

# ‘Too Interconnected To Fail’ Financial Network of US CDS Market: Topological Fragility and Systemic Risk

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## Abstract

A small segment of credit default swaps (CDS) on residential mortgage backed securities (RMBS) stand implicated in the 2007 financial crisis. The dominance of a few big players in the chains of insurance and reinsurance for CDS credit risk mitigation for banks’ assets has led to the idea of *too interconnected to fail (TITF)* resulting, as in the case of AIG, of a tax payer bailout. We provide an empirical reconstruction of the US CDS network based on the FDIC Call Reports for off balance sheet bank data for the 4<sup>th</sup> quarter in 2007 and 2008. The propagation of financial contagion in networks with dense clustering which reflects high concentration or localization of exposures between few participants will be identified as one that is *TITF*. Those that dominate in terms of network centrality and connectivity are called ‘super-spreaders’. Management of systemic risk from bank failure in uncorrelated random networks is different to those with clustering. As systemic risk of highly connected financial firms in the CDS (or any other)

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financial markets is not priced into their holding of capital and collateral, we design a super-spreader tax based on eigenvector centrality of the banks which can mitigate potential socialized losses.

*Keywords:* Credit Default Swaps, Financial Networks, Eigenvector Centrality, Financial contagion, Systemic Risk, Super-spreader tax

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## 1. Introduction

The 2007 financial crisis which started as the US ‘sub-prime’ crisis, through a process of financial contagion led to the demise of major banks and also precipitated severe economic contraction the world over. Since 2008, taxpayer bailout and socialization of losses in the financial system has transformed the banking crisis into a sovereign debt crisis in the Euro zone. In the 2002-2007 period, credit risk transfer (CRT) from bank balance sheets and the use of credit derivatives to insure against default risk of reference assets has involved big US banks and non-bank FIs in the credit derivatives market which is dominated by credit default swaps (CDS). This market has become a source of market expectations on the probability of default of the reference entity which since 2008 has increasingly included high CDS spreads on sovereigns and FIs. Banks are major protection buyers and sellers in this market and have become vulnerable as a result. Due to inherent structural weaknesses of the CDS market and also those factors arising from poor regulatory design, as will be explained, CDS which constitute up to 98% of credit derivatives have had a unique, endemic and pernicious role to play in the 2007 financial crisis. This paper will be concerned with modelling a specific weakness of CDS which is also well known for other modern risk sharing institutions involving over-the-counter (OTC) financial derivatives, and this pertains to the heavy concentration of derivatives activities among a few main participants.

The key elements of financial crises, the case of 2007 financial crisis being no exception, is the growth of innovations in private sector liquidity and leverage creation which are almost always collateralized by assets that are procyclically sensitive, viz. those that lose value with market downturns.<sup>2</sup>

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<sup>2</sup>The use of procyclical RMBS assets as collateral for bank liabilities in asset backed commercial paper (ABCP) conduits in the repo market is given as a fundamental reason for the contraction of liquidity and the run on the repo markets in the 2007 crisis, Gorton

27 The specific institutional propagators of the 2007 crisis involved residential  
28 mortgage backed securities (RMBS) which suffered substantial mark downs  
29 with the collapse of US house prices.<sup>3</sup> Then it was a case of risk sharing  
30 arrangements that went badly wrong. This came about due to the role of CDS  
31 in the CRT scheme of Basel II and its precursor in the US, the Joint Agencies  
32 Rule 66 Federal Regulations 56914 and 59622 which became effective on  
33 January 1, 2002. This occurred in the context of synthetic securitization and  
34 of Collateralized Mortgage Obligations (CMO) which led to unsustainable  
35 trends and to systemic risk. Both holders of the RMBS and CMO assets in  
36 the banking sector and those servicing credit risk via the CDS market (cf.  
37 American Insurance Group (AIG)) required tax-payer bailouts.<sup>4</sup>

38 The Basel II risk weighting scheme for CRT of assets on bank balance  
39 sheets and its forerunner in the US which set out the capital treatment in the  
40 Synthetic Collateralized Loan Obligations guidance published by the Office  
41 of Comptroller of the Currency (OCC 99-43) for the 2002 Joint Agencies  
42 Rule 66, stand implicated for turbo charging a process of leverage that in-  
43 creased connectivity between depository institutions and as yet unregulated  
44 non-depository financial intermediaries and derivatives markets. Under Basel  
45 I since 1988, a standard 8% regulatory capital requirement applied to banks  
46 with very few exceptions for the economic default risk of assets being held  
47 by banks. In the run up to Basel II since 2004 and under the 2002 US Joint  
48 Agencies Rule 66, the 50% risk weight which implied a capital charge of 4%

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(2009). The loss of confidence arising from the uncertainty as to which bank is holding impaired RMBS assets that were non-traded, typically called a problem of asymmetric information, exacerbated the problem.

<sup>3</sup>See, Brunnermeier (2009), Stulz (2010), Ashcroft and Schuermann (2008) and Gorton and Metrich (2009). They, respectively, cover the unfolding phases of the crisis, the specific characteristics of credit derivatives, the features relevant to sub-prime securitization and the collateralized debt obligations.

<sup>4</sup>Kiff et al. (2009) place the size of increased collateral calls on AIG's CDS guarantees following its ratings downgrades at a relatively modest \$15 bn that it was unable to meet. While the current cost to the US tax payer of the AIG bailout stands at \$170 bn, the initial \$85 bn payment to AIG was geared toward honouring its CDS obligations to counterparties totalling over \$66.2 bn. These include payouts to Goldman Sachs (\$12.9 billion), Merrill Lynch (\$6.8 bn), Bank of America (\$5.2 bn), Citigroup (\$2.3 bn) and Wachovia (\$1.5 bn). Foreign banks were also beneficiaries, including Société Générale and Deutsche Bank, which each received nearly \$12 bn; Barclays (\$8.5 bn); and UBS (\$5 bn). The following 15 March 2009 press release "AIG Discloses Counterparties to CDS, GIA and Securities Lending Transactions" provides useful information.

49 on residential mortgages could be reduced to a mere 1.6% through the process  
 50 of synthetic securitization and external ratings which implied 5 times more  
 51 leverage in the system.<sup>5</sup> In synthetic securitization and CRT, an originating  
 52 bank uses CDS or guarantees to transfer the credit risk, in whole or in part, of  
 53 one or more underlying exposures to third-party protection providers. Thus,  
 54 in synthetic securitization, the underlying exposures remain on the balance  
 55 sheet of the originating bank, but the credit exposure of the originating bank  
 56 is transferred to the protection provider or covered by collateral pledged by  
 57 the protection provider. This strongly incentivized the use of CDS by banks  
 58 which began to hold more MBS on their balance sheets and also brought  
 59 AAA players such as AIG, hedge funds and erstwhile municipal bond insurers  
 60 called Monolines into the CDS market as protection sellers.<sup>6</sup> Only banks  
 61 were subject to capital regulation while about 49% (see, British Bankers  
 62 Association for 2006 for the breakdown of institutions involved as CDS pro-  
 63 tection sellers and buyers) of those institutions which were CDS sellers in the  
 64 form of thinly capitalized hedge funds and Monolines,<sup>7</sup> were outside the reg-  
 65 ulatory boundary. This introduced significant weakness to the CRT scheme  
 66 leading to the criticism that the scheme was more akin to banks and other  
 67 net beneficiaries of CDS purchasing insurance from passengers on the Ti-  
 68 tanic. Indeed, a little known Monoline called ACA which failed to deliver  
 69 on the CDS protection for RMBS held by Merrill Lynch is what finally led  
 70 to its absorption by Bank of America.<sup>8</sup> Further, as cited in the ECB CDS  
 71 Report (ECB, 2009, p.57-58), in its 2007 SEC filing, AIG FP (the hedge

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<sup>5</sup>The risk weight of 20% applies when a bank asset has CDS protection from an AAA rated guarantor.

<sup>6</sup>Acharya and Richardson (2010), Blundell-Wignall and Atkinson (2008), Hellwig (2010), Markose et al. (2010, 2012) have given detailed analyses of how the regulatory framework based on risk weighting of capital and CRT resulted in perverse incentives which left the financial system overleveraged and insolvent.

<sup>7</sup>At the end of 2007, AMBAC, MBIA and FSA accounted for 70% of the CDS contracts provided by Monolines with the first two accounting for \$625 bn and \$546 bn of this. The capital base of Monolines was approximately \$20 bn and their insurance guarantees are to the tune of \$2.3 tn implying leverage of 115.

<sup>8</sup>Standard and Poor Report of August 2008 states that Merrill Lynch had CDS cover from Monolines to the tune of \$18.8bn and of that ACA accounted for \$5bn. ACA, 29% of which was owned by Bear Stearns, along with other Monolines suffered a ratings downgrade in early 2008 and ACA demised in 2008 defaulting on its CDS obligations. ACA had \$69 bn of CDS obligations and only had \$425 million worth of capital.

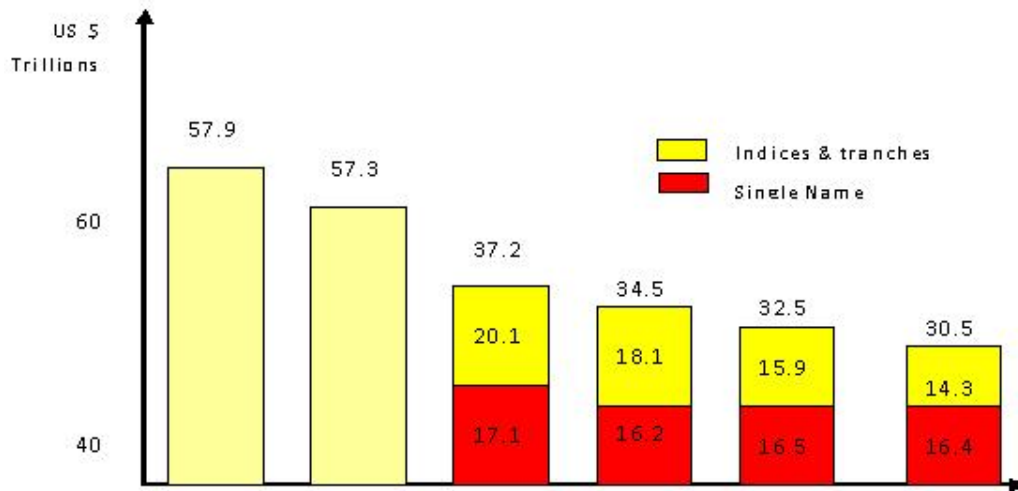


Figure 1: Credit Default Swaps Outstanding Gross Notional. Source: BIS December 07, June 08 which include all CDS contracts; DTCC for other dates record only 90% of CDS.

fund component of AIG) explicitly stated that it supplied CDS guarantees, in particular to European banks, in order for them to reduce capital requirements. The benefits that accrued to banks from CRT fell far short of the intended default risk mitigation objectives and as shown by Markose et al. (2012) participants of the CRT scheme were driven primarily by short term returns from the leveraged lending using CDS in synthetic CDOs as collateral in a carry trade.

Figure 1 shows how the CDS market peaked at about \$58 trillion in the run up to the 2007 crisis. In the post Lehman period the gross notional value<sup>9</sup> of CDS has contracted due to the compression of CDS contracts with bilateral tear ups and a decline of CDS issuance. Tranche CDS shrank faster than single name CDS. During the short lived period of the CDO market for RMBS which peaked at over \$2 trillion in 2007, about \$1 trillion of the tranche based CDS was on sub-prime RMBS.

Undoubtedly, the main rationale behind CRT in the context of credit derivatives which led regulators to endorse these activities (see, e.g., IMF

<sup>9</sup>Following the DTCC, the CDS notional refers to the par value of the credit protection bought or sold. Gross notional value reported on a per trade basis is the sum of the CDS contracts bought (or equivalently sold) in aggregate.

88 (2002); OECD (2002); IAIS (2003); BIS (2004)) is that it allows financial  
 89 intermediaries (FIs) to diversify away concentrated exposures on their bal-  
 90 ance sheet by moving the risks to AAA rated institutions that seem better  
 91 placed to deal with them. However, similar to the argument made by Darby  
 92 (1994) about derivatives markets in general in their role in risk sharing, many  
 93 have noted (see, Persuad (2002), Lucas et al. (2007), Das (2010) and Gibson  
 94 (2007)) that the benefits of CRT will be compromised by the structural con-  
 95 centration of the CDS market. Clearly, Basel II and III schemes for CRT<sup>10</sup>  
 96 suffer from the fallacy of composition. The premise that the transfer of credit  
 97 risk from banks' balance sheets, which is a good thing from the perspective  
 98 of a bank especially as the capital savings incentives allow short run asset  
 99 expansion, will also lead to diversification of risk does not follow at a collec-  
 100 tive level. There is growing counterparty and systemic risk due to fragility in  
 101 the network structures. Few have provided tools to quantitatively model and  
 102 visualize the systemic risk consequences of what is called *too interconnected*  
 103 *to fail (TITF)* that come with high concentration of CDS counterparties.<sup>11</sup>  
 104 Markose et al. (2012) has pointed out that the fallacy of composition type er-  
 105 rors can be reduced with holistic visualization of the interconnections between  
 106 counterparties using financial network models. The structural signature of  
 107 such financial networks given by the heavy concentration of exposures needs  
 108 to be modelled and analysed to understand the network stability properties  
 109 and the way in which contagion propagates in the system. In view of the  
 110 growing *structural* concentration in the provision of risk guarantees through  
 111 financial derivatives, we claim the topological fragility of the modern risk  
 112 sharing institutions is germane to issues on systemic risk.

113 Given the US centric nature of the CDS market for RMBS and the fact  
 114 that the FDIC Call Reports comprehensively give data on gross notional,  
 115 gross positive fair value (GPFV)<sup>12</sup> and gross negative fair value (GNFV) of

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<sup>10</sup>Hellwig (2010) has correctly noted that as long as incentives for capital reduction are given for the use of CDS risk mitigants, it is business as usual in Basel III.

<sup>11</sup>In the publicly available slides of a study by Cont et. al. (2009), Measuring Systemic Risk in Financial Networks cited in the 2009 ECB CDS Report (ECB, 2009), Cont et. al. simulate the CDS market network connectivity and exposure sizes on the basis of the empirical properties of the Brazilian and Austrian interbank markets. We maintain that the CDS market, especially as it affects US bank solvency, has considerably more clustering and concentration risk than interbank markets.

<sup>12</sup>The sum total of the fair values of contracts involves the money owed to a bank by its counterparties, without taking into account netting. This represents the maximum losses

116 CDS for all FDIC FIs, this paper will confine the CDS network model to  
 117 fit the FDIC data set. Note, the activities of the FDIC financial firms are  
 118 given in their capacity as national associations rather than in terms of global  
 119 consolidated holdings. The number of US FDIC financial firms involved  
 120 in CDS is very few ranging from between 26-38 or so in the period since  
 121 2006 when this data has been reported. In 2006, we find that that top 5  
 122 US banks (J.P. Morgan, Bank of America, Citigroup, Morgan Stanley and  
 123 Goldman Sachs) accounts for 95% of gross notional sell and over 97% in 2007  
 124 of the total CDS gross notional sell of FDIC banks. In terms of the \$34 tn  
 125 global gross notional value of CDS for 2008 Q4 given by BIS and DTCC,  
 126 these top 5 US banks account for 92% of market share. Of the top 100  
 127 SP-500 firms surveyed by Fitch in 2009 for derivatives use<sup>13</sup>, only 17 were  
 128 found to be active in the CDS market and the top 5 US banks accounted for  
 129 96% of CDS gross notional in 2009. While the network for CDS exposures  
 130 for US banks in the 2007 Q4 period showed that Monolines and insurance  
 131 companies were dominant as CDS protections sellers, by 2008 Q4 we have  
 132 an even greater dominance of 5 US banks in the CDS market. This came  
 133 about with the demise or merger of investment banks Bear Stearns, Lehman  
 134 Brothers and Merrill Lynch, contraction of CDS activities by the Monolines  
 135 and the nationalization of AIG. It is a sobering fact that the origins of the  
 136 financial contagion as it emanated from CDS on RMBS on US banks' balance  
 137 sheets accounts for only 13% of gross notional of total US bank holdings of  
 138 CDS in 2006 Q1 and falling to 7% in 2007 Q2 (see Markose et al. (2012)).

139 This paper is concerned with characterizing the systemic risk from this  
 140 class of derivatives by considering the topology of the financial network for  
 141 counterparty exposures. Following the methods of the IBM project of MIDAS  
 142 (see, Balakrishnan et al. (2010)) which aims to automate, access and visualize  
 143 large financial datasets this paper will use the Markose et al. (2010) network  
 144 'visualizer' for the CDS activities of FDIC firms. One of the objectives of the  
 145 paper is to highlight the hierarchical core-periphery type structures within a

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a bank could incur if all its counterparties default and there is no netting of contracts, and the bank holds no counter-party collateral. Fair values are market determined or model determined.

<sup>13</sup>The report by Fitch Ratings, 2009, "Derivatives: a Closer Look at What New Disclosures in the U.S. Reveal". The 100 companies reviewed were those with the highest levels of total outstanding debt in the S&P 1,500 universe. They represent approximately 75% of the total debt of S&P 1,500 companies.

146 highly sparse adjacency matrix to give a more precise depiction of financial  
147 firms being *TITF* in that the highly connected financial firms will bring down  
148 similarly connected financial firms implying large socialized loss of capital for  
149 the system as a whole. It aims to give a more rigorous characterization in  
150 terms of network statistics of extreme concentration of exposures between five  
151 top US banks. We will highlight the high asymmetry in network connectivity  
152 of the nodes and high clustering of the network involving a few central hub  
153 banks (some-times called the ‘rich club’) which are broker-dealers in of the  
154 CDS network.

155 By its nature of being a negative externality, systemic risk implications of  
156 a bank’s connectivity and concentration of obligations are not factored into  
157 the capital or collateral being held by banks. In a ratings based system, as  
158 succinctly pointed out by Haldane (2009), leniency of capital and collateral  
159 requirements for a few large highly rated FIs has resulted in excessive expansion  
160 of credit and derivatives activities by them which is far beyond what can  
161 be sustained in terms of system stability. Haldane (2009) calls such highly  
162 interconnected financial intermediaries ‘super-spreaders’ and we will retain  
163 this epithet in the financial network modelling that follows. Haldane (2009)  
164 recommends that super-spreaders should have larger buffers. We design a  
165 super-spreader tax based on eigenvector centrality of the nodes and we test  
166 it for its efficacy to reduce potential socialized losses.

167 Section 2 gives a brief description of CDS and discusses the potential  
168 systemic risk threats that arise from them. This includes the practice of  
169 offsetting which creates dense connections between broker-dealers. In Section  
170 3, we will briefly review the technical aspects of network theory and the  
171 economics literature on financial networks. The main drawback of the pre  
172 2007 economics literature on financial networks has been that models that  
173 are based on empirical bilateral data between counterparties were few in  
174 number to establish ‘stylized’ facts on network structures for the different  
175 classes of financial products ranging from contingent claims and derivatives,  
176 credit related interbank obligations and exposures and large value payment  
177 and settlement systems. Where bilateral data on financial exposures is not  
178 available, both empirical and theoretical models assumed network structures  
179 to be either uncorrelated random ones (see, Nier et al. (2007)) or complete  
180 network structures (see, Upper and Worms (2004)). As will be argued, these  
181 approaches crucially do not have what we call the *TITF* characteristics.  
182 While the stability of financial networks have been usually investigated using  
183 the classic Furfine (2003) algorithm, sufficient emphasis has not been given



184 to the way in which contagion propagates in highly tiered and clustered  
185 networks and stability of the system in terms of network characteristics has  
186 not been studied. Section 4 discusses the necessary network stability results  
187 and derives the super-spreader tax fund that can mitigate potential socialized  
188 losses from the failure of highly connected banks. The super-spreader tax is  
189 based on the eigen-vector centrality of the FI in order to internalize the  
190 system wide losses of capital that will occur by failure of big CDS broker-  
191 dealers.

192 In the empirical Section 5, a quantitative analysis leading to the empirical  
193 reconstruction of the US CDS network based on the FDIC Q4 2007 and Q4  
194 2008 data is given in order to conduct a series of stress tests that investigate  
195 the consequences of the high concentration of activity of 5 US banks. In  
196 2007 Q4, non-bank FIs such as Monolines and hedge funds are found to be  
197 dominant in terms of eigen-vector centrality. In 2008 Q4, J.P. Morgan is  
198 identified as the main super-spreader. The substantial threat to US banks  
199 from non-US (mainly European) banks as net CDS sellers is also identified.  
200 An equivalent uncorrelated random network equivalent in size, connectivity  
201 and total GNFV and GPFV for each bank is also constructed and systemic  
202 risk from bank failure in uncorrelated random networks is shown to be dif-  
203 ferent from the empirically calibrated CDS network. Results are provided  
204 on how the super-spreader tax fund operates. Section 6 concludes the paper  
205 and outlines future work.

## 206 **2. Over the Counter CDS Contracts: Potential Systemic Risk Threats**

### 207 *2.1. CDS Contract and Inherent Problems*

208 A single name credit default swap is a bilateral credit derivative contract  
209 specified over a period, typically 5 years, with its payoffs linked to a credit  
210 event such as default on debt, restructuring or bankruptcy of the underlying  
211 corporate or government entity. The occurrence of such a credit event can  
212 trigger the CDS insurance payment by the protection seller who is in receipt  
213 of periodic premia from the protection buyer. Figure 2 sets out the structure  
214 of a CDS contract.

215 Every over the counter (OTC) CDS contract is bilaterally and privately  
216 negotiated and the respective counterparties and the contracts remain in  
217 force till the maturity date. This raises problems with regard to counterparty  
218 risk and also indicates why gross exposure matters. The periodic payments  
219 of premia are based on the CDS spread and quoted as a percentage of the

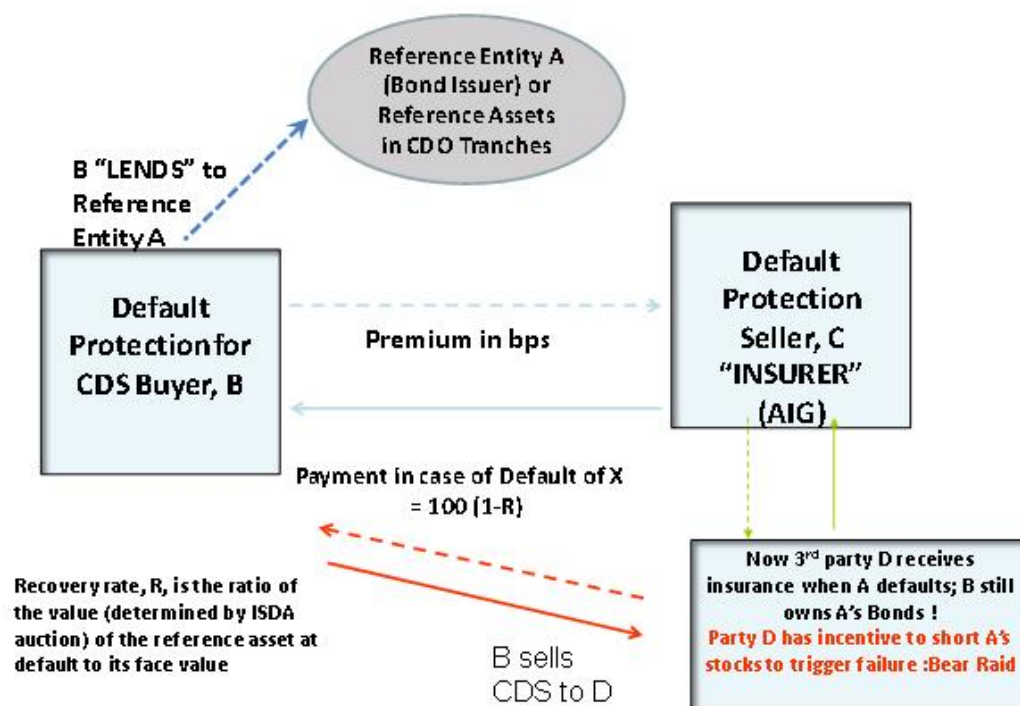


Figure 2: Credit Default Swap Structure, CDS Chain and Bear Raid. Note: Direction of CDS sale or protection guarantee is the unbroken arrow.

gross notional value of the CDS at the start of the contract. The CDS spreads being quoted fluctuate over time. As the payoff on a CDS contract is triggered by the default on debt, the CDS spread represents, in general, credit worthiness of the reference entity and specifically, the probability of default and the recovery value of the reference assets. All else being equal, higher spreads indicate growing market expectations of the default on the debt with a jump to default spike at the time of the credit event. Net CDS sellers and their counterparties holding impaired CDS reference assets may also find that CDS spreads on themselves as reference entities are adversely affected. This could hasten their own insolvency as liquidity risk in the form of the ability to raise funds is affected. This has been called ‘wrong way risk’. The 2009 ECB CDS report estimated this as the correlation in the CDS spreads of CDS sellers and their respective reference entities, and finds this has grown for sellers of CDS which rely on government bailout and then sell CDS with their respective sovereigns as reference entities. Circularity of risk arises from the fact that as noted by the DTCC in December 2008, 7 top dealers are themselves among the 10 top reference entities by net protection amounts.<sup>14</sup>

Hence, CDS spreads have strong self-reflexive properties in that they do not merely reflect the financial state of the underlying obligor, they can in turn accelerate the default event as ratings downgrade follow, cost of capital rises and stock market valuation falls for the obligor as the CDS spreads on them increase. These systemic risk factors are hard to model in formulaic CDS pricing models and hence such counterparty and circular risk are typically not modelled in CDS pricing models.

The controversial aspect about a CDS that makes the analogy with an insurance contract of limited use is that the buyer of a CDS need not own any underlying security or have any credit exposure to the reference entity that needs to be hedged. The so called naked CDS buy position is, therefore, a speculative one undertaken for pecuniary gain from either the cash settlement in the event of a default or a chance to offset the CDS purchase with a sale at an improved CDS spread. This implies that gross CDS notional values can

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<sup>14</sup>In December 2008, the DTCC lists the following financial reference entities by net protection amounts: GE Capital (\$11.074 bn), Deutsche Bank (\$7.163 bn), Bank of America (\$6.797 bn), Morgan Stanley (\$6.318 bn), Goldman Sachs (\$5.211 bn), Merrill Lynch (\$5.211 bn), Berkshire Hathaway (\$4.632 bn), Barclays Bank (\$4.358 bn), UBS(\$4.311 bn), RBS(\$4.271 bn).

252 be several (5-10) multiples of the underlying value of the debt obligations of  
 253 the reference entity. It has been widely noted that naked CDS buyers with no  
 254 insurable interest will gain considerably from the bankruptcy of the reference  
 255 entity. Note the ‘bear raid’ in Figure 2 refers to the possibility that when  
 256 the CDS protection cover on a reference entity has been sold on to a third  
 257 party, here D, who does not own the bonds of the reference entity, D has an  
 258 incentive to short the stock of the reference entity to trigger its insolvency in  
 259 order to collect the insurance to be paid up on the CDS. A naked CDS buy  
 260 position is equivalent to shorting the reference bonds without the problems  
 261 of a short squeeze that raises the recovery value of the bonds (and lowers  
 262 the payoff on the CDS) when short sellers of the bonds have to ‘buy back’  
 263 at time of the credit event. Hence, naked CDS buying is combined with  
 264 shorting stock of the reference entity. There is also the case that even those  
 265 CDS buyers who have exposure to the default risk on the debt of the reference  
 266 entity may find it more lucrative to cash in on the protection payment on  
 267 the CDS with the bankruptcy of the reference entity rather than continue  
 268 holding its debt. This is called the empty creditor phenomenon (see, Bolton  
 269 and Oehmke (2011)).

270 Finally, as noted by Duffie et al. (2010) and as what happened in the  
 271 case of the Bear Stearns hedge funds that had large CMO holdings, is that  
 272 there can be a ‘run’ on the collateral posted by large CDS protection sell-  
 273 ers if they suffer an actual or potential ratings downgrade. Counterparty  
 274 credit risk rises to the level of systemic risk when the failure of a market  
 275 participant with an extremely large derivatives portfolio can trigger large  
 276 losses on its counterparties, which accelerates their failure. This can be ac-  
 277 companied by fire sales of the collateral which can lead to significant price  
 278 volatility or price distortions. Those CDS contracts operating on the ISDA  
 279 (International Swaps and Derivatives Association) rules also have a provision  
 280 of cross-default. If a counterparty cannot post collateral in a specified time  
 281 frame, it can deem to have defaulted and if the shortfall of collateral ex-  
 282 ceeds a threshold, the counterparty is deemed to have defaulted across other  
 283 ISDA CDS. These cross-defaults (a potential situation that AIG was in) can  
 284 trigger a domino effect as all parties close out. Attempts at novating CDS  
 285 contracts guaranteed by the ‘closed out’ firm especially when the underlying  
 286 is potentially devalued (as in the case of RMBS assets) with other protection  
 287 sellers may be difficult and if successful it increases market concentration and  
 288 network fragility as now there are fewer CDS protection sellers.

## 2.2. Broker-Dealer Concentration

The main strategy adopted by CDS dealers and counterparties to manage liquidity requirements is a practice called “offsets” which though individually rational may collectively contribute to systemic risk as the chains of CDS obligations increase and also merge. Offsets involve a strategy by which CDS participants can maximize revenue from spread trades and minimize collateral and final payouts. In Figure 2, for example, B having bought CDS cover from C, finds that the spreads have increased and may choose to eschew its hedge on the bonds of the reference entity A to earn the difference between the premia it pays to C and the higher premia it can now charge by an offset sale of CDS to D. This is marked by the red arrows in Figure 2 and is a typical spread trade. In this system, the ultimate beneficiary of CDS cover, in case of default of reference entity A, is the naked CDS buyer D. Assuming par value of \$10m for each CDS contract and zero recovery rate on reference entity bonds in Figure 2, note in the above scenario, C has an obligation to settle \$10m and then B’s obligations net to zero having settled with D. We will call this an open chain or tree.

Consider the case that C offsets with D (ie. the green arrows in Figure 2 are active). We now have a closed chain of reflexive obligations (B sells to D, D sells to C and C sells to B) with the gross notional CDS value at \$30m. Should the reference entity A default, then at settlement, if *all* parties in the CDS chain remain solvent (note that B has eschewed its hedge on the reference entity), aggregate/multilateral net CDS payouts for B, C and D are zero. Zero net notional CDS value<sup>15</sup> gives nobody any non-premia related benefits, least of all cover on the reference entity bonds. If, however, any one of the counterparties fails, say C in a double default with the reference entity A, in the closed chain of CDS obligations, the whole chain may be brought down as B now has to face its obligation to D in terms of its gross amount

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<sup>15</sup>We use the DTCC definition of aggregate net notional for each reference entity, ie. the sum of net protection bought by net buyers (or net protection sold by net sellers). See, <http://www.dtcc.com/products/derivserv/data/>. This is calculated at the level of each CDS market participant and based on the gross notional of buy and sell CDS contracts, separately aggregated over all counterparties, every participant is deemed a net buyer or net seller. The net buyers (or net sellers) values are summed up to get the aggregate net notional. Note also, this assumes zero recovery rate at time of settlement. This definition of net notional involves multilateral netting while reduction of counterparty risk can arise only from what can be bilaterally netted and nullified by mutual tear ups with the failed counterparty.

317 of \$10 m.

318 Bilateral offsets and a reflexive closed chain configuration provide the  
319 most efficient *ex ante* net settlement liquidity requirements<sup>16</sup> *if* all coun-  
320 terparties deliver. Bilateral offsets on the same reference entity will reduce  
321 collateral requirements and also counterparty risk as there will be mutual tear  
322 ups when the counterparty fails. This is characteristic of network linkages in  
323 inter-dealer relationships (Bliss and Kaufman, 2006). It must be noted that  
324 extensive non-bilateral offsets, described above, using spread trades that aim  
325 to maximize income from CDS spreads is essential for the price discovery  
326 process. It will reduce aggregate net notional but not counterparty risk as  
327 non-bilateral offsets will result in clustered interconnections and a high level  
328 of systemic risk. Also, reduction in aggregate net notional comes at a price of  
329 reducing the aggregate capacity of the CDS market to deliver hedge benefits  
330 on reference assets.

331 In summary, the network topology which favours concentration of netted  
332 flows between broker-dealers is efficient in regard to liquidity and collateral  
333 requirements. However, it can be less stable than the one that requires more  
334 *ex ante* net liquidity or collateral. Liquidity or collateral provision driven  
335 from the vantage of individually rational calculations will fall short of the  
336 amounts needed for system stability (see also footnote 15). The process of  
337 offsets can nullify gross obligations if the reference entity defaults, but this  
338 requires that net CDS sellers settle. Inability to do so, can make net CDS  
339 sellers the main propagators of the financial contagion.<sup>17</sup> The network struc-  
340 ture, where key CDS net sellers with large market shares have heavy CDS  
341 activity on them as reference entities, will show up as highly interconnected  
342 linkages amongst these same players. This highly interconnected multi-hub

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<sup>16</sup>Galbiati and Giansante (2010) have also find that networks that achieve economies in liquidity to be posted for settlement have reciprocal bilateral structures and also high interconnectivity in the form of clustering among key participants which facilitates efficient netting. Duffie and Zhu (2009) are somewhat misleading about the role of bilateral netting in the stability of the CDS market. They emphasize the savings in liquidity but, as they acknowledge, their model does not deal with so called “knock-on effects”, or the problem of how the default of one CDS counterparty can lead to a chain reaction affecting others.

<sup>17</sup>The 2009 ECB report on CDS indicates how the potential threat from AIG was not properly identified as the Fitch survey ranked AIG as only the 20th largest in terms of gross CDS obligations and failed to note that AIG was primarily a one way seller and its net CDS sell positions at \$372 bn was double the net notional amount sold by all DTCC dealers combined in October 2008.

like structure that characterizes inter-dealer CDS obligations will feature in the empirically determined CDS network model we develop.

### 3. Financial Network Analysis

Networks are defined by a pair of sets  $(N, E)$  which stand for nodes  $N = 1, 2, 3, \dots, n$ , and  $E$  is a set of edges. In financial networks, nodes stand for financial entities such as banks, other financial intermediaries and their non-financial customers. The edges or connective links represent contractual flows of liquidity and/or obligations to make payments and receive payments. Let  $i$  and  $j$  be two members of the set  $N$ . When a direct link originates with  $i$  and ends with  $j$ , viz. an out degree for  $i$ , we say that it represents payments for which  $i$  is the guarantor. Note, an agent's out degrees corresponding to the number of its immediate neighbours is denoted by  $k_i$ . In degrees represent receivables from the bank  $j$  to the bank  $i$ . In a system of linkages modelled by undirected graphs, the relationships between  $N$  agents when viewed in  $N \times N$  matrix form will produce a symmetric matrix as a link between two agents will produce the same outcome whichever of the two partners initiated it. In contrast, directed graphs are useful to study relative asymmetries and imbalances in link formation and their weights.

#### 3.1. Bilateral Flow Matrices

##### 3.1.1. Adjacency Matrix and Gross Flow Matrix For CDS

Key to the network topology is the bilateral relations between agents and is given by the adjacency matrix. Denote the  $(N + 1) \times (N + 1)$  adjacency matrix  $A = (a_{ij})^I$ , here  $I$  is the indicator function with  $a_{ij} = 1$  if there is a link between  $i$  and  $j$  and  $a_{ij} = 0$ , if not. The  $N^{th}$  agent will be represented by the US non-bank sector such as Monolines, hedge funds and insurance companies. The  $N + 1^{th}$  agent represents the non-US participants. This is also used to balance the system. The adjacency matrix becomes the gross flow matrix  $X$  such that  $x_{ij}$  represents the flow of gross financial obligations from the protection seller (the row bank) to the protection buyer  $j$  (the column bank). The FDIC Call Report Data gives the Gross Negative Fair Value (GNFV) for payables and Gross Positive Fair Value (GPFV) for receivables on all CDS products that a firm is involved in with all of its counterparties. Note GNFV and GPFV is a fraction (typically by a factor of 10) of the gross notional for which the firm is a CDS seller or buyer, respectively. The total gross payables in terms of GNFV for bank  $i$  is the sum over  $j$  columns or

378 counterparties,  $G_i = \sum_j x_{ij}$  while the total gross receivables or total GPFV  
 379 for each  $i$  is the sum taken across the  $i$  rows  $B_i = \sum_i x_{ij}$ . This is shown  
 380 below :

$$\begin{aligned}
 \mathbf{X} = & \begin{bmatrix} 0 & x_{12} & x_{13} & \dots x_{1N} & \dots & x_{1N+1} \\ x_{21} & 0 & x_{23} & \dots & \dots & x_{2N+1} \\ . & . & 0 & \dots & \dots & . \\ x_{i1} & . & . & 0 & & x_{iN+1} \\ . & . & . & & 0 & \\ x_{N+11} & . & . & x_{N+1j} & \dots & 0 \end{bmatrix} \left| \begin{array}{l} \Gamma = \sum_i G_i \\ G_1 \\ G_2 \\ . \\ G_i \\ . \\ G_{N+1} \end{array} \right. \\
 \Phi = \sum_j B_j & \begin{array}{cccccc} B_1 & . & . & B_j & \dots & B_{N+1} \end{array}
 \end{aligned} \tag{1}$$

381 The zeros along the diagonal imply that banks do not lend to themselves  
 382 (see, Upper, 2007) or in this case of CDS, provide protection to themselves.  
 383 There can be asymmetry of entries such that for instance  $G_1$  need not equal  
 384  $B_1$ . However, aggregate GNFV including that of the  $N + 1$  entity  $\Gamma = \sum_i G_i$   
 385 will be made to balance with  $\Phi = \sum_j B_j$ .

### 386 3.1.2. Bilaterally Netted Matrix of Payables and Receivables

387 Consider a matrix  $M$  with entries  $(x_{ij} - x_{ji})$  gives the netted position  
 388 between banks  $i$  and  $j$ . For each bank  $i$  the positive entries,  $m_{ij} > 0$ , in row  
 389  $i$  give the net payables vis-à-vis bank  $j$  and the sum of positive entries for  
 390 bank  $i$  is its total bilaterally netted payables across all counterparties. This  
 391 can be called  $i$ 's CDS liabilities. The sum of the negative entries,  $m_{ij} < 0$ ,  
 392 for each bank  $i$  in the  $i$ th row gives its total bilaterally netted receivables,  
 393 which is often called CDS assets.<sup>18</sup> Note the matrix  $M$  is skew symmetric

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<sup>18</sup>Note, FDIC Call Reports give the derivatives assets (liabilities) which is the GPFV (GNFV) bilaterally netted by counterparty and product and also adjusted for collateral for each bank. However, this is reported in aggregate for all derivatives products and there is no publicly available bilaterally netted data on a bank's assets and liabilities for CDS. Hence, what we will take the  $i^{th}$  bank's CDS assets and liabilities to be the sum of the



394 with entries  $m_{ij} = -m_{ji}$ . To analyse the dynamics of the cascade of failure of  
 395 the  $i$ th bank on the  $j$ th one, the matrix that is relevant will only contain the  
 396 positive elements of the  $M$  matrix. The direction of the contagion follows  
 397 from the failed bank  $i$  owing its counterparty  $j$  more than what  $j$  owes  $i$ .  
 398 Further, as we will discuss in the next section, it is customary for the net  
 399 exposures of bank  $j$  to bank  $i$  relative to  $j$ 's initial capital at time  $t$ ,  $C_{j0}$ , to  
 400 be greater than a threshold (signifying a proportion of  $j$ 's capital) before  $j$   
 401 is said to have failed. The matrix  $\Theta$  that is crucial for the contagion analysis  
 402 will have elements given as follows:

$$\Theta = \begin{bmatrix} 0 & \frac{(x_{12} - x_{21})^+}{C_{20}} & \frac{(x_{13} - x_{31})^+}{C_{30}} & .0. & .... & 0 \\ 0 & 0 & \frac{(x_{23} - x_{32})^+}{C_{30}} & .... & .... & \frac{(x_{3N} - x_{N3})^+}{C_{N0}} \\ \frac{(x_{1i} - x_{i1})^+}{C_{10}} & . & 0 & .... & .... & . \\ \frac{(x_{1N} - x_{N1})^+}{C_{10}} & . & ... & 0 & ... & \frac{(x_{iN} - x_{Ni})^+}{C_{N0}} \\ \frac{(x_{N1} - x_{1N})^+}{C_{10}} & . & ... & \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & 0 & . \\ \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & . & ... & \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & ... & 0 \end{bmatrix} \quad (2)$$

### 403 3.2. Topology of Financial Networks: Complete, Random and Uncorrelated, 404 Correlated and Small World

405 Like many real world networks, namely, socio-economic, communication  
 406 and information networks such as the www, financial networks are far from  
 407 random and uncorrelated. In order to construct a network for the US CDS  
 408 market which shows dominance of few players with a 92% and upwards of  
 409 concentration of CDS exposures, we will use what are referred to as small  
 410 world networks<sup>19</sup> (Watts (1999) and Watts and Strogatz (1998)). These  
 411 networks have a top tier multi-hub of few agents who are highly connected  
 412 among themselves (often called rich club dynamics) and to other nodes who

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bilaterally netted positive amounts  $\sum_j (x_{ij} - x_{ji})^+$  and the sum of the bilaterally netted negative amounts  $\sum_j (x_{ij} - x_{ji})^-$ , respectively.

<sup>19</sup>This is named after the work of the sociologist Stanley Milgram (Milgram, 1967) on the six degrees of separation in social networks. It has been found that globally on average everybody is linked to everybody else in a communication type network by no more than six indirect links.

show few if any connections to others in the periphery. The properties of small world networks and how contagion propagates through them will be briefly contrasted with that for the uncorrelated Erdős-Renyi random graph and also the Barabási and Albert (1999) scale free networks.

Networks are mainly characterized by the following network statistics (a) Connectivity of a network is given by the number of connected links divided by the total number of links. There are  $N(N - 1)$  possible links for directed graphs and  $\frac{N(N-1)}{2}$  for undirected graphs. (b) The measure of local interconnectivity between nodes is called clustering coefficient, ( $\Delta_i$  denotes the clustering coefficient for node  $i$  and  $\Delta$  is the coefficient for the network); (c) The shortest path length of the network estimates the average shortest path between all pairs of randomly selected nodes; and (d) Degree distribution which gives the probability distribution  $P(k)$  of links of any number  $k$ , and  $p(k)$  gives the probability that a randomly selected node has exactly  $k$  links. The average number of links per node is given by  $\langle k \rangle = \sum_k kp(k)$  and the variance of links  $\langle k^2 \rangle = \sum_k k^2 p(k)$ . Where empirical sample data is used,  $p(k) = \frac{N_k}{N-1}$  where  $N_k$  is the number of nodes with  $k$  links.

Clustering in networks measures how interconnected each agent's neighbours are and is considered to be the hallmark of social and species oriented networks. Specifically, there should be an increased probability that two of an agent's neighbours are also neighbours of one another. For each agent with  $k_i$  neighbours the total number of all possible directed links between them is given by  $k_i(k_i - 1)$ . Let  $E_i$  denote the actual number of links between agent  $i$ 's  $k_i$  neighbours, viz. those of  $i$ 's  $k_i$  neighbours who are also neighbours. The clustering coefficient  $\Delta_i$  for agent  $i$  is given by

$$\Delta_i = \frac{E_i}{k_i(k_i - 1)} \text{ and } \Delta = \frac{\sum_{i=1}^N \Delta_i}{N}. \quad (3)$$

The second term which gives the clustering coefficient of the network as a whole is the average of all  $\Delta_i$ 's. Note that the clustering coefficient for an Erdős-Renyi random graph is  $\Delta^{random} = p$  where  $p$  is the same probability for any pair of nodes to be connected. This is because in a random graph the probability of node pairs being connected by edges are by definition independent, so there is no increase in the probability for two agents to be connected if they were neighbours of another agent than if they were not. A high clustering coefficient for the network corresponds to high local

interconnectedness of a number of agents in the core. In an Erdős-Renyi network, the degree distribution follows a Poisson distribution. In contrast, scale free networks have highly skewed distribution of links that follows a power law in the tails of the degree distribution, that is the probability of a node possessing  $k$  degrees is given by

$$p(k) = k^{-\alpha}, \quad (4)$$

where  $\alpha > 0$  is called the power law exponent. Hence, there are some nodes which are very highly connected and many that are not. To generate power law statistics for nodes either in terms of their size or the numbers of links to/from them, Barabási and Albert (1999) proposed a process called preferential attachment, whereby nodes acquire size or numbers of links in proportion to their existing size or connectivity.

An important discovery that was made by Watts (1999) and Watts and Strogatz (1998) with regard to socio-economic networks is that while small world networks like scale free networks have in-egalitarian degree distribution with some very highly connected nodes, the central tiering of highly clustered nodes which work as hubs for the peripheral nodes (who have few direct connections to others in the periphery) is a signature feature only of small worlds. In order to get the core-periphery structure with a highly clustered central core, we follow the suggestion in Zhou and Mondragon (2003) and include the scope for preferential attachment or assortative mixing among the nodes with large number of outdegrees and not just a preference for high degree nodes (disassortative mixing) by low degree nodes. Note, the hubs also facilitate short path lengths between two peripheral nodes. We have indicated how such a tiered structure arise in broker-dealer structures as the hub members minimize liquidity and collateral costs by implementing offsets.

Finally, the statistic that will be used to characterize high concentration of activity, one which is closely related to the stability of the financial network is the eigenvector centrality statistic for the nodes characterizing CDS activity obtained for matrix  $\Theta$  in (2). The algorithm that determines it assigns relative centrality scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Denoting  $v_i$  as the eigenvector centrality for the  $i$ th node, let the centrality score be proportional to the sum of the centrality scores of all nodes to which it is connected (ie. out degrees). Hence,

$$v_i = \frac{1}{\lambda} \sum_j \theta_{ij} v_j. \quad (5)$$

For the centrality measure, we take the largest real part of the dominant eigenvalue,  $\lambda_{max}$ , matrix  $\Theta$  in (2) and the associated eigenvector. The  $i^{th}$  component of this eigenvector then gives the centrality score of the  $i^{th}$  node in the network. Using vector notation for this, we obtain the eigenvector equation from matrix in (2) as:

$$\Theta \mathbf{v} = \lambda_{max} (\Theta) \mathbf{v}. \quad (6)$$

As the eigenvector of the largest eigenvalue of a non-negative real matrix  $\Theta$  in (2) has only components, highly central nodes are guaranteed positive eigenvector values by the are guaranteed by Perron-Frobenius theorem (see, (Meyer, 2000), Chapter 8). Note,  $\mathbf{v}$  is the right eigenvector of the matrix  $\Theta$  and will be shown to be the relevant centrality measure for the design of a super-spreader tax.

### 3.3. Economics Literature on Financial Networks

Pre 2007 financial network models in the economics literature have yielded mixed results. An influential and early work on connectivity in a financial network and that of financial contagion is that of Allen and Gale (2001). They gave rise to a mistaken view (see, Battiston et al. (2009)) that follows only in the case of homogenous graphs<sup>20</sup>, ie. increasing connectivity monotonically increases system stability in the context of diversification of counterparty risk. A number of the analytical and numerically based studies in financial contagion work were confined to Erdős-Renyi random graphs such as Nier et al. (2007) and Gai and Kapadia (2010) which are interesting in terms of qualitative understanding one needs to get but as financial networks are far from random, they have some way to go.

As little empirical work has been done to date on network structures of the specific markets underpinning off-balance bank activity such as CDS

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<sup>20</sup>In a complete graph, if bank  $i$ 's total exposure is equally divided among its  $N - 1$  counterparties, then risk is shared equally at the rate of  $\frac{1}{N-1}$ . The demise of a single counterparty has a very small impact on  $i$ . In contrast, Allen and Gale (2001) consider an incomplete circle network where each bank is exposed to only one other for the full 100% of its receivables, then the failure of any bank in the circle will bring the others down.

507 responsible for triggering and propagating the 2007 crisis, it must be noted  
508 that the bulk of the empirical financial network approach has been confined  
509 to interbank markets for their role in the spread of financial contagion (see,  
510 Furfine (2003) and Upper (2011)). However, the use of the entropy method<sup>21</sup>  
511 (see, Upper and Worms (2004) and Boss et al. (2004)) for the construction  
512 of the matrix of bilateral obligations of banks which results in a complete  
513 network structure for the system as a whole, greatly vitiates the potential  
514 for network instability or contagion. Recent work by Craig and von Peter  
515 (2010) using bilateral interbank data from German banks have identified the  
516 tiered core-periphery structure and find that bilateral flow matrix (X) in (1)  
517 unlike in a complete or as in a Erdős-Renyi random networks is sparse in the  
518 following way:

$$X = \begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix}. \quad (7)$$

519 Here, CC stands for the financial flows among the core banks in the centre  
520 of the network, CP stands for those between core and periphery banks, PC  
521 between periphery and core banks and PP stand for flows between periphery  
522 banks. The sparseness of the matrix relates to the fact that PP flows are  
523 zero and banks in the periphery of the network do not interact with one an-  
524 other. This structure resembles the small world network described in Section  
525 3.1 above as being a characterization of *TITF* structure in the core of the  
526 network. Hence, the criticism Craig and von Peter level at extant financial  
527 networks literature is worth stating here. They say that many interbank mod-  
528 els proposed in the economics literature (e.g. Allen and Gale (2001), Freixas  
529 et al. (2000), and Leitner (2005)) ignore the tiered structure and do not anal-  
530 yse it in any rigorous way : “the notion that banks build yet another layer  
531 of intermediation between themselves goes largely unnoticed in the banking  
532 literature”. Craig and von Peter (2010) find that the tiered character of this  
533 market is highly persistent. This could coincide with an outcome of com-  
534 petitive co-evolution in that to retain status quo in market shares, the core  
535 banks are hugely geared to the arms race involved there (see, also Galbiati  
536 and Giansante (2010)). Craig and von Peter (2010) go on to note that “the

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<sup>21</sup>For a recent criticism of the entropy method in the construction of networks, see, the 2010 ECB Report on *Recent Advances in Modeling Systemic Risk Using Network Analysis* (ECB, 2010).

537 *persistence of this tiered structure poses a challenge to interbank theories that*  
538 *build on Diamond and Dybvig (1983). If unexpected liquidity shocks were the*  
539 *basis for interbank activity, should the observed linkages not be as random*  
540 *as the shocks? Should the observed network not change unpredictably every*  
541 *period? If this were the case, it would make little sense for central banks and*  
542 *regulatory authorities to run interbank simulations gauging future contagion*  
543 *risks. The stability of the observed interbank structure suggests otherwise.”*

544 From our experience of mapping the financial networks based on actual  
545 bilateral data of FIs for the Indian financial system,<sup>22</sup> there appears to be a  
546 distinct variation in the core-periphery hierarchical structure noted by Craig  
547 and von Peter (2010) in the different types of financial activities. In their  
548 derivatives or contingent claims exposures and obligations, FIs show a far  
549 more marked concentration in the core both in terms of financial flows and  
550 connectivity, with a few banks in the core and a large number of them in  
551 the periphery. In non-contingent claims based borrowing and lending the  
552 interbank market shows more diffusion in the core with a larger number of  
553 banks in the core. The least hierarchical is the RTGS payment and settle-  
554 ments systems where there is a distinct lack of identifiable periphery banks.  
555 That the credit based interbank markets have different network properties to  
556 RTGS payment and settlement systems has also been noted by Kyriakopou-  
557 los et al. (2009).<sup>23</sup> Their findings on the network topology of the Austrian  
558 payment and settlement systems have been found to correspond to the study  
559 of the Fedwire payment and settlement system by Soramaki et al. (2006).  
560 Bech and Enghin (2008) did a detailed study of the network topology of  
561 Fed Funds market and found that the clustering of the system was limited  
562 and that small banks lend more to big banks than to their own sized banks  
563 showing disassortative linkages. They found that this disassortativity was  
564 reduced when links were weighted by value of flows. Hence, we emphasize  
565 the need for empirical calibrations that reflect actual market concentration in  
566 the financial activity or the use of full bilateral data on financial obligations  
567 between counterparties.

568 Finally, the presence of highly connected and contagion causing players  
569 typical of a clustered complex system network perspective is to be contrasted

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<sup>22</sup>See, Reserve Bank of India Financial Stability Report, December 2011.

<sup>23</sup>Note, as shown in Kyriakopoulos et al. (2009) the network mapping of electronic real time payment and settlement systems is highly sensitive to the time scale over which flows are estimated. This problem is not something that has been resolved yet.

570 with what some economists regard to be an equilibrium network. Recently,  
571 Babus (2009) states that in “an equilibrium network the degree of systemic  
572 risk, defined as the probability that a contagion occurs conditional on one  
573 bank failing, is significantly reduced”. Indeed, the premise of *TITF* is that  
574 the failure of a highly connected bank will increase the failure of another  
575 similarly bank, which we find to be the empirical characteristic of the network  
576 topology of the CDS market involving US banks, indicates that the drivers  
577 of network formation in the real world are different from those assumed in  
578 economic equilibrium models.

579 Our analysis of the stability of highly clustered financial networks has  
580 been influenced by the work of Robert May and studies on the spread of epi-  
581 demics in non-homogenous networks with hierarchies (see, Kao (2010, p.62).  
582 May (1972, 1974) seminally extended the Wigner condition of eigenvalues for  
583 complete random matrices to sparse random networks. He was the first to  
584 state that the stability of a dynamical network based system will depend on  
585 the size of the maximum eigenvalue of the weighted adjacency matrix of the  
586 network. Assuming the matrix entries are zero mean random variables, May  
587 (1974) derives the maximum eigenvalue of the network, which we denote as  
588  $\lambda_{max}$ , in terms of three network parameters  $p$ , the probability of connectiv-  
589 ity,  $N$  the number of nodes and  $\sigma$  which is the standard deviation of node  
590 strength. The May (1974) result states that network instability follows when  
591  $\sqrt{Np}\sigma > 1$ . There is a trade off between heterogeneity in node strength,  $\sigma$   
592 and connectivity,  $p$ , in order for the network to remain stable. In a non-zero  
593 mean random matrix, highly connected networks can remain stable only if  
594 they are homogenous in node strength, viz.  $\sigma$  should be very small. In net-  
595 works with high variance to mean ratio in degrees and with tiered hierarchies  
596 of highly connected nodes where there is higher probability that a node is  
597 connected to a highly connected one, the direction of the epidemic which  
598 starts in a central hub follows a distinct hierarchical pattern with the highly  
599 connected nodes being infected first and the epidemic then cascading toward  
600 groups of nodes with smaller degrees, Kao (2010). Further, the epidemic  
601 dies out at great speed once the super-spreaders are eliminated. In contrast,  
602 in uncorrelated random graphs, the epidemic lasts longer and also reaches  
603 more nodes. For epidemic control, clustered networks enable targeting of  
604 specific individuals as opposed to inoculating the whole population in a ran-  
605 dom graph. Sinha (2005) and Sinha and Sinha (2006), also find that while  
606 both the small world and the Erdős-Renyi random graph show instability  
607 according to the condition given by May (1974), the lack of structure in a

608 random graph results in a worse capacity of the system to cope with the  
609 contagion.

610 In terms of propagation of failure, therefore and as it will be shown, it  
611 is not true that financial systems where no node is too interconnected or  
612 involved in a cluster (as in an Erdős-Renyi random network) are necessarily  
613 easier to manage in terms of structural coherence and stability. Hence, we will  
614 report on the stability analysis of the empirically calibrated US CDS network  
615 and also of an equivalent random graph of the same size and functionality in  
616 terms of the CDS fair value flows. The instability propagation in the highly  
617 clustered empirically based CDS network and the equivalent random graph  
618 is radically different and the less interconnected system is in some respects  
619 more difficult to manage. This suggests the need for caution in espousing  
620 an ideal network topology for financial networks. This also underscores the  
621 importance of calibrations for networks in contagion analysis to be based  
622 on actual financial flows for the market or some close empirical proxies for  
623 network connectivity.

#### 624 4. Contagion and Stability Analysis

625 The study of the topology of network in order to characterize its dy-  
626 namical and stability properties has been actively studied especially in the  
627 context of ecology of species and in epidemiology. In financial network model  
628 the analysis of contagion from specific node failure has used the classic Furfine  
629 (2003) methodology.

##### 630 4.1. Furfine (2003) Methodology : Failure of A Single Trigger bank at Initial 631 Period

632 We follow the round by round or sequential algorithm for simulating con-  
633 tagion that is now well known from Furfine (2003). Starting with a trigger  
634 bank  $i$  that fails at time 0, we denote the set of banks that fail at each round  
635 or iteration by  $D^q$ ,  $q = 1, 2, \dots$ . Note, the superscript  $q$  shows the  $q^{th}$   
636 iteration. The cascade of defaults occur in the following way:

- i Assuming tear ups but no novation of CDS contracts and zero recovery rate on the trigger bank  $i$ 's liabilities, bank  $j$  fails if its direct bilateral net loss of CDS cover vis-à-vis the trigger bank  $i$  taken as a ratio of its capital (reported in the fifth column of Tables A.4, A.5 in the Appendix



A) is greater than a threshold  $\rho$ . That is,

$$\frac{(x_{ij} - x_{ji})^+}{C_j} > \rho.$$

637 This threshold  $\rho$  signifies a percentage of bank capital which can be re-  
 638 garded as a sustainable loss. This is assumed to be the same for all  
 639 banks.

- ii A second order effect of contagion follows if there is some bank  $z, z \notin D^1$ , ie. those that did not fail in round 1, suffers losses due to counterparty failure such that the losses are greater than or equal to a proportion  $\rho$  of its capital:

$$\frac{\left[ (x_{iz} - x_{zi})^+ + \sum_{j \in D^1} (x_{jz} - x_{zj}) \right]}{C_z} > \rho.$$

640 The summation term aggregates the net loss of CDS cover to  $z$  from all  
 641 banks  $j, j \neq i$ , which demised in the first iteration.

- iii This then iterates to the  $q^{th}$  round of defaults if there is some bank  $v, v \notin D^1 \cup D^2 \dots \cup D^{q-1}$ , ie. has not failed till  $q - 1$ , such that

$$\frac{\left[ (x_{iv} - x_{vi})^+ + \sum_{j \in \bigcup_{s=1}^{q-1} D^s} (x_{jv} - x_{vj}) \right]}{C_v} > \rho.$$

- 642 iv The contagion is assumed to have ended at the round  $q^\#$  when there are  
 643 no more banks left or none of those that have survived fail at  $q^\#$ .

#### 644 4.2. Network Stability Analysis

645 Using the matrix  $\Theta$  in (2) whose entries give bilateral net liabilities of  
 646 bank  $i$  to  $j$  as a ratio of bank  $j$ 's capital, in matrix notation the equations  
 647 for the dynamics of the cascade of failure given the failure of the trigger  
 648 bank can be given as follows. Consider the column vector  $\mathbf{U}_q$  with elements  
 649  $(u_{1q}, u_{2q}, \dots, u_{nq})$  which give the probability of 'infecting' at the  $q$ th iteration.  
 650 We have  $u_{iq} = 1 = u_{iq}^1$  are those banks that fail at the  $q$ th iteration and infect  
 651 all non-failed counterparties with probability 1. Those that fail prior to  $q$   
 652 have  $u_{iq} = 0$ , viz. they do not infect anybody. The non-failed banks at  $q$   
 653 have  $0 < u_{iq} < 1$  and at  $q + 1$  their probability of failure/infecting is given  
 654 by :

$$\begin{aligned} \mathbf{U}_{iq+1} &= (1 - \rho)u_{iq} + \sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}} u_{jq}^1 \\ &= (1 - \rho) \left(1 - \frac{C_{iq}}{C_{i0}}\right) + \sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}} u_{jq}^1, \quad 0 < u_{iq+1} < 1. \end{aligned} \quad (8)$$

Here, in the first term in (8)  $\rho$  can be taken the capital buffer for CDS assets, it can be considered to be equivalent of the rate of cure in the epidemic literature. Thus,  $(i - \rho)$  gives worst case rate of failure for a bank. It is convenient to assume the initial  $u_{i0} = \rho/(1 - \rho)$  while  $u_{iq} = \left(1 - \frac{C_{iq}}{C_{i0}}\right)$ . That is, the probability of failure is determined by the rate at which  $i$ 's capital is depleted by losses from failed banks. The second term in (10) sums up the infection rates sustained from its failed counterparties. Note, therefore,  $u_{jq+1}^1 = 1$  or  $i$  fails at  $q + 1$  when the R.H.S of (8) is greater than 1.

Thus, in matrix notation the dynamics of bank failures is given by:

$$\mathbf{U}_{q+1} = [\mathbf{\Theta}' + (1 - \rho)I] \mathbf{U}_q \quad (9)$$

Here,  $\mathbf{\Theta}'$  is the transpose of the matrix in (2) with each element  $\Theta'_{ij} = \Theta_{ji}$  and  $I$  is the identity matrix. Recall the elements of the  $2^{nd}$  row of  $\mathbf{\Theta}'$  take the following form with for example, positive entries in (10) for counterparties 1, 3 and N and with  $\Theta_{22} = 0$  to indicate that an FI does not 'infect' itself:

$$\mathbf{\Theta}'_{2t} = \left( \frac{x_{12} - x_{21}}{C_{20}}, 0, \frac{x_{32} - x_{23}}{C_{20}}, \dots, \frac{x_{N2} - x_{2N}}{C_{20}} \right). \quad (10)$$

The system stability of (9) will be evaluated on the basis of the power iteration of the initial matrix  $\mathbf{Q} = [\mathbf{\Theta}' + (1 - \rho)I]$ . From (9),  $\mathbf{U}_q$  takes the form:

$$\mathbf{U}_q = [\mathbf{\Theta}' + (1 - \rho)I]^q \mathbf{U}_0 = \mathbf{Q}^q \mathbf{U}_0. \quad (11)$$

It can be shown that the stability of the system is governed by the maximum eigenvalue of the initial matrix  $\mathbf{Q} = [\mathbf{\Theta}' + (1 - \rho)I]$  when it satisfies the condition :

$$\lambda_{max}(\mathbf{Q}) < 1. \quad (12)$$

$$\lambda_{max}(\mathbf{\Theta}') < \rho. \quad (13)$$

674 Finally,  $\lambda_{max}(\Theta') = \lambda_{max}(\Theta)$  that is the maximum eigenvalue of a real  
675 non-negative matrix is equal to that of its transpose. The Furfine (2003)  
676 contagion analysis highlights how a FI fails due to its exposures to the trigger  
677 bank and hence as will be shown the stabilization of the financial network  
678 system will exploit the role of row sums in  $\Theta'$  as in a typical row given in  
679 (10). However, for purposes of managing systemic risk and the design of  
680 a super-spreader tax on a FI to have it internalize the cost to others from  
681 the excessive liabilities and connectivity that it has, we will use the right  
682 dominant eigenvector from matrix  $\Theta$  which was defined in (6).

### 683 4.3. Super-spreader Tax

684 Financial systems determined by an initial matrix  $\mathbf{Q} = [\Theta' + (1 - \rho)I]$   
685 in (9) that are prone to instability and contagion will have  $\lambda_{max}(\mathbf{Q}) > 1$  and  
686 where pre-funded capital thresholds such as  $\rho > 0$  apply, instability ensues at  
687  $\lambda_{max}(\Theta) > \rho$ . There are 4 ways in which stability of the financial network can  
688 be achieved: (i) constrain the bilateral exposure of financial intermediaries;  
689 (ii) *ad hocly* increase the threshold  $\rho$  in (9,11); (iii) change the topology of  
690 the network (iv) Levy a capital surcharge or a capital buffer commensurate  
691 to the right eigenvector centrality of a FI in (6). The first two measures  
692 do not price in the negative externality from systemic risk associated with  
693 the failure of highly weighted network central nodes. Network topologies  
694 emerge endogenously and are hard to manipulate exogenously. The aim of the  
695 super-spreader tax is to have financial intermediaries with high eigenvector  
696 centrality parameters to internalize the costs that they inflict on others by  
697 their failure and to mitigate their impact on the system by reducing their  
698 contribution to network instability as given by  $\lambda_{max}(\Theta')$ . Hence, this can be  
699 considered to be a Pigovian tax.

700 Critical to the von-Mises power iteration algorithm (see Ralston (1965))  
701 for the calculation of  $\lambda_{max}(\Theta')$  is the row sum  $S_i$  of the  $i^{th}$  row in  $\Theta'$ ,

$$S_i = \sum_j \theta_{ji} = \frac{1}{C_i} \sum_j (x_{ji} - x_{ij})^+.^{24} \quad (14)$$

---

<sup>24</sup>It should be noted that the upper bound of the maximum eigenvalue  $\lambda_{max}(\Theta')$  is given by maximum of row sums of the matrix  $\Theta'$ :  $\lambda_{max} \leq \|\Theta'\|_\infty = \max_i \sum_j \theta_{ji} = \max_i S_i$ . Here,  $\|\cdot\|_\infty$  infinity norm of a matrix is the maximum of row sums  $S_i$  where  $S_i = \sum_j \theta_{ji}$ . Hence, high connectivity to large number of counterparties and also large exposures relative to capital contribute to the high row sums for FIs and with the largest of these being the

702 We create a new row sum  $S_i^\#$ , for each node so that a super-spreader  
 703 tax denoted as  $\tau(v_i)$  applies on the capital of the  $i^{th}$  node in proportion to  
 704 its right eigenvector centrality  $v_i$  defined in (6):

$$S_i^\# = \sum_j \theta_{ji}^\# = \frac{1}{(1 + \tau(v_i)) C_i} \sum_j (x_{ji} - x_{ij})^+. \quad (15)$$

705 Thus,

$$S_i^\# < S_i \text{ for } \tau(v_i) > 0. \quad (16)$$

706 We set the super-spreader tax :

$$\tau(v_i) = \alpha v_i, \quad 0 < \alpha \leq 1 \text{ or } \alpha > 0. \quad (17)$$

707 The new matrix associated with  $S_i^\#(\alpha)$ , for all  $i$ , will be denoted as  
 708  $\Theta^\#(\alpha)$ . The alpha parameter when set at 0 obtains the  $\lambda_{max}$  associated with  
 709 the untaxed initial matrix  $\Theta'$ . When  $\alpha = 1$ , each node is exactly penalized  
 710 by  $v_i^2$ , which yields the  $\lambda_{max}$  for  $\Theta'^\#(\alpha = 1)$ . Considering,  $0 < \alpha \leq 1$ , there  
 711 is a monotonic reduction in the  $\lambda_{max}$  associated with the matrices  $\Theta^\#(\alpha)$   
 712 corresponding to the monotonic reduction in row sums  $S_i^\#(\alpha = 1) < \dots <$   
 713  $S_i^\#(\alpha = 0.75) < \dots < S_i^\#(\alpha = 0.5) < \dots < S_i(\alpha = 0)$ . Clearly, the size of  $\alpha$ ,  
 714 in particular if  $\alpha > 1$  is needed to stabilize the system, the sustainability of  
 715 such a market for risk sharing is in question.

716 The nature of the systemic risk stabilization super-spreader fund is that  
 717 it operates like an escrow fund. The super-spreader taxes that are collected  
 718 aim to cover the losses that the most connected nodes will inflict on their di-  
 719 rect ‘big’ neighbours in the first tier. The empirical section will demonstrate  
 720 the extent to which a super-spreader tax has to be levied in order to stabi-  
 721 lize the system. It is designed to work in a clustered hierarchical network  
 722 where contagion takes a specific pathway amongst the central tier if a highly  
 723 connected node fails. In fact, often reducing  $\lambda_{max}$  to a desired level may not  
 724 be technically feasible and may involve exorbitant levels of tax. Instead, we  
 725 aim to secure a super-spreader *lite* escrow fund which will escrow sufficient  
 726 funds to cover the largest amount of first round losses from the failure of the  
 727 dominant bank in terms of eigen-vector centrality.

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upper bound of  $\lambda_{max}(\Theta')$ . For a more detailed discussion of this and how stabilization using alternative applications of the right eigen-vector centrality of FIs, see Markose (2012).

## 728 5. Empirical Results

### 729 5.1. Empirical (Small World) Network Algorithm

730 We study the US banks involved in the CDS market as recorded in the  
 731 FDIC Call Reports for 2007 and 2008 Q4. In order to exclusively focus on the  
 732 systemic risk from potential counterparty risk leading to loss of cover from  
 733 CDS, FDIC data is obtained for CDS gross notional (buy and sell), Gross  
 734 positive fair value (GNFV), Gross negative fair value (GNFV) and Tier 1  
 735 capital. Tables A.4, A.5 in the Appendix A reports the key data for 2007  
 736 and 2008 Q4.

737 As discussed, we use an algorithm that assigns network links on the basis  
 738 of market shares (see, Tables A.4, A.5 in Appendix A) in order to reflect the  
 739 very high concentration of network connections among the top 6 banks in  
 740 terms of bilateral interrelationships. We first construct the  $X$  matrix given  
 741 in (1). Our algorithm assigns in degrees and out degrees for a bank in terms  
 742 of its respective market shares for gross notional values for CDS purchases  
 743 and sales. Thus, in 2007 Q4 J.P. Morgan with a 50% share on both sides  
 744 of the market will approximately have 15 in and out degrees. The choice of  
 745 these 15 banks J.P. Morgan has out degrees to is assortative, i.e. 15 banks  
 746 are chosen from the largest to the smallest in terms of their CDS activity.

- 747 •  $S_i^G$  :  $Bank_i$  market share in terms of the gross notional on the sell side  
 748 of CDS
- 749 •  $S_i^B$  :  $Bank_i$  market share in terms of the gross notional on the buy side  
 750 of CDS
- 751 •  $G_i$  : Gross Negative Fair Value for which  $Bank_i$  is a guarantor vis-à-vis  
 752 its counterparties
- 753 •  $B_i$  : Gross Positive Fair Value for which  $Bank_i$  is beneficiary vis-à-vis  
 754 its counterparties

755 The algorithm then allocates to each row bank  $i$ 's counterparties  $j$ , a value  
 756 of  $i$ 's GNFV equal to  $S_j^B G_i$  and if  $\sum_j S_j^B G_i < G_i$ , then bank  $i$  allocates the  
 757 remaining to the external non-US bank entity which is the  $N + 1$  agent. The  
 758 column sums of matrix  $X$  in (1) are made to satisfy the  $GPFV_j$  or  $B_j$  for  
 759 each bank, the following allocation rule is used such that if  $S_j^B \sum_i G_i < B_j$ ,  
 760 the remaining is bought from the external entity.

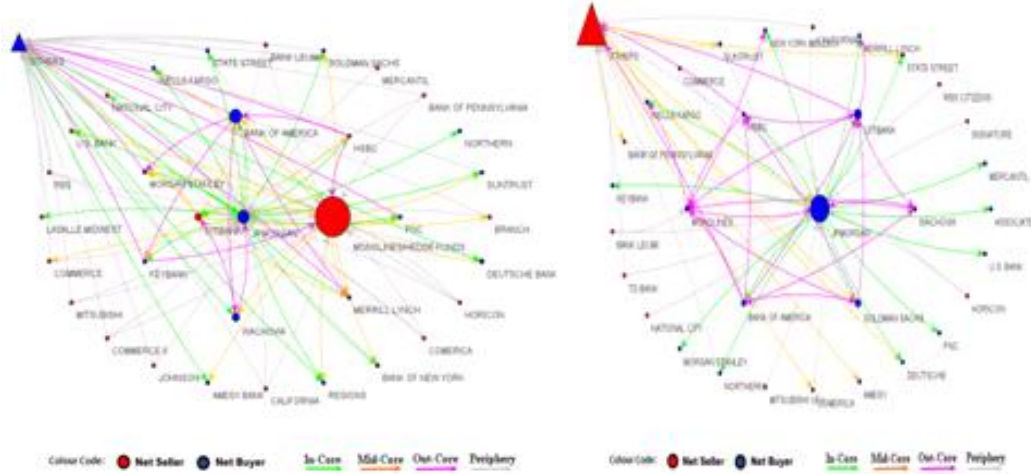


Figure 3: The Empirically Constructed CDS Network (Bilaterally Netted) for US Banks and Non-US Financial Intermediaries (Triangle): Empirical Small World Network in Tiered Layout (LHS 2007 Q4 and RHS 2008 Q4).

761 In order to determine each bank's share of GNFBV to the US non-bank  
762 sector which includes Monolines and hedge funds we use data from Table  
763 RCL-16a, "Derivatives and Off-Balance Sheet Items", from FDIC Call Re-  
764 ports which gives a sectoral break down. Finally, the share of a bank's  
765 GNFBV for the entity called 'others' which denotes non-US counterparties  
766 is obtained as a balancing item to satisfy the condition given in (1) that  
767  $\sum_i G_i = \sum_j B_j$ . The gross flow  $X$  matrix so constructed using the above  
768 algorithm is a sparse matrix with a very high concentration of activity. We  
769 then derive the bilaterally netted exposures between a pair of banks which  
770 can be read off accordingly as  $(x_{ij} - x_{ji})$  with  $x_{ij}$  denoting GNFBV for CDS  
771 protection from  $i$  to  $j$  and  $x_{ji}$  is GNFBV protection cover from  $j$  to  $i$ . Hence,  
772 the size of bilateral net sell amount is given by  $(x_{ij} - x_{ji}) > 0$ . The resulting  
773 network for this is graphed below in Figure 3.

774 In Figure 3 red nodes denote net CDS sellers and blue nodes are net CDS  
775 buyers. The main difference between the US CDS networks for 2007 Q4 and  
776 2008 Q4 is that the dominant role of the Monolines and hedge funds as net  
777 CDS sellers (largest red coloured node, LHS) has almost all been phased out  
778 by the end of 2008. By 2008 Q4 J.P. Morgan has increased its dominance as  
779 the sole member of the inner core and non-US banks (red triangle) become  
780 net protection providers. Hence, there are clear threats from the non-US

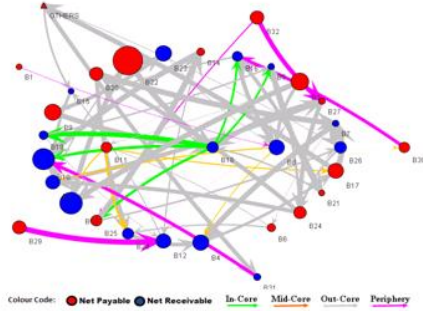


Figure 4: Erdős-Renyi Random Graph ( Equivalent to 2008 Q4 CDS Network in Figure 3 RHS) for US Banks and Non US Sector (Triangle): Absence of an identifiable core-periphery structure

sector, viz. European banks, which we will briefly analyse. The other top 5 US banks remain in the central core of the network in somewhat weaker positions with the exception of Goldman Sachs which migrates more to the centre in 2008 Q4. Over 80% of the banks are in the periphery with almost no connectivity among themselves manifesting a very sparse adjacency matrix.

The tiered layout in Figure 3 is constructed in the following way. We take the range of connectivity of all banks as a ratio of each bank's total in and out degrees divided by that of the most connected bank. Banks that are ranked in the top 20 percentile of this ratio constitute the inner core. This is followed by a mid core between 80 and 50 percentile and a 3rd tier between 10 and 50 percentile. Those with connectivity ratio less than 10 percentile are categorized as the periphery.

The links are weighted and thicker the links, the larger the size of their obligations. The links are colour coded. The triangle entity representing non-US banks constitutes the mid-core. So the yellow links show where the second tier (mid core) banks are offering protection. As can be seen, the banks with the pink arrows in the core almost always interact with one another. In 2008 Q4 the largest size rich club with a coefficient of 1 (defined in equation (??)) has only 4 members. The banks in the periphery are mostly sold protection by J.P. Morgan.

Table 1 gives the network statistics for the empirically constructed CDS networks and also for the equivalent random graph representing the 2008 CDS data given in Figure 4. The random graph is constructed with the same connectivity of about 6% as the market share based empirically con-

Initial Network Statistics	Mean	Standard Deviation ( $\sigma$ )	Skewness	Kurtosis	Connectivity	Clustering Coefficient	$\langle k^2 \rangle / \langle k \rangle$ : Variance to Mean Ratio
2008 Q4 In Degrees CDS Buyers	1.94	2.95	3.27	12	0.06	0.619	4.48
2008 Q4 Out Degrees CDS Sellers	1.94	3.07	3.41	14.12			4.85
2007 Q4 In Degrees CDS Buyers	2.97	5.29	3.48	13.481	0.087	0.35	9.42
2007 Q4 Out Degrees CDS Sellers	2.97	3.80	3.09	9.86			4.86
2008 Q4 Random Graph In Degrees	1.91	1.13	-0.089	-0.752	0.059	0.107	0.648
2008 Q4 Random Graph Out Degrees	1.91	1.13	1.161	2.21			0.648

Table 1: Network Statistics for Degree Distribution for CDS Network: Small World Network Properties Compared with Random Graph with Same Connectivity

805 structured network for 2008 Q4 (see, Appendix B for the algorithm used in  
806 the construction of the random graph.) The main difference in the network  
807 statistics for the 2007 Q4 and 2008 Q4 CDS networks is the jump in the  
808 clustering coefficient in 2008 Q4 to 62% from 35% while connectivity has  
809 fallen from about 8% to 6%. The random graph has a much lower cluster  
810 coefficient of 10% compared to that of about 62% for the empirical CDS net-  
811 work based on the 2008 Q4 data. Also, the random graph has substantially  
812 low variance to mean ratio than the empirically calibrated CDS networks.  
813 The highly asymmetric nature of the empirical CDS network is manifested  
814 in the large kurtosis or fat tails in degree distribution which is characterized  
815 by a few (two banks in this case) which have a relatively large number of in  
816 degrees (up to 14) while many have only a few (as little as 1).

## 817 5.2. Eigenvector Centrality and Furfine Stress Test Results

818 Here we will investigate the idea about the role of super-spreaders of con-  
819 tagion in terms of their network connectivity, dominance as CDS protection  
820 sellers and their right eigenvector centrality. As already noted, in the post  
821 Lehman era of 2008 Q4, the dominance of J.P. Morgan is the key aspect of



Trigger Bank (1)	Share of out (in) degrees	Weighted Eigenvector Centrality	Loss to Tier 1 Capital at q=1 ( % ) *Not Including that of Trigger Bank	Number of Banks Failed Not Including the Trigger Bank
JP Morgan	0.5 (0.48)	0.749	\$55.19 bn* (11.49%)	8 including Monolines
Goldman Sachs	0.093 (0.094)	0.1097	\$14.55bn*(2.87%)	2 including Monolines
HSBC	0.093(0.094)	0.0302	\$4.53bn* (0.89%)	Only Monolines
Citibank	0.125(0.125)	0.0862	\$0.43bn (0.000%)	0
Bank of America	0.156(0.0625)	0.0622	6.82 (1.34%)	2 including Monolines
Morgan Stanley	0 (0.03125)	0		
Merrill Lynch	0(0.0625)	0		
Monolines	0.125(0.156)	0.069		0
Others		0.6436		

Table 2: 2008 Q4 Eigenvector Centrality and Furfine Stress Tests (for selected banks) with capital threshold.

822 the US sector of the CDS market. Table 2 shows that in terms of connec-  
 823 tivity, J.P. Morgan stands out by a large margin with 55% share of total  
 824 out degrees. Citi has 12.5% of outdegrees while Goldman Sachs and HSBC  
 825 come in at third place with a modest 9.3% share. In terms of eigenvector  
 826 centrality which correlates best with contagion losses the trigger bank inflicts  
 827 on others, again J.P. Morgan with eigen vector centrality of 0.749 followed  
 828 by *Others* at 0.64 and with Goldman Sachs and Citibank at 0.1. This is  
 829 borne out in the Furfine stress tests results given in Table 2 and Figure 5.  
 830 Over all, J.P. Morgan as trigger bank results in the failure of Morgan Stanley,  
 831 Citigroup, Bank of America, Goldman Sachs, HSBC and Merrill Lynch in  
 832 the first tier of the network. This results in \$55.19 bn loss of Tier 1 Capital  
 833 to the direct counterparties of JP Morgan. One of the objectives is to see if  
 834 the super-spreader tax escrow fund can raise this amount of funds.

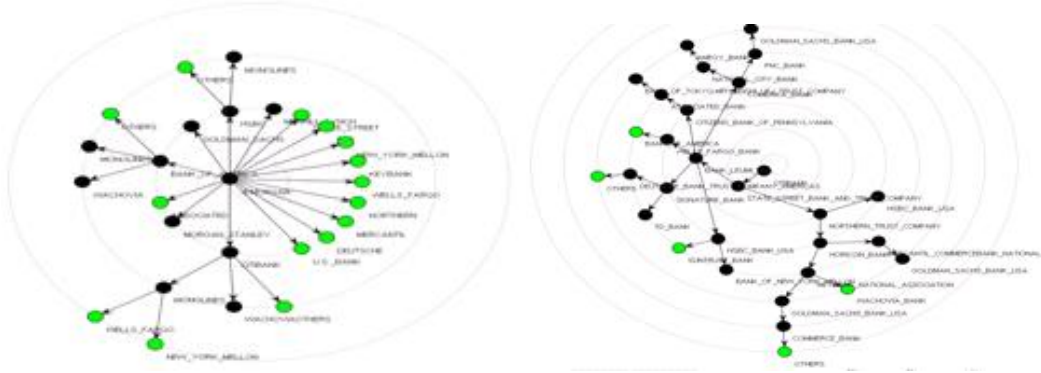


Figure 5: Instability propagation in Clustered CDS Network(2008 Q4 LHS) and in Equivalent Random Network (RHS) NB: Concentric circles mark the iterations  $q$  given in section 4.1; failed banks are black nodes and green nodes are those that are ‘hit’ but do not fail.

### 5.3. Contagion: Clustered Small World vs Random CDS Network

For the 2008 Q4 period, we will compare the CDS network stability of a random graph of the same size, connectivity and gross flow functionalities with that of the more clustered empirically based CDS network. Some very interesting issues, discussed in Section 4, are highlighted here. Recall the marked difference in structure is the clustering coefficient of the two networks and high variance to mean ratios (see, Table 1). The high clustering of the small world network in regard of what we understand to be the most likely structure for the CDS network in order to reflect the high concentration of exposures between 5 or so counterparties, results in a similar pattern in the propagation of financial contagion from the demise of the dominant bank, J.P. Morgan. As shown in Figure 5 (LHS) in the clustered network, there are only direct failures in a closed sector rather than higher order failures spreading to the whole system. It is, ofcourse, cold comfort that the first order shock wipes out the top 5 banks. Together they lead to the failure of the non-bank US CDS users. In contrast, in the random graph, while no node is either too big or too interconnected, the substantial part of the system unravels (up to 17 banks fail) in a series of multiple knock on effects. Note the concentric circles denote the sequence of cascade or iteration  $q$  described in section 4.1. The black nodes are the failed banks and the green ones are those that are hit but do not fail.

#### 5.4. Quantification and Evaluation of the Super-spreader Tax (2008 Q4)

With a maximum eigenvalue of 1.18 for the  $\Theta$  matrix in 2008 Q4, the system is deemed unstable and the losses to the system as a whole from the failure of the eigenvector dominant bank, J.P. Morgan, remains substantial with the failure of 5 top banks (see Figure 5 LHS). Socialized losses have to be internalized by the banks themselves. In this section, we will evaluate the super-spreader tax based on the theoretical derivation in Section 4.3 and equation (17). A surcharge on bank capital commensurate to the eigenvector centrality of a bank using the formula in equation (17)  $\tau(v_i) = \alpha v_i$  is applied to the rows of  $\Theta'$  for different values of  $0 < \alpha \leq 1$ . Note the eigenvector centrality for the top 5 US banks, Monolines and *Others* is given in Table 2. Compared to the target maximum eigenvalue of 1.06, the application of the capital surcharge in (17) to the matrix  $\Theta'$  results in some small reduction in  $\lambda_{max}$ . As shown in Table 3 and results in a monotonic reduction in the maximum eigenvalue  $\lambda_{max}^\#$  associated with the matrices  $\Theta'^\#(\alpha)$  corresponding to the monotonic reduction in row sums  $S_i^\#(\alpha = 1) < \dots < S_i^\#(\alpha = 0.75) < \dots < S_i^\#(\alpha = 0.5) < \dots < S_i(\alpha = 0)$ . This is given in Figure ?? and Table 3.

Figure 6 gives the rate of super-spreader capital surcharge that needs to be levied on the banks in order that they internalize the systemic risk costs arising solely from their network centrality. The super-spreader tax rate is obtained by multiplying the eigenvector centrality of each node  $v_i$  by the alpha parameter given in equation (17) which can then reduce the  $\lambda_{max}$  of the matrix  $\Theta'$ . Table 3 will focus on the case of when  $\alpha = 0.125$  for which we find that the super-spreader escrow fund can stabilize the system. It is important to see if the super-spreader escrow fund can obtain sufficient funds which can cover the Tier 1 capital losses sustained (approximately \$67 bn in the absence of any pre-existing threshold and \$55 bn if a 6% threshold exists) when the most eigen-vector dominant bank J.P. Morgan fails. What is clear from the analyses is that in the post Lehman period, the systemically important players in the US sector of the CDS market are JP Morgan and the non-US European banks taken in aggregate form as Others. The bulk of the Pigovian taxes fall on these two entities and only four other US banks need to be levied a non-zero tax on the basis of their network centrality parameter to fully price in the potential threat to the tax payer if they fail. As shown in Figure 6 and Table 3, J.P. Morgan's capital surcharge stands at about 9.37%, 8.04% for the nonUS banks (Others), 1.372% for Goldman Sachs, 0.37% for HSBC, 1.077% for Citigroup and 0.77% for Bank of America. Table 3 gives

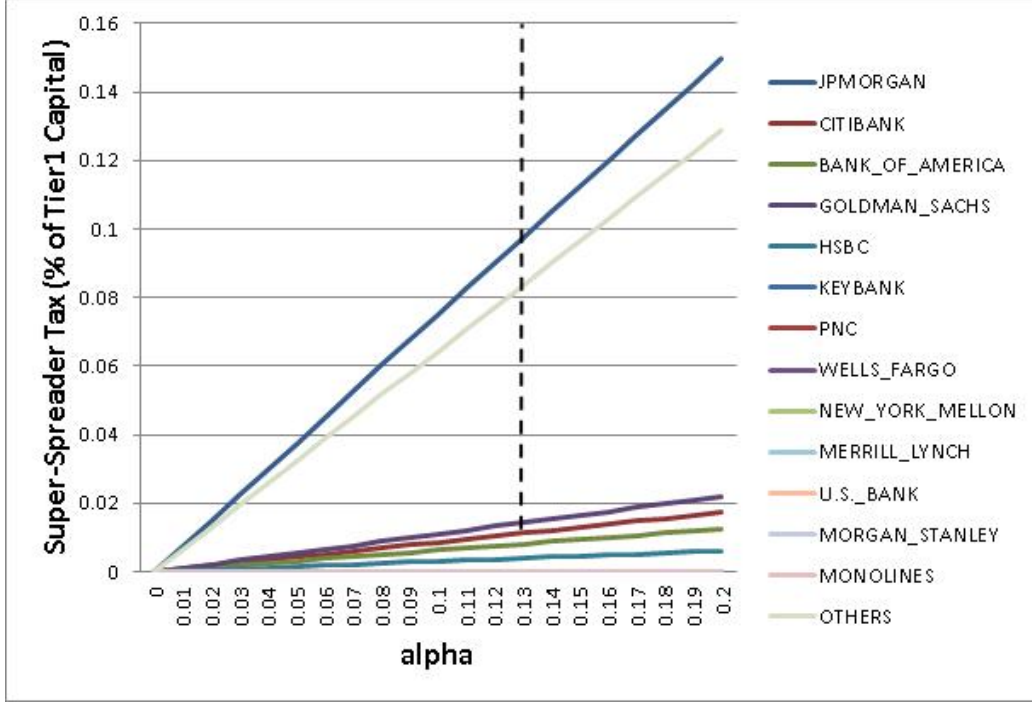


Figure 6: Super-spreader Tax Rates On Banks and Alpha (Equation 17) to Achieve Different Levels of Network Stability (Vertical line shows the tax rates and alpha necessary to secure the super-spreader lite funds necessary to \$55.19 bn 1st round losses of dominant eigen-vector central bank.

the amounts that will accrue in the super-spreader fund and we verify that this will cover over \$ 55.18 bn losses that will be incurred by the demise of the 5 top tier banks due to the failure of the dominant eigenvector central bank J.P. Morgan.

## 6. Concluding Remarks

This paper investigated the systemic risk posed by the topological fragility of the CDS market due to the concentration in CDS exposures between few highly connected US banks. To date, till the work of Craig and von Peter (2010), financial network modellers have failed to sufficiently focus on the core-periphery structure of financial intermediaries. A large number of financial network models have either assumed a Erdős-Renyi random network structure (see, Nier et al. (2007)) or complete graphs constructed by entropy

<b>Banks</b>	<b>Eigen Vector Centralit y</b>	<b>Tier 1 Capital</b>	<b>Super Spreader Tax Rate (alpha=0 .125)</b>	<b>Super Spreader Tax \$bns (alpha=0 .125)</b>	<b>\$bns Loss Round 1; r= 0</b>	<b>\$bns Loss above r= 0.06</b>
<b>JP Morga</b>	0.7494	100.597	9.37%	9.42325		
<b>Citibank</b>	0.0862	70.977	1.08%	0.76434	33.12	2.86
<b>Bank of A</b>	0.0622	88.97902	0.78%	0.69214	19.69	14.35
<b>Goldman</b>	0.1097	13.212	1.37%	0.18117	8.91	8.118
<b>HSBC</b>	0.0302	10.82192	0.38%	0.04087	2.75	2.099
<b>Keybank</b>	0	8.012102	0.00%	0	0.026	
<b>PNC</b>	0	8.337592	0.00%	0	0.19	
<b>Wells Fa</b>	0	33.129	0.00%	0	0.066	
<b>Merill L</b>	0	4.321213	0.00%	0	0.966	
<b>U.S. Banl</b>	0	14.55817	0.00%	0	0.0056	
<b>Morgan S</b>	0	5.776	0.00%	0	0.0056	1.75
<b>OTHERS</b>	0.6436	544.383	8.05%	43.79339		
<b>TOTAL</b>				<b>54.8952</b>	<b>67.988</b>	<b>55.187</b>

Table 3: Super-spreader Tax Escrow Fund (Total and selected banks) and Value of Round 1 Tier 1 Capital Losses (Super-spreader Tax (\$bns) calculated by multiplying Tier1 capital by the tax rate (%)).

906 methods. The entropy based models are known not to produce financial con-  
 907 tagion with the failure of any trigger bank (see, Upper and Worms (2004)).  
 908 The core-periphery tiered network is particularly relevant for derivatives mar-  
 909 kets. The framework we use to build an empirically based network for the  
 910 CDS obligations primarily between US banks and an aggregated non-US sec-  
 911 tor reveals the high clustering phenomena of small world networks along with  
 912 a sparse adjacency matrix. We used the market share of CDS activity by  
 913 banks to determine the network structures as discussed above.

914 We have characterized *TITF* phenomena of the CDS market with the  
 915 tiered structure given in Figure 3. The 2008 Q4 CDS network is seen to  
 916 have substantially more clustering than in 2007 Q4 and gives evidence of the  
 917 greater concentration of CDS exposures among even fewer US banks than  
 918 in 2007. The threat to the US sector of the CDS market primarily from  
 919 the European banks has been identified in the post Lehman period. The  
 920 clustered network as seen in Figure 4 showed the radically different way in  
 921 which contagion propagates in contrast with an Erdős-Renyi network. This  
 922 is well understood in network models of epidemics, but not so much in finan-  
 923 cial models. Clustered small world network structure has some capacity for  
 924 containment of contagion and in complex system terms these highly intercon-  
 925 nected multi-hub based systems can have some stabilizing effects compared to  
 926 the unstructured random graphs. However, it is clear that the increased ca-  
 927 pacity to bear the first order shocks by the hub entities could only be achieved  
 928 by installing ‘super-spreader reserves’, overturning the current practice of le-  
 929 niency in this direction.

930 The financial network implied by the bilateral exposures given in a matrix  
 931 such as  $\Theta'$  in section 4 is examined for its stability in terms of its maximum  
 932 eigenvalue. We found the empirically calibrated CDS network for the bilat-  
 933 erally netted exposures for the US FDIC banks for 2008 Q4 has maximum  
 934 eigenvalue of about 1.18. The network shows that J.P. Morgan is the most  
 935 dominant bank in regard to eigenvector centrality, followed closely by the  
 936 European banks and then only by a long margin by other US banks such  
 937 as Goldman Sachs and Citigroup. In order for banks to internalize the sys-  
 938 temic risk from their high network centrality, we recommend that banks be  
 939 taxed by a progressive tax rate based on their eigenvector centrality and to  
 940 escrow these funds. This is the first operationalization of this concept with  
 941 the application of the super-spreader tax demonstrated to better stabilize  
 942 the matrix of netted liabilities of financial intermediaries. We ‘back tested’  
 943 the capacity of this fund to cover the maximum losses from the most net-

944 work central bank. The stability analysis is one that can be used to evaluate  
945 the adequacy of the amounts of collateral or capital to absorb losses from  
946 a potential failure of counterparties even in a Central Clearing Platform  
947 without tax payer bailouts. Further experimentation with a multi-agent fi-  
948 nancial network model is needed to answer questions such as: how well will  
949 the super-spreader tax fund perform, one which is based only on unweighted  
950 eigenvector centrality of the financial intermediaries which requires much less  
951 information ? How will banks change their behaviour when faced by the full  
952 cost of being *TITF*? Can the super-spreader tax be applied and altered like  
953 traffic congestion pricing scheme as the behaviour of agents adapt to the  
954 regulatory changes (see Markose et al. (2007))?

955 It is our view that the size of derivatives markets and CDS markets, in  
956 particular, far exceed their capacity to internalize the potential losses that  
957 follow from the failure of highly connected financial intermediaries. The large  
958 negative externalities that arise from a lack of robustness of the CDS financial  
959 network from the demise of a big CDS seller further undermines the justifi-  
960 cation in Basel II and III that banks be permitted to reduce capital on assets  
961 that have CDS guarantees. We recommend that the Basel II provision for  
962 capital reduction on bank assets that have CDS cover should be discontin-  
963 ued. Banks should be left free to seek unfunded CDS cover for bank assets  
964 without the incentive of capital reduction and leverage. Indeed, this may  
965 enhance price discovery role of the CDS market relating to the probability  
966 of default of reference assets or entities.

## 967 **Appendix A. FDIC Data**

Name	Gross Notional CDS Buy		Gross Notional CDS Sell		GPFV		GNFV		Tier 1 Core Capital
JPMORGAN	4016.58	51%	3860.57	50%	130.19	44%	126.08	44%	78.45
BANK OF AMERICA	1483.96	19%	1522.46	20%	55.88	19%	51.25	18%	75.40
CITIBANK	1610.32	20%	1505.62	19%	76.59	26%	78.08	27%	81.95
HSBC	586.65	7%	638.07	8%	19.71	7%	19.79	7%	9.70
WACHOVIA	179.63	2%	188.35	2%	14.53	5%	12.65	4%	40.47
KEYBANK	4.35	0%	3.33	0%	0.07	0%	0.06	0%	7.14
PNC	3.96	0%	2.10	0%	0.10	0%	0.06	0%	7.85
WELLS FARGO	1.88	0%	0.87	0%	0.08	0%	0.03	0%	29.55
NATIONAL CITY	1.38	0%	0.85	0%	0.01	0%	0.01	0%	8.36
SUNTRUST	0.78	0%	0.31	0%	0.02	0%	0.02	0%	12.34
MITSUBISHI UFJ	0.01	0%	0.15	0%	0.00	0%	0.02	0%	0.78
REGIONS	0.07	0%	0.13	0%	0.01	0%	0.00	0%	9.80
COMMERCE BRANCH BANKING AND TRUST	0.00	0%	0.07	0%	0.00	0%	0.00	0%	2.49
COMMERCE	0.00	0%	0.03	0%	0.00	0%	0.00	0%	1.15
RBS	0.00	0%	0.02	0%	0.00	0%	0.00	0%	7.93
CITIZENS BANK LEUMI	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.42
JOHNSON	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.31
COMERICA	0.01	0%	0.01	0%	0.00	0%	0.01	0%	5.73
HORICON	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.04
CITIZENS BANK OF PENNSYLVANIA	0.00	0%	0.00	0%	0.00	0%	0.00	0%	2.26
BANK OF NEW YORK	2.09	0%	0.00	0%	0.04	0%	0.00	0%	6.46
CALIFORNIA BANK & TRUST	0.00	0%	0.00	0%	0.00	0%	0.00	0%	0.69
AMEGY BANK	0.00	0%	0.00	0%	0.00	0%	0.00	0%	0.74
MORGAN STANLEY	15.32	0%	0.00	0%	0.27	0%	0.03	0%	3.15
DEUTSCHE BANK	0.10	0%	0.00	0%	0.38	0%	0.02	0%	8.49
MERCANTIL COMMERCE BANK	0.01	0%	0.00	0%	0.00	0%	0.00	0%	0.44
STATE STREET BANK	0.24	0%	0.00	0%	0.00	0%	0.00	0%	6.91
U.S. BANK	0.06	0%	0.00	0%	0.00	0%	0.00	0%	13.21
GOLDMAN SACHS	0.56	0%	0.00	0%	0.01	0%	0.00	0%	1.21
MERRILL LYNCH	8.73	0%	0.00	0%	0.23	0%	0.01	0%	6.51
NORTHERN TRUST	0.28	0%	0.00	0%	0.00	0%	0.00	0%	3.02
LASALLE BANK MIDWEST	2.10	0%	0.00	0%	0.00	0%	0.00	0%	2.05
<b>AGGREGATE</b>	<b>7919.07</b>		<b>7723.03</b>		<b>298.11</b>		<b>288.13</b>		<b>443.48</b>

Table A.4: FDIC Data (2007 Q4) for 33 US Banks With CDS Positions (\$ bn)



Name	Gross Notional CDS Buy		Gross Notional CDS Sell		GPFV		GNFV		Tier 1 Core Capital
JP Morgan Chase	4166.76	53%	4199.10	54.3%	538.87	48%	455.56	46%	100.61
Citibank	1397.55	18%	1290.31	16.7%	211.65	19%	188.43	19%	70.98
Bank of America	1028.65	13%	1004.74	13.0%	132.04	12%	123.75	13%	88.50
Goldman Sachs	651.35	8%	614.40	7.9%	144.67	13%	131.75	13%	13.19
HSBC	457.09	6%	473.63	6.1%	64.83	6%	64.49	7%	10.81
Wachovia	150.75	2%	141.96	1.8%	24.08	2%	23.35	2%	32.71
Morgan Stanley	22.06	0%	0.00	0.0%	2.13	0%	0.03	0%	5.80
Merrill Lynch	8.90	0%	0.00	0.0%	1.19	0%	0.02	0%	4.09
Keybank	3.88	0%	3.31	0.0%	0.19	0%	0.17	0%	8.00
PNC	2.00	0%	1.05	0.0%	0.29	0%	0.09	0%	8.34
National City	1.29	0%	0.94	0.0%	0.00	0%	0.01	0%	12.05
The Bank of NY Mellon	1.18	0%	0.00	0.0%	0.08	0%	0.00	0%	11.15
Wells Fargo	1.04	0%	0.49	0.0%	0.15	0%	0.08	0%	33.07
SunTrust	0.59	0%	0.20	0.0%	0.26	0%	0.24	0%	12.56
The Northern Trust Company	0.24	0%	0.00	0.0%	0.04	0%	0.00	0%	4.39
State Street Bank and Trust Company	0.15	0%	0.00	0.0%	0.11	0%	0.00	0%	13.42
Deutsche Bank Trust Company Americas	0.10	0%	0.00	0.0%	0.00	0%	0.00	0%	7.87
Regions Bank	0.08	0%	0.41	0.0%	0.00	0%		0%	9.64
U.S. Bank	0.06	0%	0.00	0.0%	0.01	0%	0.00	0%	14.56
Commerce Bank	0.02	0%	0.03	0.0%	0.00	0%	0.00	0%	1.37
Mercantil Commercebank	0.01	0%	0.00	0.0%	0.00	0%	0.00	0%	0.54
Associated Bank	0.01	0%	0.12	0.0%	0.00	0%	0.00	0%	1.58
Comerica Bank	0.01	0%	0.05	0.0%	0.01	0%	0.03	0%	5.66
Signature Bank	0.00	0%	0.00	0.0%	0.00	0%	0.00	0%	0.76
RBS Citizen	0.00	0%	0.06	0.0%	0.00	0%	0.00	0%	8.47
Bank of Tokyo-MF	0.00	0%	0.05	0.0%	0.00	0%	0.04	0%	0.70
<b>Aggregate</b>	<b>7893.77</b>		<b>7730.85</b>		<b>1120.60</b>		<b>988.04</b>		<b>480.82</b>

Table A.5: FDIC Data (2008 Q4) for 27 US Banks With CDS Positions (\$ bn)

## 968 Appendix B. Random Network Algorithm

969 The algorithm that creates a random network of CDS obligations proceeds  
970 on the following steps:

- 971 1. An adjacency matrix  $\mathbf{A}(N \times N)$  is created where each element has  
972 value 1 with probability  $p$  (this probability is set to be equal to the  
973 connectivity of the empirical network we want to compare with), 0  
974 otherwise.
- 975 2. A matrix  $\mathbf{R}(N \times N)$  of random numbers is created where each element  
976  $r_{ij}$  is randomly drawn from a uniform distribution in the range  $[0, 1]$ .
- 977 3. The matrix  $\mathbf{B}(N \times N)$  of random values is generated as follows:  $B =$   
978  $A * R$  (element by element multiplication). The matrix  $\mathbf{B}$  is now a sparse  
979 matrix with many zero elements.
4. The final flow matrix corresponding to  $X$  in equation (1) of CDS obli-  
gations  $\mathbf{X}$  is defined as

$$\mathbf{X} = \mathbf{B} \frac{\Gamma}{\sum_i \sum_j b_{ij}}$$

980 . Here,  $\Gamma$  is the total CDS GNFBV in the market as required by the  
981 empirically constructed matrix

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