financial World? Cahiers de la Maison Des Sciences Economiques, Universite Pairs Pantheon-Sorbonne.

72. Watts, D., & Strogatz, S. H. (1998). Collective Dynamics of "Small-World" Networks. Nature, 393(6684), 440–442 .

73. Wells, S. (2004). U.K. Interbank Exposures: Systemic Risk Implications. Journal of Monetary Economics 2(1) 66-77.

74. Wigner, E.P. (1957). Characteristic Vectors of Bordered Matrices with Infinite Dimensions II. Annals of Mathematics, 65(2), 203-207.

75. Wilkins, C., & Woodman, E. (2010). Strengthening the Infrastructure of Over-the-Counter Derivatives Markets. Bank of Canada Financial System Review. (December): 35–41.

76. Yang, J., & Zhou, Y. (2010). Finding Systemically Important Financial Institutions around the Global Credit Crisis: Evidence from Credit Default Swaps. paper prepared for the 13th conference of the ECB-CFS Research Network: Macro-prudential Regulation as an Approach to Contain Systemic Risk: Economic Foundations, Diagnostic Tools and Policy Instruments 27-28 September 2010.

77. Yavorsky, A. (2009). Analyzing the Potential Impact of Credit Default Swaps in Workout Situations. Special Comment, Moody's Investor Services.