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Monitoring the European CDS Market through networks: Implications for Contagion Risks[*]

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Abstract

Based on a unique data set referencing exposures on single name credit default swaps (CDS) on European reference entities, we study the structure and the topology of the European CDS market and its evolution from 2008 to 2012, resorting to network analysis. The structural features revealed show bilateral CDS exposures describing growing scale-free networks whose highly interconnected hubs constitute both a strength and weakness for the stability of the system. The potential "super spreaders" of financial contagion, identified as the most interconnected participants, consist mostly of banks. For some of them net notional exposures may be particularly large relative to their total common equity. Our findings also point to the importance of some non-dealer/non-bank participants belonging to the shadow banking system.

JEL Classification: E17, E44, E51, G21, G28.
Keywords: Credit Default Swaps; Financial Networks; Centrality measures; Contagion

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Executive summary

This paper studies the topology of networks of CDS exposures on European reference entities based on a unique dataset covering the period from January 2008 to January 2012.[1]

We analyse both the absolute levels and the changes over time of a set of well-established network metrics. We try to discern the economic intuition behind the time patterns revealed, and how contagion could spread across the structure. Thereafter, we focus on a set of network centrality measures in order to assess the prominence of CDS buyers and sellers in the structure of credit exposures, assigning different rankings to the most interconnected participants and analysing their evolution over the years as well as their distribution in the cross-section. We also compare our metrics with price-based indicators of systemic risk. While there is evidence of a positive correlation between network measures and the contribution-CoVar of Adrian and Brunnermeier (2011), other price measures display rather ambiguous results. Finally, we use balance sheet data to ascertain the financial resilience of the banks that dominate the market in terms of network centrality.

The structural network features uncovered are in line with what one would expect given important economies of scale, capacity issues, and key information asymmetries in CDS markets, and are highly indicative of growing "scale-free" networks. In effect, our analysis shows bilateral CDS exposures describing networks that are very sparse, with the vast majority of market participants being exposed only to a few others; exposures are highly concentrated, and follow a fat-tailed (power-law) distribution; market participants, if not directly linked, are typically indirectly exposed to each other via other two or three counterparties only; firms with many counterparties tend to be exposed to firms with few and vice-versa. These features are robust across the four years of our sample period, although various time patterns point to a higher concentration of exposures over time. All in all, the networks studied in this paper can be described as consisting of a low number of highly interconnected *hubs* – the largest dealers – and a high number (increasing over time) of peripheral or less connected buyers. A key financial stability implication of such structures is that hubs are both a strength and weakness of the networks. Thus, adequate regulatory and supervisory action with respect to the more connected players is more likely to prevent shocks from spreading throughout the system.

When we relate the identification of banking institutions that are the most central to balance sheet indicators of their financial soundness, we observe that the largest CDS dealers, while on average perceived as "safer" in the CDS market, tended to be less well capitalised than the non-dealer banks. While we cannot analyse an indicator of financial soundness for the very interconnected non-bank firms identified, we find that the average size of their bilateral exposures to other firms can be much higher than that of many bank-dealers. This is a concern as parts of these entities may belong to the shadow banking system operating under lighter regulation than other institutions and may not have sufficient loss absorption capacity to withstand financial shocks stemming from the CDS market.

The nominal values of outstanding positions, and thus bilateral and multilateral net exposures, do seem to be an adequate metric for the purpose of studying the structural properties of CDS networks and obtaining insights into the potential impact of their complexity and interconnectedness on systemic risk. Nonetheless, it is worth noting that a complete analysis of the amounts at risk in derivatives contracts would also necessitate considering the price level and/or volatility of the reference entity, and the availability and extent of risk-mitigation mechanisms such as collateralisation and collateral netting agreements. Such an analysis is beyond the scope of this paper.

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[1] The dataset was provided to the European Securities and Markets Authority (ESMA) by the Depository Trust & Clearing Corporation (DTCC).

1. Introduction

The credit default swap (CDS) market has attracted significant attention since the beginning of the 2007-2008 financial crisis. While designed as a hedging instrument to protect investors against counterparty risk, CDS have raised significant concerns amongst supervisors with regard to their potential risks in a situation of generalised financial distress. The three main concerns relate to the capacity of the CDS market to settle the failure of a major reference entity; the ability to cope with the consequences of default by a major dealer; the major role played by banks as protection sellers and consequently their potential vulnerability given the evidence of under-collateralization of CDS positions. Such fears have been exacerbated by the fact that this market is perceived in some quarters as a very opaque over-the-counter derivatives market with too little information on bilateral exposures, notwithstanding the increase in the amount of public information on CDS in recent years.[2]

The evidence gathered so far on these concerns is mixed. On the one hand, the market has proven resilient and shown its capacity to settle major credit events, such as the default of big financial institutions, like Lehman Brothers, or such as the events in Greece. On the other hand, the dominance of a few big players in the market and fear of contagion led some public authorities to bailout these “too interconnected to fail” institutions, as in the case of AIG. The shock waves following these events also raised the issue of the role and relevance of this market for the transmission of financial shocks.

So far, most analyses carried out on the CDS market have relied on CDS price correlations and co-movements (see Alter and Schueler, 2012, Jorion and Zhang, 2009, among others). Moreover, CDS spreads have been used to rank institutions or reference entities according to their contribution to systemic risk (Yang and Zhou, 2012). While very useful these price-based measures present three main drawbacks. First, they tend to be volatile, which in turn renders volatile related rankings of systemic institutions; second, CDS markets may not always be very liquid; and third, by looking at interdependencies merely via price data one cannot study the full landscape of interconnections in the CDS market. On the other hand, given the size and, perhaps more importantly, the highly concentrated nature of the CDS market, a network analysis of bilateral exposures among CDS traders can be instrumental to an assessment of the impact of the topological features of the market on contagion and systemic risk.

Network theory provides direct insights into highly complex and interconnected financial systems (see Soramäki et al., 2007, for one of the earliest applications of network analysis to payments system data, and Iori et al. 2008, for an application to the Italian money market). Similarly to bilateral exposures in the interbank market, the analysis of bilateral CDS exposures allows to directly capture counterparty risk, which is an important channel of contagion. In addition, some well-established network statistics provide a synthetic way to characterize key structural properties of the networks formed by CDS positions and to assess their stability. Monitoring their absolute levels and, more importantly, their developments over time can deliver important intelligence on the tendency of the CDS market to spread and amplify shocks or, conversely, to act as a regular insurance market allowing for better repartition and diversification of risks. Finally, network analysis can help identify those institutions whose difficulties have greater potential to jeopardize the resilience of the entire system.

Against this background, this paper studies the topology of networks of CDS exposures on European reference entities. We rely on a unique data set provided to the European Securities and Markets Authority (ESMA) by the Depository Trust & Clearing Corporation (DTCC), the world’s largest CDS trade repository. We worked on an anonymised dataset,

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[2] See Stulz (2010) for a throughout analysis of the benefits and costs of over-the-counter versus on exchange trading of CDS.

which records weekly the notional value of CDS positions outstanding each Friday from 4 January 2008 until 27 January 2012. These positions are used to reconstruct 213 networks (one per each Friday for which positions are registered) of net bilateral exposures. In each network, a net bilateral seller or buyer of CDS protection represents a *node*; a *link* is defined if one institution is a net buyer of protection from another. Four different network representations are considered, corresponding to different levels of CDS aggregation: Financials, Non-Financials, Sovereigns and the CDS market as a whole (where all CDS positions are included regardless of the specific underlying reference entity or its market sector).

We analyse both the absolute levels and the changes over time of a set of well-established network metrics. We try to discern the economic intuition behind the time patterns revealed, and how contagion could spread across the structure. Thereafter, we focus on a set of network centrality measures in order to assess the prominence of CDS buyers and sellers in the structure of credit exposures, assigning different rankings to the most interconnected participants and analysing their evolution over the years as well as their distribution in the cross-section. We also compare our metrics with price-based indicators of systemic risk. While we find evidence of a positive correlation between network measures and the contribution-CoVar of Adrian and Brunnermeier (2011), other price measures display rather ambiguous results. Finally, we use balance sheet data to ascertain the financial resilience of the banks that dominate the market in terms of network centrality.

Our analysis of the network topology shows bilateral exposures describing growing "scale-free" networks. These are very sparse, with the vast majority of market participants being exposed only to a few others; exposures are highly concentrated, and follow a fat-tailed (power-law) distribution; market participants, if not directly linked, are typically indirectly exposed to each other via other two or three counterparties only (i.e. they are at a short average distance from one another); firms with many counterparties tend to be exposed to firms with few and vice-versa (i.e. networks display strong *disassortative mixing*). These features are robust across the four years of our sample period, although various time patterns point to a higher concentration of exposures over time. All in all, the networks studied in this paper can be described as consisting of a low number of highly interconnected *hubs* – the largest dealers – and a high number (increasing over time) of peripheral/less connected buyers.

The analysis of various centrality metrics confirms the intuitive assumption that, due to highly asymmetric returns on CDS positions, net sellers can be considered the primary locus of systemic counterparty risk in the CDS market. However, taking indirect exposures (i.e. exposures to sellers of sellers of CDS) into account points to the importance of some non-dealer (and non-bank) participants for the resilience of the whole network. Finally, when we relate the identification of banking institutions that are the most central to balance sheet indicators of their financial soundness, we observe that the largest CDS dealers, while on average perceived as "safer" in the CDS market, tended to be less well capitalised than the non-dealer banks. In effect, the results show that for some banks net CDS exposures may be particularly large relative to their total common equity. While we cannot analyse an indicator of financial soundness for the very interconnected non-bank firms identified, we find that the average size of their bilateral exposures to other firms can be much higher than that of many bank-dealers.

This paper contributes to an increasing body of literature that looks at the role of CDS as transmitters of contagion through the large and complex network of financial linkages they create across financial institutions (see Brunnermeier et al., 2013 for a broad overview of possible contagion channels in the CDS market). For instance, Heise and Kühn (2012) examine CDS-induced contagion in a stylized network of corporates and financial institutions. They find that CDS can create additional contagion channels which may lead to greater instability of the entire network in times of stress, especially when banks use CDS to expand their loan book. Vuillemey and Peltonen (2012) model sovereign default and its spillovers into the European banking system. By contrast with former papers, they consider not only CDS exposures but also the portfolio of underlying credit exposures. They point out that a main driver of contagion is related to collateralization and variation margins, CDS sellers being exposed to sudden increases in collateral requirements on multiple correlated exposures. They conclude that risk mitigating mechanisms, such as collateral netting agreements and collateralisation, can considerably reduce the scope for contagion. Importantly, their results point to the limits of a default cascade analysis of the kind traditionally performed to study contagion in national interbank markets (see Upper, 2011) to assess the financial stability implications of a shock in the CDS market.

Given the unavailability of any information on the collateralisation of CDS positions in the DTCC dataset, we decide not to run this kind of domino simulations – whereby several rounds of contagion are triggered by the initial default of one institution due to exposures to the defaulting bank(s) and to the size of related losses relative to bank capital; we estimate that they would provide a too simplified and unrealistic view of the potential for contagion via CDS exposures (see also Brunnermeier et al.). Instead, we resolve to rely on network techniques for the identification and monitoring over time of the key topological properties of networks of CDS exposures.

Mainly due to data unavailability few papers exist in the literature documenting the actual characteristics of CDS networks. Two recent exceptions are Markose et al. (2012) and Peltonen et al. (2013). In the first paper the authors reconstruct the US CDS network using the FDIC Call Reports on off-balance sheet bank data for Q4 2007 and Q4 2008. They study the domino propagation of financial contagion in the network, identify a few participants that dominate the market in terms of network centrality, and based on the latter propose a "super-spreader tax". Peltonen et al. study the determinants of certain properties of CDS networks (for specific reference entities) based on actual outstanding bilateral exposures on 191 global sovereign and financial reference entities at end 2011.

Our paper implicitly provides a test for the results of recent theoretical models of strategic network formation and intermediation in over-the-counter (OTC) markets. In particular, our findings support the model by Babus and Kondor (2013), predicting equilibrium networks with few very well connected (and well informed) and many less connected (and less well informed) dealers based on the informational content of the strategies of the counterparties that the dealers trade with. The main intuition behind their network formation game is related to information aggregation through trade: The equilibrium price in each transaction partially aggregates the private information of all agents; this leads to a system where only a small number of sophisticated financial institutions are responsible for the bulk of the trading volume.[3]

Finally, it is worth noting that a complete analysis of the amounts at risk in derivatives contracts would also necessitate considering the price level or volatility of the reference entity, the duration and liquidity of contracts, the creditworthiness of counterparties and, last but not least, the availability and extent of risk-mitigation mechanisms such as collateralisation, collateral netting agreements and close-out netting[4]. Such an analysis is beyond the scope of this paper. Nevertheless, the nominal values outstanding, and thus bilateral and multilateral net positions, do seem to be an adequate metric for the purpose of studying the structural properties of networks of CDS exposures and obtaining insights into the potential impact of their complexity and interconnectedness on systemic risk. In addition,

3 The emergence of dealer-centric markets, where one agent acts as intermediary and trading counterparty for all other agents, is also at the centre of Babus (2013). In her model, a link between two agents grants each of them access to information about the other. When acquiring information is costly, and repeated interactions are allowed, agents optimally choose to trade with a broker-dealer because paying intermediation fees is less expensive than acquiring information. In equilibrium one agent intermediates all the trades.

4 Close-out netting is the mechanism whereby all derivative transactions concluded under a given contract (*single* or *master agreement*) can be terminated in the case of a counterparty default. It is one form of netting that typically occurs under the ISDA (International Swaps and Derivatives Association) Master Agreement.

the aggregation of CDS positions across different reference entities belonging to the same market sector appears meaningful if the aim is to understand counterparty risk, and if the resilience of the CDS market to the default of one of its participants is of greater concern than assessing contagion stemming from the default of individual reference entities. In effect, the growing importance of risk mitigation mechanisms in the OTC derivatives market has probably contributed to shaping CDS networks as graphs highly structured around bi-directional gross exposures, i.e. widely used mechanisms such as close-out netting may have reinforced the importance of bilateral relationships in this market. In this respect, the aggregation of CDS positions even across different market sectors allows us to focus more clearly on the risks related to counterparty failure.

The rest of the paper is organised as follows. The following section presents the data used for the analysis and the main characteristics and recent developments of the CDS market for European reference entities. Section 3 describes the methodology used for the analysis and discusses the key structural properties of the networks of CDS exposures, their evolution over time and the possible implications for financial stability. Section 4 identifies the most interconnected market participants by means of network centrality and compares these rankings with systemic risk measures based on CDS prices or equity returns. Section 5 seeks to assess their potential role in spreading financial shocks through the network by relating centrality indicators to banks' financial soundness, measured with reference to selected balance sheet items. The last section concludes.

2. The credit default swap (CDS) market for European reference entities

2.1. CDS contracts and counterparty risk

A CDS is an over-the-counter derivative financial instrument used to hedge against the risk of default by a particular reference entity. CDS resemble insurance policies on an entity's debt obligations. The buyer of the swap holds the insurance, while the seller takes the risk: the former receives positive pay-outs from the seller when a credit event on the underlying entity is deemed to have occurred and in return pays periodic premiums to the seller.

One key characteristic of CDS contracts is that, due to their dominantly over-the-counter (or off-exchange) nature, each of the parties involved could have credit risk concerns with respect to the other. The CDS seller is exposed to the buyer in relation to the possible default of the underlying reference entity. The buyer is in turn exposed to a default of the seller: If the latter defaults, the buyer will not get his pay-off in case of a credit event and will have to write down the face value of its contracts. Another crucial feature is the high asymmetry of pay-offs between buyers and sellers, which is heightened in periods of stress as defaults are more likely while recovery rates tend to be lower under such circumstances. As a consequence, the risk that buyers of protection will incur huge losses increases, making large net sellers more vulnerable to counterparty risk. Finally, among the several ways of terminating the exposure to the reference entity underlying a CDS contract (apart from a credit event), the most common one is by entering into a transaction with the opposite sign with other market participants (*offsetting transactions*)[5]. Offsetting transactions create a complex network of net exposures resulting in increased counterparty risk, which is the scope of this paper.

[5] For instance, the "novation" entails the replacement of one of the two original counterparties to the contract with a new one. Some changes may also be related to early termination clauses (for instance in the event that one of the counterparties defaults) or to "compression" mechanisms designed to cancel redundant contracts due to offsetting positions. For more details, see the documentation established by the International Swap and Derivatives Association (ISDA).

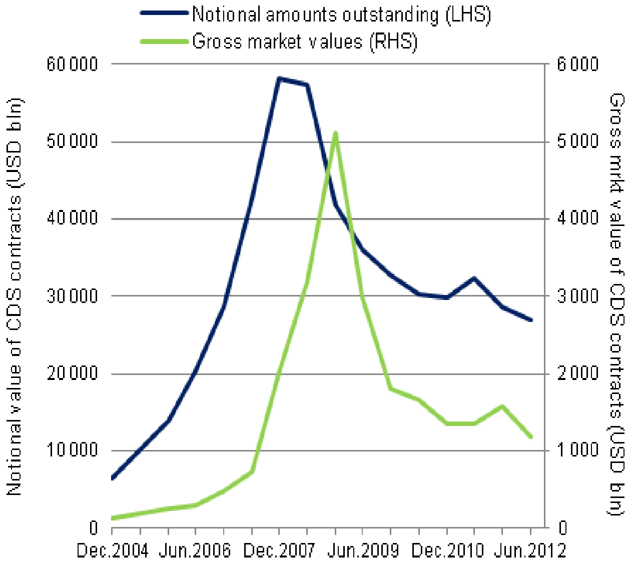
2.2. DTCC data

The data we use consist of weekly notional positions on single name CDS (i.e. CDS linked to a specific reference entity as opposed to "index" CDS, related to a portfolio of entities) registered in the DTCC's Trade Information Warehouse (TIW). The notional value registered in DTCC's TIW represents the par amount of credit protection bought or sold, equivalent to debt or bond amounts, and is used to derive the coupon payment calculations for each payment period and the recovery amounts in the event of a default.[6] This source of data differs from the data provided by the Bank for International Settlements (BIS). The latter is collected through a voluntary survey while DTCC's data is based on the repository system that collects actual settlement instructions. According to the BIS, the notional value outstanding of CDS globally was USD 26,900 billion in June 2012 (Fig. 1, upper chart), whereas DTCC reported about USD 23,000 billion. This difference between the two values is due mostly to the more limited coverage within DTCC data of CDS contracts written by non-dealers.

2.3. Main market developments

In contrast to the decline observed in the global CDS market since 2008 (BIS, 2012) the figures gathered through the DTCC's Warehouse for European (EU) reference entities show that the gross value of outstanding CDS positions on all EU reference entities grew by 32% from 2008 to the beginning of 2012, climbing from an average of USD 3,500 billion in 2008 to USD 4,600 billion in the opening weeks of 2012 (Fig. 1, lower chart). A break in the uptrend in CDS sales can be seen to occur in September 2008, related to the default of Lehman Brothers. This credit event resulted in the closure of outstanding positions involving the failed investment bank, reducing the gross notional outstanding. Thereafter, the market continued to grow but at a slower pace.

Gross values provide an important indication of the size and growth of market activity, but they are not the most suitable for assessing the risks stemming from participants' exposures. For this purpose, net notional exposures are more interesting to look at. The net notional outstanding also witnessed an uptrend, at least until the third quarter of 2009, but the pace of increase was slower. Net notional amounts are significantly lower than the gross transaction values.



[6] It is important to note that the notional values provided in the Warehouse do not reflect the market price of the contracts and may correlate or not with mark-to-market values.

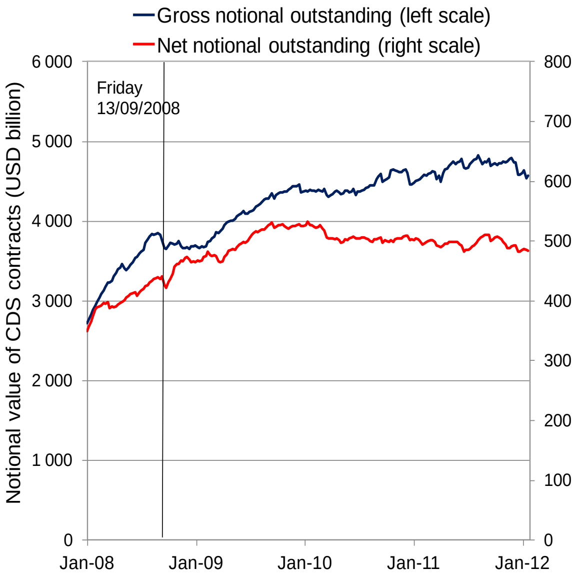


Fig. 1.

Above: Global CDS market developments (Source: BIS survey, June 2012).

Below: Developments in the market of CDS on European reference entities (Source: DTCC's Trade Information Warehouse).

The dataset used in this paper allows us to provide an overview of the EU CDS landscape and to describe some of its structural trends, thus filling a gap in the literature. While the growth observed may reflect partly an increasing coverage of CDS transactions by DTCC, it is likely to reflect as well a specific European trend due, in particular, to the euro area debt crisis and the need for investors to hedge against sovereign default risk. Notably, DTCC data reveal that the net notional outstanding on EU-25[7] sovereigns increased from less than USD 100 billion in 2008 to about USD 200 billion in January 2012 . This applies notwithstanding the BIS reporting that sovereign CDS notional remained relatively stable at a global level in Q2 2012 relative to end 2011 (at USD 3,000 billion). The market share of CDS referencing EU sovereign debt out of the total notional outstanding (all EU reference entities) rose from 24 percent in 2008 to 42 percent in early 2012 (see Fig. 2). At the same time, the share of net notional outstanding on financials remained roughly constant or dipped slightly throughout the sample period. This evidence may hint at the presence of moral hazard in the European financial system, in the form of a government put: the beginning of the most intense phase of the crisis, in September 2008, coincides with a shift in CDS positions from EU financials and non-financials to EU sovereigns.

7 EU-27 excluding Luxembourg and Czech Republic.

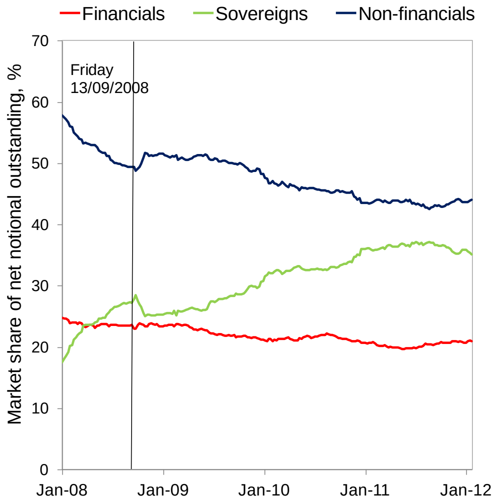


Fig. 2. Market shares of net CDS notional outstanding by market sector of the underlying reference entity.

2.4. Market participants and market concentration

The strong and rapid growth of the CDS market on EU reference entities is linked to a rapid increase in the number of market participants, which grew remarkably over our sample period. The upward trend in the number of buyers was similarly driven by financial, corporate and sovereign reference entities until September 2008; thereafter, it started to be driven mainly by buyers of CDS on EU sovereigns. The number of sellers, instead, started to gather pace after autumn 2009 following the release of bad news on Greece's public finances. The significantly lower number of sellers compared to buyers (almost half, see Fig. 3) is a first indication of the prominent role that the former play in this market.[8]

The highly concentrated nature of the market is thrown into sharp focus by a consideration of participants' market shares in terms of the notional amounts of protection sold. Notwithstanding the very high number of asset managers and hedge funds selling CDS (approximately 60% of the total number of sellers at the beginning of 2012), these institutions account (on average) for a mere 2.1 percent of the total CDS sales over the sample period. By contrast, banks (the red area in Fig. 4) represent about 30% of the total number of sellers but account for more than 96 percent of CDS sales until the end of 2009 and about 88 percent at the beginning of 2012.

Banks are, therefore, the most prominent players in this market. The decline in their market share since 2010 follows the regulatory move to centralised clearing for standardised over-the-counter derivatives. Accordingly, the percentage of contracts sold by central clearing counterparties (CCP) (readable on the right-hand scale) rose rapidly from less than 1% in January 2010 to almost 10% at the beginning of 2012. As noted above, until CCPs entered the market, hedge funds held the second largest sales share, at around 1.3%, with asset managers' and financial services' share below 1%. Zooming in the plot after excluding banks and CCPs (Fig. 4, right-hand chart), we can see hedge funds stepping up their selling activity in CDS on European entities after the default of Lehman and reducing it progressively since the second half of 2009. Also worth noting is that from September 2010 asset managers became more active than hedge funds, although their volumes continued to represent less than 1.5 percent of total market sales.

8 For further details on the type of market participants acting as CDS buyers and sellers see Brunnermeier *et al.* (2013).

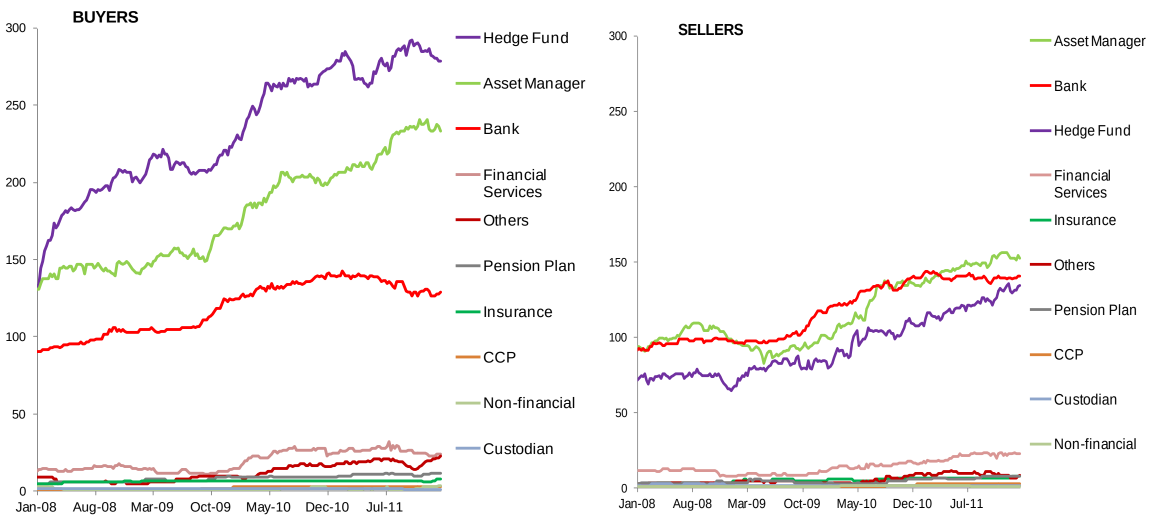


Fig. 3.

Left: Buyers of CDS by type of institution.

Right: Sellers of CDS by type of institution.

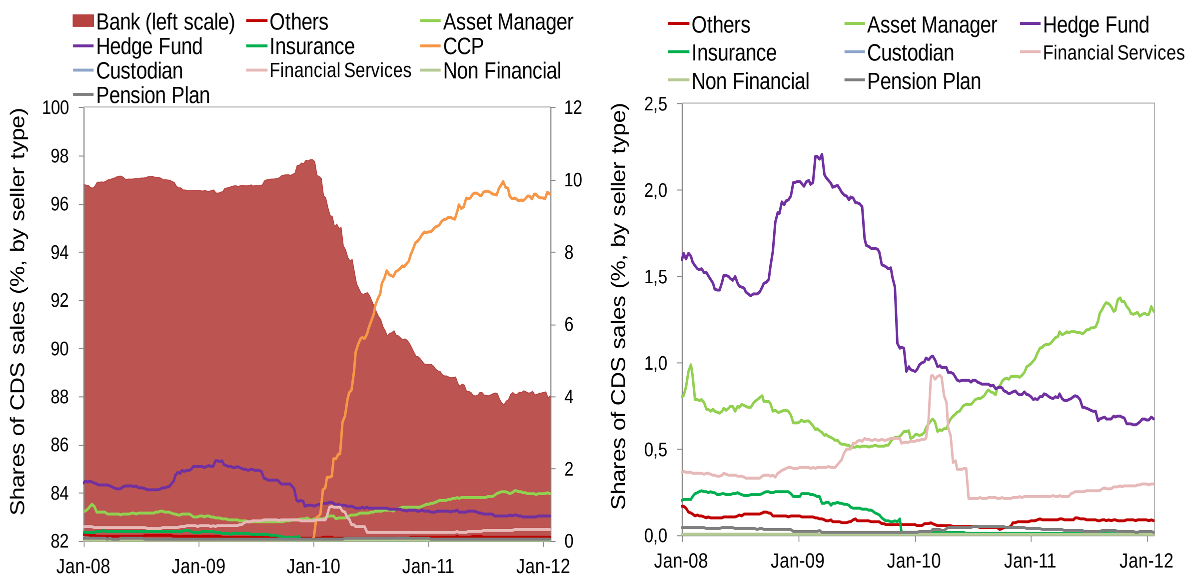


Fig. 4.

Left: Shares of CDS sales by seller type.

Right: Shares of sales by seller type excluding banks and CCP.

3. The networks of CDS exposures

In this section, we first describe shortly the methodology used to study the structural properties of directed networks in which market participants are linked bilaterally via net CDS exposures. Second, we visualize some "snapshots" of sectoral CDS networks on 27 January 2012 hinting to some key characteristics of a very complex set-up. Third, we discuss the findings of our network analysis, the stability of the properties revealed over time, and the implications for financial stability.

3.1. Methodology

We construct weekly networks based on CDS notional positions registered in DTCC's TIW each Friday from 4 January 2008 to 27 January 2012. In each network, net bilateral sellers or buyers of CDS protection represent the *nodes*; a *link* is defined where one institution is a net buyer of protection from another. Each link is weighted and directed: The weight represents the size of the seller's net exposure vis-à-vis the buyer in case of a credit event, as well as the size of the buyer's exposure to the seller in terms of the pay-off he could lose in case of a seller's default; the direction goes from the buyer to the seller of CDS protection. This amounts to building 213 asymmetric adjacency matrices where $g_{ij} = 1$ if i is a net buyer of protection from node j, with w_{ij} being the net bilateral selling position of node j vis-à-vis node i (see Appendix A for more details).[9]

We consider four different network representations: three representations correspond to the three market sectors in which the reference entities are classified in the data (Financials, Non-Financials, and Sovereigns); the fourth is the network for the CDS market as a whole, independently of the specific sector of the underlying reference entity. Therefore, in the first three "sectoral" networks, the net bilateral exposures are calculated using CDS written against Financials/Non-Financials/Sovereigns respectively. In the fourth, net bilateral exposures are computed bundling together all CDS positions.

Both the net bilateral exposure and the gross amount of protection sold have been considered for definition of the links, and we verify that the uncovered changes in the networks are not driven by this choice.[10] In the following, however, we present evidence derived from networks based on net notional positions: Net notional values represent the maximum possible net funds transfers between sellers and buyers of protection that could be required on the occurrence of a credit event relating to a particular reference entity[11]; thus they are arguably more relevant from the point of view of assessing contagion risk in the context of a potential market stress situation (be it the default of a reference entity or the default of a protection seller). Also, one has to keep in mind that netting is a crucial means of mitigating credit risks associated with OTC derivatives. For instance, under the widely used close-out netting mechanism all derivative transactions concluded under a given *master agreement* can be terminated in case of default of a counterparty, and negative and positive position values can be combined into a single net payable or receivable, as illustrated in Fig. 5.

9 Network indicators have been estimated using the R package Graph. The analysis concerns the largest connected component of each weekly network of exposures, i.e. the largest sub-network in which all nodes are connected via undirected paths. Appendix A provides an overview of basic concepts and definitions in network theory.

10 A comparison of network statistics built on the basis of gross *versus* net bilateral positions is available upon request.

11 Actual net funds transfers are dependent on the recovery rate for the underlying bonds or other debt instruments.

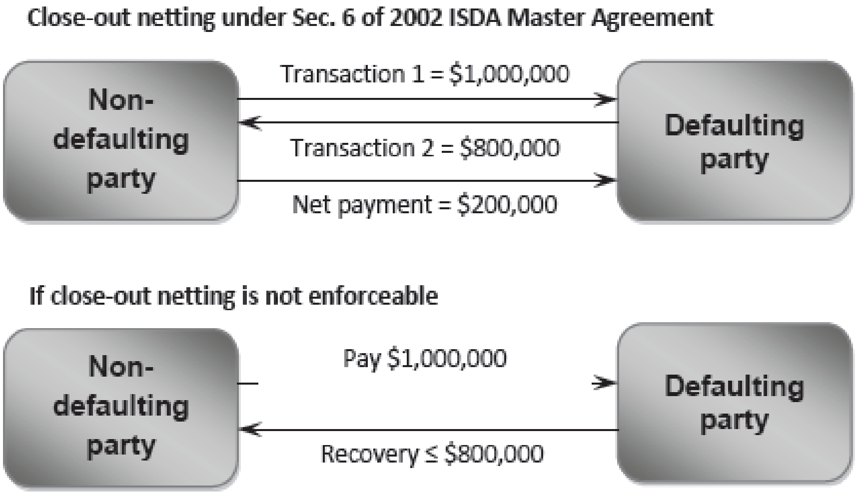


Fig. 5. Payment obligations with and without close-out netting (Source: ISDA, 2010).

3.2. Visualization of CDS networks

Fig. 6 (left-hand side) portrays the CDS network for EU sovereign reference entities on January 27, 2012. The chart offers a synthetic view of some of the main features of the market: CDS activity is clearly highly concentrated on the major market dealers (the green nodes are exposed to other participants for more than USD 3 billion both as sellers and buyers); some of them are more active on the selling side (the longer ones), while others are more active as buyers (the wider); most of the nodes cannot even be distinguished. Zooming into the previous chart to consider only the largest net exposures (right-hand side figure), we observe 104 links carrying an amount above USD 1 billion and accounting for more than 45.4% of the total net notional outstanding as of January 27, 2012. In this case the size of the nodes is proportional to the sum of their net bilateral selling and buying exposures in the market. The green nodes emerge as the major dealers, the blue one is a “buy-side” (i.e. non-dealer) bank, while the red firm is a non-dealer/non-bank participant. In this case too, the other participants are barely visible compared to the largest ones. Unlike the previous chart, in this one the links are proportional to the size of the underlying net exposures. We can see that the largest net exposure (the thick black link) connects two dealer banks, while the second and third connect two buy-side firms (an asset manager and a bank) to two different dealers.

Similarly, in the network for EU financials (Fig. 7) the green dealers stand out. The blue nodes are buy-side banking firms. Some non-banks are also present, but active only on one side of the market: They are too small in comparison to the other nodes. The orange node is a CCP; its rounded shape shows that it is similarly active both as a net bilateral seller and net bilateral buyer of CDS protection. Interestingly, the financials graph is almost twice as dense as the sovereign graph, revealing that the network on sovereigns is significantly more concentrated. The core of the network on EU financials comprises 14 dealers (in green), one CCP (in orange), two hedge funds (in red), and only one non-dealer bank. The core shows the “first tier” of the market, in which the largest links typically connect the dealers among themselves. However, one exception is plainly visible, with the second largest link connecting a hedge fund to a dealer.

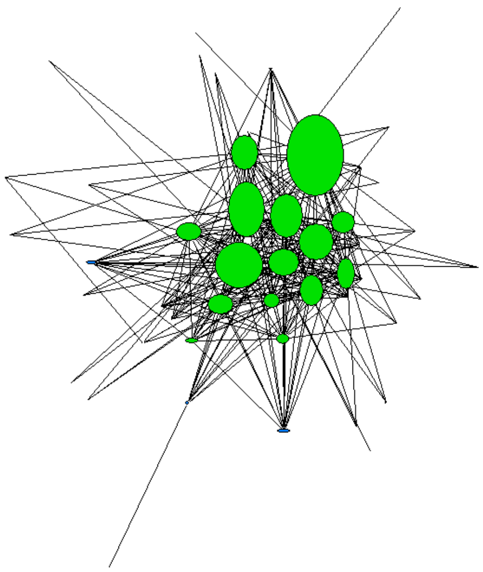
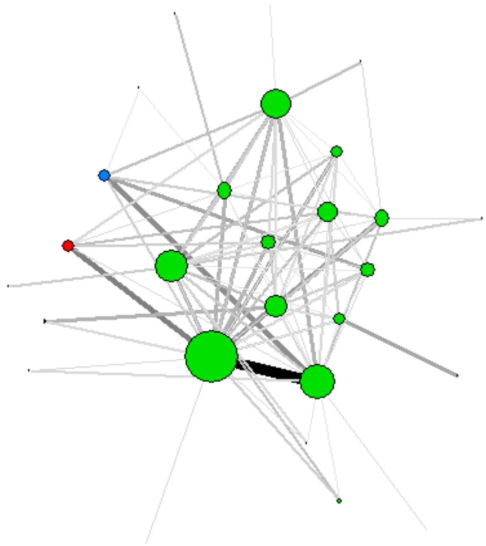



Fig. 6.

Left: CDS network on EU sovereign ref. entities on 27 January 2012.

Right: core of the network.The graph on the left consists of 182 participants and 716 links; only net exposures larger than USD 100 million have been plotted (a graph considering all outstanding exposures would consist of 548 nodes and almost 2,500 links). The size of the nodes is proportional to participants' activity in the market: The length and width are proportional respectively to the net amount of protection sold and the net amount bought. The core of the network (right-hand chart) consists of 27 nodes and 104 links above USD 1 billion. The thickness of the links is proportional to the size of bilateral net exposures.

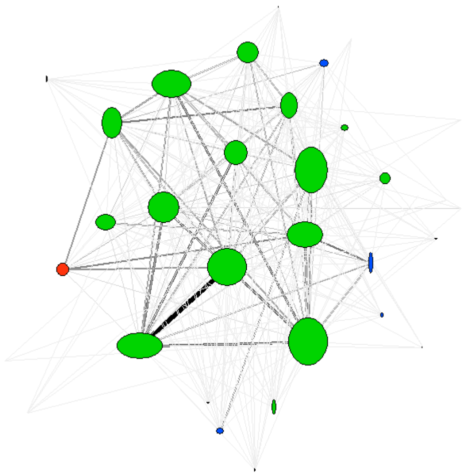
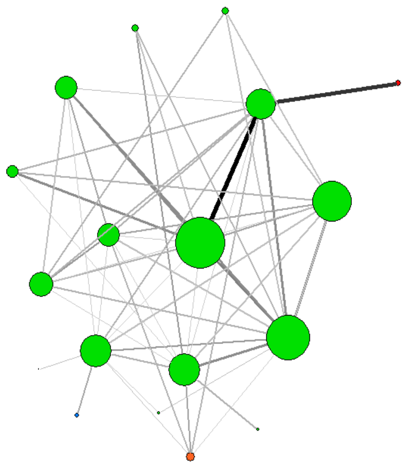



Fig. 7.

Left: CDS network on EU financial reference entities on 27 January 2012.

Right: core of the network.The graph on the left consists of 87 participants and 495 links; only net exposures larger than USD 100 million have been plotted. The size of the nodes is proportional to participants' activity in the market: The length and width are proportional respectively to the net amount of protection sold and the net amount bought. The core of the network (right-hand chart) consists of 18 nodes and 61 links above USD 1 billion; links' size is proportional to the size of bilateral net exposures.

3.3. Results and financial stability implications

Table 1 reports summary descriptive statistics for the networks of all reference entities from 2008 to 2012. Summary statistics for the three different (sectoral) sub-networks are reported in Appendix B.

Table 1
Yearly summary statistics for the networks of all CDS contracts (average, minimum, maximum, standard dev.)

Year	2008	2009	2010	2011	2012[a]
Nodes (avg)	480	534	694	776	803
Min	410	490	599	746	799
Max	514	595	747	807	805
St. Dev.	27	27	44	20	-
Links (avg)	2582	2829	3419	3704	3730
Min	2220	2615	3142	3584	3718
Max	2767	3131	3619	3856	3738
St. Dev.	134	130	133	67	-
Density (avg)	1.13%	1.00%	0.72%	0.62%	0.58%
Min	1.04%	0.89%	0.64%	0.58%	0.58%
Max	1.32%	1.09%	0.89%	0.65%	0.58%
St. Dev.	0.07%	0.05%	0.07%	0.02%	-
Disassortativity (avg)	-70.3%	-69.3%	-69.7%	-72.3%	-71.8%
Min	-71.4%	-71.2%	-71.5%	-72.9%	-71.9%
Max	-68.2%	-67.9%	-67.9%	-70.8%	-71.7%
St. Dev.	0.7%	1.0%	1.1%	0.4%	-
Average shortest distance (avg)	2.52	2.48	2.52	2.53	2.53
Min	2.48	2.46	2.47	2.51	2.53
Max	2.55	2.50	2.56	2.55	2.53
St. Dev.	0.01	0.01	0.02	0.01	-
Diameter (avg)	5	5	5	5	5
Min	4	5	5	4	5
Max	5	5	5	5	5
St. Dev.	0	0	0	0	-
Clustering coeff. (avg)	15.0%	13.1%	10.6%	8.8%	8.5%
Min	13.5%	12.2%	9.2%	8.3%	8.4%
Max	17.5%	13.7%	12.1%	9.2%	8.5%
St. Dev.	1.0%	0.4%	0.8%	0.3%	-

[a] The data for 2012 cover only the first four weeks of the year. This is why we do not report standard deviations.

3.3.1. Results

a. Interconnectedness

With 803 nodes (participants) and 3,730 links (net buyer-net seller order pairs) active in the first weeks of 2012, the overall CDS network stands as a large and complex set-up. The same holds true for the CDS network in 2008, although the number of participants was much lower (480 ± 27) at that time, as was the number of links (2,582 ± 134). While the CDS market's long-term growth is flagged up clearly by the figures reported in Table 1, we observe that the time series of CDS network metrics do not reflect the short-term periodic patterns that are typically observed in the networks of payment flows or money market loans studied in the economic literature. This is related to the “stock” nature of the exposures data we use.

The network *connectivity* or *density* for all-references CDS networks averaged around 1% over the sample period. This means that CDS networks are highly sparse, with participants typically directly exposed to a small set of other institutions: in 2012, most market participants were holding net selling/net buying positions vis-à-vis only another five. As regards sectoral networks, the density of the sovereign networks has declined very considerably over time. Bearing in mind the rapid increase in the number of institutions forming these networks, we calculate that in a typical week each institution was exposed to another three or four, be it in 2008 or in 2012.

The connectivity shows a high, negative correlation with the net value of outstanding contracts (Fig. 8). This suggests that the market has undergone increasing concentration: while the notional amounts outstanding continued to expand, the higher turnover was concentrated on an even smaller number of large links out of all the possible links between market participants. This is validated by the figures on network reciprocity computed on gross-exposure networks.[12] Reciprocity is null by construction for networks based on net exposures but turns out to be particularly high for the overall CDS network based on gross bilateral positions (it stood at 65% on average over the full time span). Or, in a randomly constructed graph, reciprocity and connectivity are equal, therefore in a network with the same average number of nodes and links as the gross-CDS network we are dealing with, reciprocity would be 1.3%. As the actual reciprocity we find for gross-CDS networks is 50 times that of comparable random graphs, the former can be seen as highly structured around bi-directional gross CDS exposures between institutions. This trend, however, came to something of a halt in the first quarter of 2010 and saw a slight reduction in the closing months of 2011.

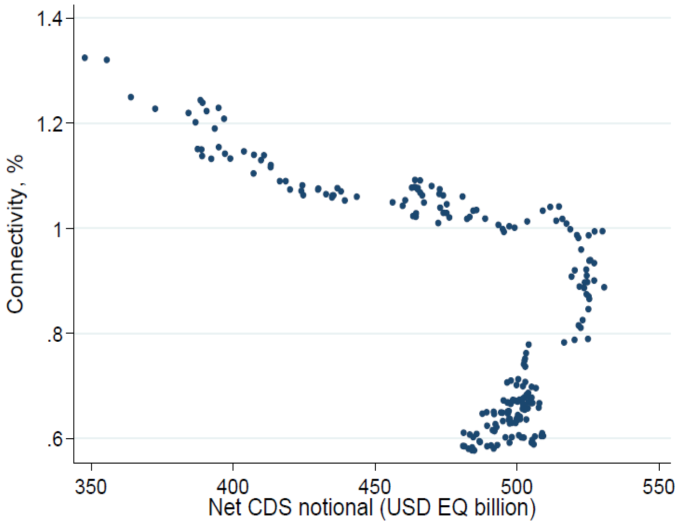


Fig. 8. Network connectivity against net CDS notional value (2008-2012)

Based on all CDS positions in the first weeks of 2012, the upper histogram of Fig. 9 plots the *in-degree distribution* of the network, i.e. the percentage of market participants who were net bilateral sellers of CDS protection to a given number of buyers (readable on the x-axis); the lower histogram displays the *distribution of out-degree*, i.e. the percentage of participants who were net bilateral buyers of CDS from a given number of sellers (readable on the x-axis). From the perspective of net bilateral sellers, we can see that whereas a limited number of nodes are highly interconnected and sell protection to many other participants, most nodes are linked to only a few others. More specifically, more than 50% of the nodes are

[12] Reciprocity measures the percentage of links for which there is also a connection in the opposite direction.

on average net buyers of protection (thus they do not have any incoming link and their in-degree is zero); in any typical reporting week, 69% sell protection to one participant at most and 94% to a maximum of ten other institutions. At the other extreme, ten *hubs* were exposed to more than 100 counterparties on average in the first weeks of 2012 and only four of them were exposed to more than 200. Similarly, if we consider the distribution from the perspective of net buyers, we immediately realise that most market participants buy CDS from a few net sellers (almost half buy from only one), while only six buyers buy CDS from more than 100 counterparties. Comparing the two distributions, we see that the maximum (and also the average) number of participants who are net bilateral sellers of CDS is less than half the maximum (or average) number of participants who are net bilateral buyers. All the institutions in the tails are G14 dealers.[13]

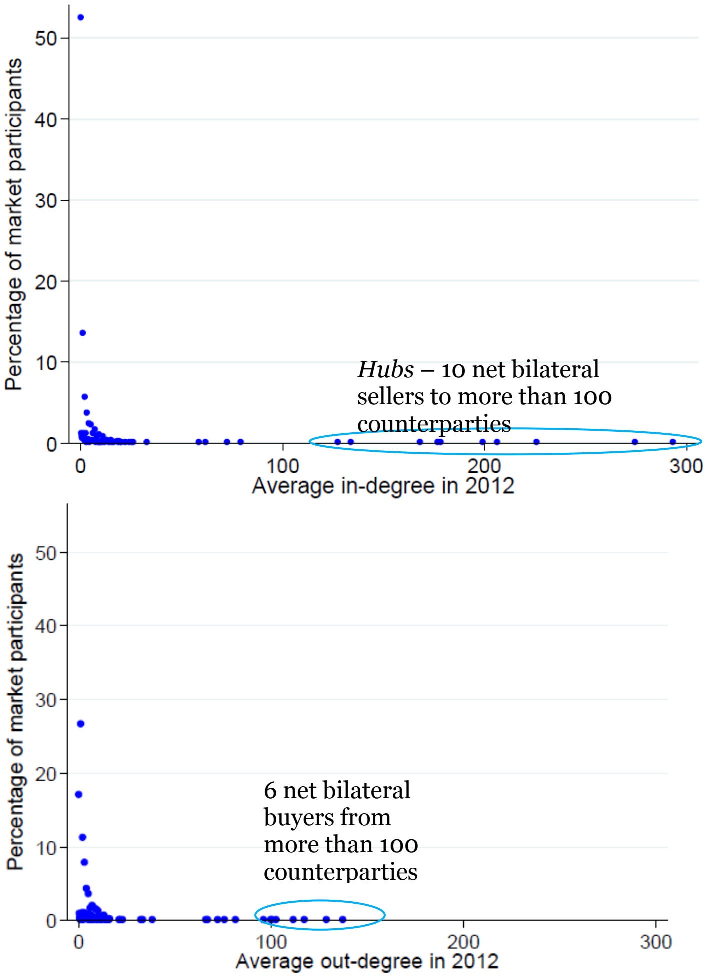


Fig. 9.

Above: Distribution of the no. of institutions to which each participant sells CDS (*in-degree*) in 2012.

Below: Distribution of the no. of institutions from which each participant buys CDS (*out-degree*) in 2012.

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[13] The G14 is the industry group comprising the largest global derivatives dealers (Bank of America, Barclays, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo). Nomura joined the group in September 2011 and Crédit Agricole in the first quarter of 2012, causing it to be renamed G16. Note that the CCP active on CDS on EU references has only eight incoming and six outgoing links.

b. *Network structure*

The tendency of "similar" nodes to be linked, or *assortativity*, is measured in terms of node degree, i.e. how often highly (or little) connected nodes tend to be connected to other highly (or little) connected nodes. With an average level of assortativity of -70%, overall CDS networks appear to be strongly *dis*assortative: Participants with many counterparties tend to be linked to institutions with few and vice-versa.

Fat-tailed degree distributions, high negative assortativity and very high sparseness point to a wide cross-sectional variation of individual institutions' connectivity (or degree centrality), suggesting that CDS exposures trace so called *scale-free* networks. The latter have attracted particular attention in scientific literature for their structural and dynamic properties. In particular, the scale-free property has been found to correlate strongly with the network's robustness to failure (see Callaway et al., 2000). It turns out that the major hubs are closely followed by smaller ones. These, in turn, are followed by other nodes with an even smaller degree, and so on. This hierarchy, which is present in many real-world networks, allows *fault tolerant* behaviour. That is to say, if failures occur at random and the vast majority of nodes are low-degree, the likelihood of a hub being affected is almost negligible. Even if a hub failure does occur, the network will not generally lose its connectedness due to the remaining hubs. On the other hand, if we choose a few major hubs and remove them from the network, it is turned into a set of rather isolated graphs; this is called *robust-yet-fragile* property.

Scale-free systems are typically identified by testing the goodness of fit of both weighted and unweighted degree distributions to a power law by means of the Kolgomorov and Smirnoff test. In Appendix C we report the results of the test for net exposures (i.e. weighted degree) larger than an estimated threshold. The test cannot reject the null that, across the years, CDS networks resembled scale-free systems. The minimum net position above which exposures are distributed according to a power law has decreased by a third between 2008 and 2011; correspondingly, the number of exposures belonging to the tail of the distribution has increased by roughly 30%, again suggesting an increasing concentration of CDS positions over time.

Finally, as is typical of scale-free networks, the very low connectivity does not prevent the network from displaying a very *short average distance* between any two nodes, even between the two farthest away ones in the system. For the all-references network, the average distance between all pairs of two institutions was 2.51 links (± 0.02) and the diameter (i.e. the maximum distance) 5 links over the entire sample period. Not surprisingly, these figures are lower than would be the case in random networks of comparable size, which confirms the presence of relationships between institutions trading in the CDS market.[14]

c. *Clustering*

The *clustering coefficient* measures the probability that two institutions are bilaterally linked (i.e. that one of them is a net seller to the other) given that a third institution is a net seller of protection to both of them. A clustering coefficient equal to 1 indicates that the network is composed of one or more fully connected sub-networks. A network with a clustering between 0 and 1 can be seen as one with fully connected sub-networks of this kind in which, however, some links are "missing". In the EU CDS networks the clustering coefficient, which was relatively high at the beginning of 2008 – when it stood at 15% for the network of all reference entities and more than 20% for the networks of CDS on financials and sovereigns – gradually decreased thereafter for all the networks, with a particularly steep downward trend for the network on sovereigns. This pattern is driven partly by the growing

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[14] The average shortest distance in a network with the same number of nodes and links as the all-references representation would have ranged between 3.6 and 4.4 links.

number of buyers and sellers over time, which increases the number of potential groups of three nodes, thus raising the denominator of the clustering coefficient. At the same time, however, the lower clustering could be capturing a tendency among the increasingly numerous buyers to connect to the same net seller while being less, and less frequently, linked among themselves, on the one hand, and/or, on the other hand, a higher number of missing links between the large net sellers, i.e. while periphery institutions continued to cluster around more interconnected hubs, the latter became relatively less tightly connected between themselves.

3.3.2. Financial stability implications

The evidence discussed corroborates the basic intuition that, owing to highly asymmetric returns on CDS positions, large and highly interconnected net sellers of protection are the primary locus of systemic counterparty risk in the CDS market. The high negative assortativity coefficient is indicative of a core-periphery structure, where net sellers are the *hubs* in the core selling CDS protection to numerous peripheral net buyers. Such tendency appears remarkably stronger than the one evidenced for interbank money markets in the literature.[15] Also, it is important to note that in such compact networks as the ones we analyse the impact of a credit event is likely to be widespread, as no institution is remote from the others.

All these structural features are in line with what one would expect given important economies of scale, capacity issues, and key information asymmetries, and are highly indicative of scale-free networks. A key financial stability implication of such structures is that hubs are both a strength and weakness of the networks. Thus, adequate regulatory and supervisory action with respect to the more connected players is more likely to prevent shocks from spreading throughout the system. The discussion of network clustering confirms that the main hubs are surrounded by numerous peripheral nodes – representing the so-called “spokes” in graph theory terminology – typically connected only to one hub and not linked to other clusters. This suggests a system resembling to a *hubs-and-spokes* model (see Fig. 10). Ensuring the safety of the largest net sellers is therefore more likely to secure the safety of all the nodes linked to them. In general, however, it is important to note that the extent of contagion would ultimately depend on the size of exposures, the recovery rate and each institution’s financial resilience and ability to meet its payment obligations following a credit event or to post collateral following a downgrade in the credit rating of the dealer itself.

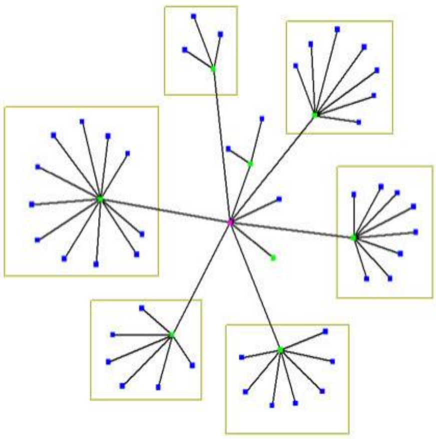

Fig. 10. Graphical illustration of a simple hub-and-spoke model: Hubs are the red node at the centre and the various green nodes to which the blue spokes (peripheral nodes) are connected.

15 See for instance Craig and von Peter (2010) for the German interbank market.

4. Identification of potential super spreaders of financial contagion

Centrality is one of the most-studied concepts in social network analysis, and certainly one that has attracted a lot of attention for its potential application to financial networks. Existing indicators provide various angles from which a market player may be deemed prominent in a network of financial linkages; and they also deliver information on the potential impact of an institution's failure on the rest of that network. Following Haldane (2009), economists, market analysts, and policymakers[16] have recognised the similarity between the potential of high-risk, high-infection individuals for the spread of epidemics and that of the most interconnected financial institutions for the spread of financial contagion. In allusion to this similarity, we refer to the most central CDS market participants as potential *super spreaders*.

4.1. Methodology

We consider two types of weighted and directed networks (all reference entities included) for each week: one based on the links incoming to the nodes (as for the global properties analysed in section 3) and the other based on links outgoing from the nodes. Centrality metrics are thus computed over 426 directed and weighted networks from 4 January 2008 to 27 January 2012, i.e. 213 asymmetric adjacency matrices based on incoming links and 213 asymmetric adjacency matrices based on outgoing links (i.e. g_{ji} = 1 if j is a net buyer of protection from i, with w_{ji} being the net bilateral buying position of j vis-à-vis i). We consider both *local* and *global* centrality metrics (see Appendix A).

Local network centrality. In CDS networks whose links represent buyers' net notional exposures to sellers, the most natural way to identify key market participants is to look, firstly, at the number of counterparties to which each participant sells or from which it buys CDS protection and, secondly, at the value of each participant's net selling or net buying position vis-à-vis all the other market players. The first pair of properties is measured by the node degree (in- and out-degree, respectively); the second pair is measured by the node in-strength for the net bilateral selling position and by the node out-strength for the net bilateral buying position. Finally, we consider the difference between the net selling and net buying position of a node, i.e. its net multilateral position (or net-strength).

Global network centrality. In order to capture the prominence of CDS players in the whole network structure we also consider betweenness and eigenvector centrality. Provided these two measures take into account a node's direct as well as its indirect links (i.e. links to counterparties of their counterparties), they are potentially relevant for capturing the extent of feedback (or second-round) effects following a shock at one market participant.

4.2. Results and financial stability implications

4.2.1. Results

Table 2 summarizes the 2011 rankings of the top-20 institutions based on different network metrics for the network of all reference entities. (Appendix D reports the rankings based on averages over the full sample period 2008-2012).

a. Largest net bilateral sellers

The first two columns of Table 2 portray institutions' ranking according to in-degree and in-strength centrality, thus identifying the largest net bilateral sellers of CDS on EU reference entities. They show clearly that banks, especially large international entities (the so called Global Systemically Important Banks – G-SIBs[17]), play a pivotal role in the CDS market. Interestingly, however, other institutions such as an asset manager, a hedge fund and a CCP

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16 See for instance Markose et al. (2012), Tumpel-Gugerell in her introductory remarks in ECB (2009) or Yellen (2013).

17 The list, published on 1/11/2012, is available at http://www.financialstabilityboard.org/publications/r_121031ac.pdf.

also show up as large net sellers. The institutions' ranking has remained remarkably stable over the past four years. Not surprisingly, the average number of incoming links and the average net selling position are positively and strongly correlated (Pearson coefficient of 87% in Fig. 11). Bank 312 clearly represents an outlier, similar to other dealers selling a large amount of protection to a relatively low number of participants (yellow highlights).

Both in-strength and in-degree vary widely even across the top-20 institutions: The average notional protection sold in 2011 by the largest net bilateral seller is more than double the average amount sold by the 8th largest bank, five times that of the 20th largest, and twentyfold compared to the 30th largest. Thus, as already discussed for degree distribution, the distribution of in-strength is also extremely heavy-tailed: On average over the whole sample period more than 40% of the banks were net buyers of protection in a typical week; only seven dealers had an average net selling position higher than USD 20 billion, and only three higher than 30 billion (Fig. 12, upper chart).

Table 2
Top-20 market participants in the CDS market for European reference entities in 2011 (by various network metrics, on average). *In-degree* measures the number of counterparties to which a firm is a net seller of CDS; *in-strength* the total net amount sold; *out-degree* the number of counterparties from which a firm is a net buyer; *out-strength* the total net amount bought; net-strength the firm's net multilateral selling position; *eigenvector centrality* the interconnectedness of a firm based on the interconnectedness of its counterparties; betweenness the importance of a firm's intermediation role.

Rank 2011	In-degree	In-strength	Out-degree	Out-strength	Net strength	Eigenvector centrality	Between-ness centrality
1	Bank 497*	Bank 312*	Bank 622*	Bank 497*	Bank 312*	Bank 497*	Bank 148*
2	Bank 622*	Bank 622*	Bank 148*	Bank 356*	AM 860	Bank 356*	Bank 1172*
3	Bank 765*	Bank 765*	Bank 356*	Bank 317*	Bank 821	Bank 1045*	Bank 622*
4	Bank 356*	Bank 497*	Bank 765*	Bank 765*	Bank 186*	Bank 276*	Bank 497*
5	Bank 148*	Bank 1045*	Bank 317*	Bank 622*	Bank 622*	Bank 148*	AM 538
6	Bank 317*	Bank 1172*	Bank 1172*	Bank 148*	HF 508	Bank 954*	Bank 765*
7	Bank 1172*	Bank 186*	Bank 497*	Bank 276*	Bank 656	Bank 317*	Bank 356*
8	Bank 276*	Bank 148*	Bank 276*	Bank 136*	Bank 389	HF 304	Bank 317*
9	Bank 136*	Bank 317*	Bank 136*	Bank 1172*	Bank 1045*	Bank 136*	Bank 276*
10	Bank 186*	Bank 136*	Bank 186*	Bank 1045*	Bank 627	Bank 1172*	HF 673
11	Bank 954*	AM 860	Bank 954*	Bank 954*	AM 104	Bank 765*	Bank 136*
12	Bank 1045*	Bank 356*	Bank 1045*	CCP 565	Bank 1176*	Bank 782	Bank 186*
13	Bank 553*	Bank 821	Bank 553*	Bank 553*	Bank 412	Bank 289	AM 937
14	Bank 804	Bank 553*	Bank 804	Bank 289	Bank 553*	AM 873	Bank 954*
15	Bank 312*	Bank 276*	Bank 289	Bank 186*	Bank 804	Bank 622*	FS 373
16	Bank 389	CCP 565	Bank 1176*	Bank 1176*	FS 920	CCP 565	AM 541
17	Bank 782	Bank 954*	Bank 312*	Bank 782	FS 1075	Bank 804	Bank 553*
18	Bank 656	HF 508	Bank 389	Bank 804	Bank 765*	HF 509	Bank 1045*
19	Bank 1176*	Bank 1176*	Bank 132*	Bank 304	Bank 1172*	HF 401	AM 621
20	Bank 122	Bank 656	Bank 137	AM 873	Bank 628	Bank 553*	AM 467

AM stands for Asset Manager (in red in the table); HF for Hedge Fund (in blue); FS for Financial Service company (orange); CCP for central clearing counterparty (green); N.A. for not available; * signals that the bank belongs to the list of Global Systemically Important Banks (G-SIBs) identified by the Financial Stability Board.

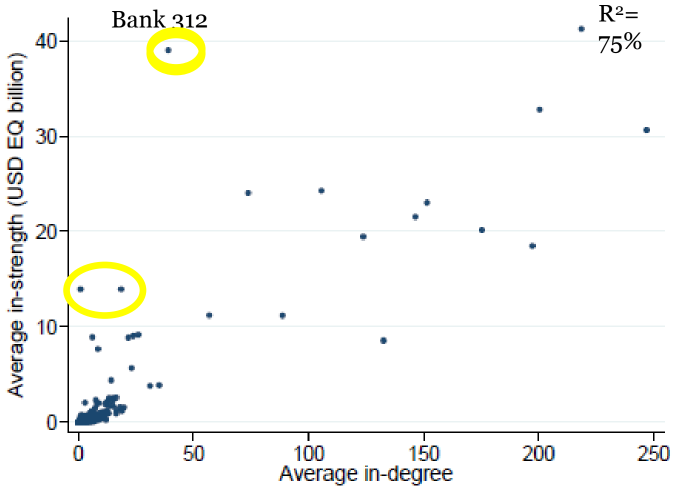

Fig. 11. Average selling position against average no. of counterparties to which protection is sold (2008-2012)

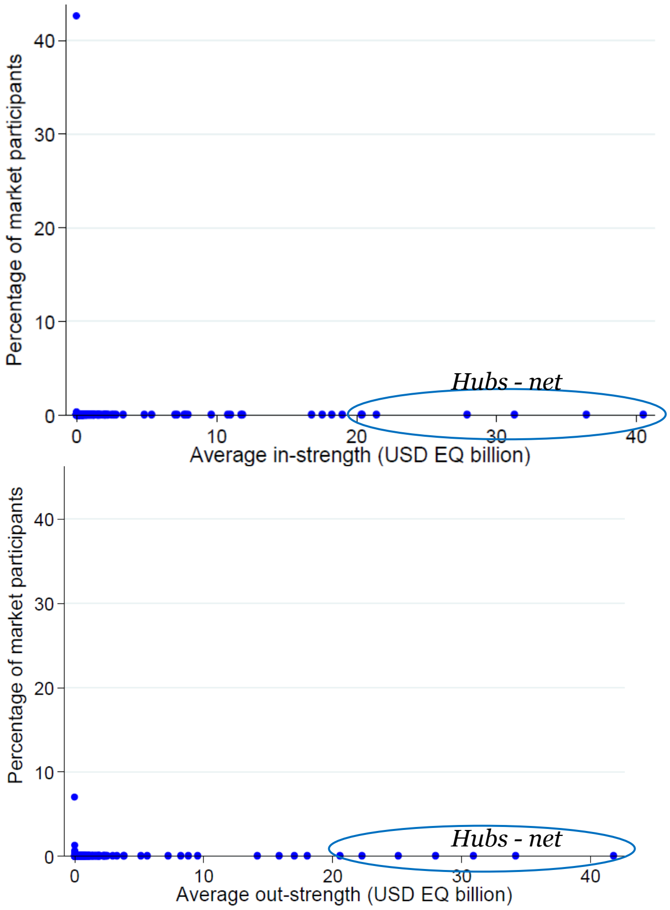

Fig. 12.

Above: Distribution of the value of participants' average selling positions (*in-strength*) over 2008-2012.

Below: Distribution of the value of participants' average buying position (*out- strength*) over 2008-2012.

b. *Largest net bilateral buyers*

Columns 3 and 4 in Table 1 report the rankings based on institutions' out-degree and out-strength respectively, i.e. they identify the largest net bilateral buyers. The participants we identified as the top-10 net sellers are also the top-10 net buyers of CDS, which confirms that these market participants act mostly as market dealers. The sole exception is bank 312, the largest net seller in 2011, which ranks only 49th as a net buyer. If we now consider the number of counterparties from whom CDS protection was bought, we can see that the rankings look very similar to those based on in-degree: Participants who sell protection to a large number of counterparties typically also buy from a large number of counterparties. However, the top dealers are net sellers of CDS to a significantly higher number of participants than the number of those from whom they are net buyers. Bank 312 again represents an exception, its in-degree being very close to its out-degree.

The average number of outgoing links and the average net buying position show a positive and strong correlation. More specifically, the net notional value of protection bought increases more than proportionally with respect to the number of counterparties from which the net protection is acquired (Fig. 13). As with node in-strength and node in-degree, out-strength and out-degree vary significantly in the cross-section and across the top-20 market participants: The average notional protection bought in 2011 by the largest net buyer is more than double the average amount bought by the 8th largest bank and almost twentyfold compared to the 20th largest. The distribution of out-strength is also very heavy-tailed (Fig. 12, lower chart) with only a few participants buying a net amount of protection much larger than the average (which stood at a mere USD 414 million over the whole sample). However, the number of firms with an average net buying position in excess of USD 20 billion was double the number of firms with a net selling position in excess of 20 billion.

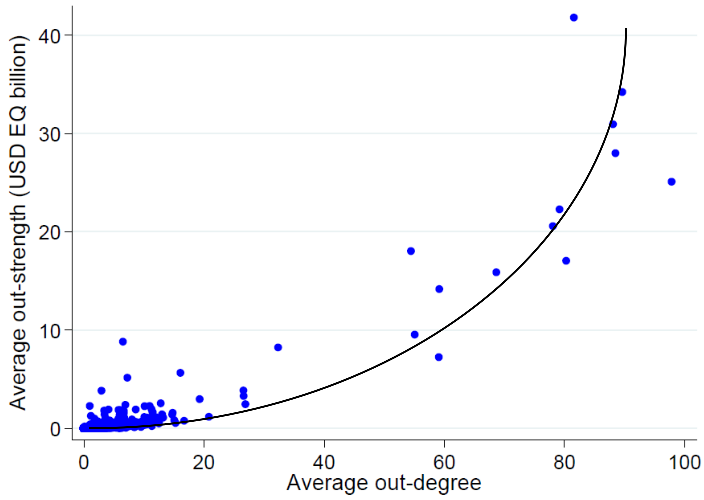

Fig. 13. Average buying position against average number of counterparties from which protection is bought (2008-12).

c. Largest net multilateral sellers

Column 5 in Table 1 depicts the top-20 ranking based on firms' net multilateral position in the CDS market. Compared with previous columns, it shows that large international banks acting as dealers in the market tend to carry out more netting along their short and long contracts. In effect, with a few exceptions their net multilateral exposures tend to be relatively lower. By contrast, the ranking in column 5 also shows that some non-bank institutions tend to hold large net exposures (in particular some asset managers and hedge funds). It also reveals the very high multilateral net exposure of some other banks not considered as G-SIBs by the FSB.

d. Most interconnected market players by global centrality

The global network metrics (columns 6 and 7) confirm the potential of bank-type dealers as super spreaders of financial contagion in CDS networks, but also indicate that a variety of other non-bank/non-dealer participants might similarly have super spreader potential. Interestingly, average eigenvector scores (column 6) are generally lower in 2011 relative to 2010 as well as compared to the full sample average, pointing to a lower degree of network centralization with respect to this indicator. This finding is consistent with the overall decrease in network clustering discussed in section 3 and both patterns are related to the increasing number of buyers and sellers in the CDS market for European reference entities over the years. On the one hand, a larger number of buyers connected to the hub-sellers without being directly exposed to each other; on the other, the growing number of sellers meant that a larger number of hubs were less often connected in triplets. All this resulted in the lower eigenvector-based importance of net sellers.[18]

While the top-15 participants by eigenvector centrality are mostly dealers (13 out of 15), the lower part of the ranking is populated by other institutions, in particular some hedge funds. With the exception of bank 312, the top bank dealers by in- and out-strength and by in- and out-degree are generally also present in the list of top-eigenvector firms. In particular, out-strength is strongly correlated with eigenvector centrality, resulting in two very similar rankings for these two indicators (at least in the first twenty places of the list). However, in contrast to the previous rankings and like the ranking based on net multilateral positions, the eigenvector list for 2011 includes in the top-15 participants two non-dealers. These are net multilateral buyers of CDS protection (asset manager 873 and hedge fund 304).

Considering the ranking based on average betweenness centrality over the full sample period or in 2011, we find that the top-10 list is almost identical to the list of the ten banks with the highest in-degree (with the sole exception of hedge fund 673, which does not appear in any of the other rankings). Average betweenness scores for 2011 broadly increased relative to the full sample average and compared to 2010. Such increased betweenness is consistent with lower eigenvector centrality: The higher number of peripheral buyers surrounding the largest hub-sellers makes the latter relatively *less* important because of their relatively fewer connections to other hubs and more numerous connections to the peripheral institutions (thus reducing their eigenvector centrality), but relatively *more* important because they stand between a higher proportion of paths connecting any two buyers (thus increasing their betweenness).

4.2.2. *Financial stability implications*

The rankings analysed in this section show clearly that large international banks (many belonging to the list of G-SIBs) are among the largest net bilateral sellers and buyers of CDS protection and are exposed to a much higher number of counterparties compared to the vast

[18] The Spearman's rank correlation coefficient for in-strength and eigenvector centrality decreased from 17% in 2008 to 1% in 2011. The null hypothesis of independence between the two variables can be rejected at 1% significance in 2008, but not from 2009 to 2011.

majority of other market participants. Acting as dealers, however, they tend to carry out more netting along their short and long contracts, so that with a few exceptions their net multilateral exposures tend to be relatively lower. Interestingly, asset managers and hedge funds also show up in the rankings, particularly in those based on global network centrality indicators. The latter displayed a large variation over the four years, while the rankings based on local network centrality remained remarkably stable. The largest net buyer and seller positions are rather balanced in our data; however, the high asymmetry revealed between the number of firms with a very large net buying position and the number of firms with a very large net selling position (14 firms versus 7) again points to the major role of CDS sellers in the market.

Finally, the positive correlations between certain local and global network measures (more specifically, between in-degree and betweenness, and between out-strength and eigenvector, see Table 3) point to the key role played in the spread of contagion by highly interconnected sellers and by large buyers. The potentially more important role of highly interconnected sellers is driven by the fact that sellers with many counterparties indirectly connect many participants who are not otherwise directly exposed to each other (i.e. they typically have also a high betweenness); in the case of large buyers, the more important contagion factor is related to the fact that the largest buyers are linked to other highly interconnected participants (i.e. they typically have a high eigenvector), so that a shock hitting one of the key players could radiate rapidly to more key players, thus endangering the connectedness of the whole network.

Table 3
Pearson's / Spearman's correlation coefficients between different centrality measures (average over 2008-2012)

	In-strength	Out-strength	Net-strength	In-degree	Out-degree	Eigen-vector
In-strength						
Out-strength	80% / 13%					
Net-strength	35% / 28%	-28%/-75%				
In-degree	**87% / 98%**	95% / 8%	-9% / 31%			
Out-degree	83% / 16%	**92% / 81%**	-12%/-59%	94%/13%		
Eigenvector	62% / 9%	**90% / 97%**	-40%/-76%	79% / 5%	79%/80%	
Betweenness	74% / 59%	84% / 29%	-12% / 3%	**88%/64%**	85%/45%	68%/26%

To complete this section, we compare the outcome of our analysis with a set of indicators derived from market prices. Standard measures, such as the Marginal Expected Shortfall (MES), the contribution-CoVaR, the exposure-CoVaR, the contribution-CoCDS and the exposure-CoCDS (which use the same logic as the CoVaR measures but are based on CDS spreads instead of equity returns), have been estimated as part of the work reported in Brunnermeier et al. (2013)[19]. The comparison is based on cross-sectional correlation coefficients calculated at two different points in time (January 2010 and January 2012, see Table 4).

[19] The Marginal Expected Shortfall (MES) of an institution can be defined as its expected equity loss when the market itself is in its left tail (Acharya et al. 2012). The CoVaR represents the Value-at-Risk (VaR) of the financial system conditional on institutions being under distress (Adrian and Brunnermeier, 2011). The contribution-CoVaR is based on equity returns and obtained from quantile regressions of the system on all individual institutions; it thus measures the marginal risk contribution of each firm to overall systemic risk. The exposure-CoVaR switches the conditioning of the quantile regressions, thus measuring which firms are most exposed when the financial system as a whole is under distress.

The table shows very mixed results and no clear correlations but for a couple of price derived measures. For instance, the contribution-CoVaR based on equity returns (as well as the marginal capital shortfall), which expresses the marginal risk contribution of each firm to overall systemic risk, is always positively correlated with all four exposure-based (network centrality) measures at a relatively high level. One can also note the negative correlation between the CDS spreads and the exposure-based measures. One interpretation is that CDS spreads reflect the "too-big-to-fail" phenomenon and consequently factor in the implicit subsidy provided by almost certain bail out of systemic institutions. The other measures display rather ambiguous and non robust signs. One explanation resides in the fact that exposure measures are rather stable while price measures are rather volatile. Finally, price-based measures are likely to also capture informational channels of contagion, while network measures mostly capture contagion due to position-based interdependencies.

Table 4

Correlations between market price-based and exposure-based measures in January 2010 and January 2012. The values of MES, relative capital shortfall and market value are considered in logs of their USD values.

(06 Jan 2012)	Eigen-vector	Between-ness	Selling exposure (in-strength)	Number of counterparties to which CDS are sold (in-degree)
Contribution CoVaR	0.542	0.545	0.688	0.635
Exposure CoVaR	0.031	-0.069	0.106	-0.013
Contribution CoCDS	0.043	-0.277	0.048	-0.300
Exposure CoCDS	-0.184	-0.247	-0.214	-0.305
CDS spread	-0.237	-0.312	-0.204	-0.330
MES value	0.138	-0.089	0.251	-0.013
Relative capital shortfall	0.639	0.583	0.712	0.643
Market value	0.107	0.266	0.202	0.220
(08 Jan 2010)	Eigen-vector	Between-ness	Selling exposure (in-strength)	Number of counterparties to which CDS are sold (in-degree)
Contribution CoVaR	0.118	-0.086	0.105	0.016
Exposure CoVaR	0.174	-0.088	0.093	0.030
Contribution CoCDS	0.012	-0.412	-0.138	-0.294
Exposure CoCDS	-0.060	-0.344	-0.200	-0.243
CDS spread	-0.233	-0.220	-0.269	-0.266
MES value	0.130	0.070	0.076	0.086
Relative capital shortfall	0.579	0.216	0.704	0.623
Market value	0.245	0.273	0.371	0.369

Source: Brunnermeier et al. (2013)

5. Resilience of the bank super spreaders identified

In this section, we relate the bank-type participants that are the most central identified in the networks of CDS exposures to indicators of their financial soundness. We consider, firstly, the statistical correlation between measures of centrality and various balance sheet items – (book value of) total common equity, total assets, last equity price, last CDS spread (basis points premium payment per year), and bank leverage (computed as the value of total common equity divided by total assets). Secondly, we compute an indicator of financial soundness for the largest bilateral and multilateral net sellers.

5.1. Correlations between centrality and selected balance sheet items

We find that large CDS sellers and buyers are on average perceived as safer by the market in 2011 (they have a lower CDS spread at year-end), and banks selling protection to a higher number of counterparties have on average a higher market value and hold a lower amount of capital; not surprisingly, both large sellers and buyers of protection are on average bigger institutions. The banks holding larger net multilateral exposures tended to perform worse in the stock market in 2011 and were less well capitalised (Table 5).

Table 5
Correlation between selected centrality indicators and balance sheet items in 2011

Year 2011	CDS net selling position (in-strength)	CDS net buying position (out-strength)	CDS net *multilateral* selling position (net-strength)
Total common equity	45%	38%	7%
Total assets	**55%**	**45%**	11%
Last stock price (as of 31/12/2011)	37%	**54%**	**-25%**
Last CDS spread (as of 31/12/2011)	**-19%**	**-20%**	2%
Leverage (Common equity / Total assets)	-4%	0%	**-5%**

5.2. Super spreaders' risk bearing capacity

Table 6 looks at the ratio between the aggregate CDS position of top bank players and their total common equity in 2011. This is reported for *(i)* the 20 largest net bilateral sellers (columns 1 and 2); *(ii)* the 20 largest net bilateral buyers (columns 3 and 4); *(iii)* the 20 largest net multilateral sellers (columns 5 and 6). Net bilateral selling positions relative to total common equity exhibit very large variation across banks and, although the ratios refer to banks' risk-bearing capacity in the highly implausible scenario in which all the seller's counterparties default, some of them do seem alarmingly high (e.g. above 65% for bank 821 and bank 656). Net bilateral buying positions relative to total common equity similarly display significant variation across banks. Three ratios are particularly high (94% for bank 317, 67% for bank 497, 63% for bank 356). The last column in the table shows the alarmingly high ratios revealed in the previous columns persisting even after netting, although they are slightly reduced. This confirms once again the key role played by the largest net (bilateral and multilateral) sellers.

Table 6
Financial soundness of the top 20 banks largest net sellers and buyers of CDS protection in 2011. The indicator considered is the ratio between the notional amount of aggregate net CDS exposures (Expo.) and total common equity (TCE). AM stands for Asset Manager (in red in the table); HF for Hedge Fund (in blue); FS for Financial Service company(orange); CCP for central clearing counterparty (green); N.A. for not available; * signals that the bank belongs to the G-SIBs identified by the Financial Stability Board.

Rank 2011	Largest net bilateral CDS sellers		Largest net bilateral CDS buyers		Largest net multilateral CDS sellers	
	Ranking	*Expo./TCE*	*Ranking*	*Expo./TCE*	*Ranking*	*Expo./TCE*
1	Bank 312*	45%	Bank 497*	67%	Bank 312*	44%
2	Bank 622*	23%	Bank 356*	63%	AM 860	N.A.
3	Bank 765*	56%	Bank 317*	94%	Bank 821	66%
4	Bank 497*	41%	Bank 765*	53%	Bank 186*	17%
5	Bank 1045*	48%	Bank 622*	15%	Bank 622*	8%
6	Bank 1172*	41%	Bank 148*	28%	HF 508	N.A.
7	Bank 186*	26%	Bank 276*	13%	Bank 656	65%
8	Bank 148*	23%	Bank 136*	10%	Bank 389	90%
9	Bank 317*	55%	Bank 1172*	38%	Bank 1045*	12%
10	Bank 136*	9%	Bank 1045*	36%	Bank 627	N.A.
11	AM 860	N.A.	Bank 954*	13%	AM 104	N.A.
12	Bank 356*	24%	CCP 565	N.A.	Bank 1176*	12%
13	Bank 821	66%	Bank 553*	7%	Bank 412	18%
14	Bank 553*	8%	Bank 289	32%	Bank 553*	1%
15	Bank 276*	7%	Bank 186*	9%	Bank 804	8%
16	CCP 565	N.A.	Bank 1176*	20%	FS 920	N.A.
17	Bank 954*	10%	Bank 782	19%	FS 1075	N.A.
18	HF 508	N.A.	Bank 804	15%	Bank 765*	3%
19	Bank 1176*	32%	Bank 304	N.A.	Bank 1172*	3%
20	Bank 656	67%	AM 873	N.A.	Bank 628	N.A.

We then consider the ratio of banks' net selling exposure per individual reference entity to their total common equity. Table 7 lists the nine net exposures representing more than 9% of bank capital. Note that while we had already identified banks 821, 656 and 389 due to their comparatively large aggregate net exposures relative to common equity in the previous tables, Table 7 highlights another two banks whose exposures merit careful monitoring: for bank 121 one net selling exposure on a single entity is particularly large relative to its capacity to withstand a negative shock on the underlying CDS reference; bank 127 is exposed to two different non-financial entities for about 9% of its common equity.

Table 7
Largest (above 9%) net selling positions on single reference entities relative to total common equity

Bank	Sector of single EU reference entity	Ratio of net selling position to total common equity
Bank 821	*Sovereign*	28.8%
Bank 656	*Sovereign*	16.0%
Bank 121	*Financials*	14.7%
Bank 389	*Sovereign*	12.0%
Bank 389	*Sovereign*	10.1%
Bank 765	*Sovereign*	9.5%
Bank 127	*Non-Financials*	9.3%
Bank 127	*Non-Financials*	9.1%
Bank 389	*Sovereign*	9.1%

Finally, we consider the level of leverage (total common equity divided by total assets) of the top-9 or top-18 banks identified as largest net multilateral sellers relative to a set of another 81 banks. Fig. 14 (left-hand side) shows that the 18 bank super spreaders tended to hold a lower buffer of equity per dollar of assets than the other banks. While the largest bank sellers increased their equity-to-asset ratio over time (the average grew from 4% in 2008 to 5.1% in 2011), it remained lower than the equity buffer of the other banks in the sample. It is also interesting to note that the 9 banks largest net sellers of CDS protection (all of which are G14 dealers and G-SIBs) typically held a slightly higher equity ratio than the top-18. However, this changed end 2011, when the top-9 reported an average ratio 0.3% below the equity ratio of the top-18 banks.

If we now consider the average ratio across the different types of potential super spreaders identified – largest net bilateral sellers, largest net bilateral buyers, and largest net multilateral sellers – we find that the top bilateral sellers and buyers of CDS protection were on average less capitalised than the top multilateral sellers in 2008 but became better capitalised in 2009, 2010 and 2011. The higher equity buffer of the top sellers and top buyers in 2011 (5.5% against 5% for the top multilateral sellers) seems to be driven by the presence in those rankings of some other big bank-dealers that are missing in the list of participants with largest net multilateral exposures. However, it remains to be established whether this indicator is indeed an appropriate means of diagnosing financial vulnerability and whether, over time, it will prove a reliable early warning indicator of financial distress.

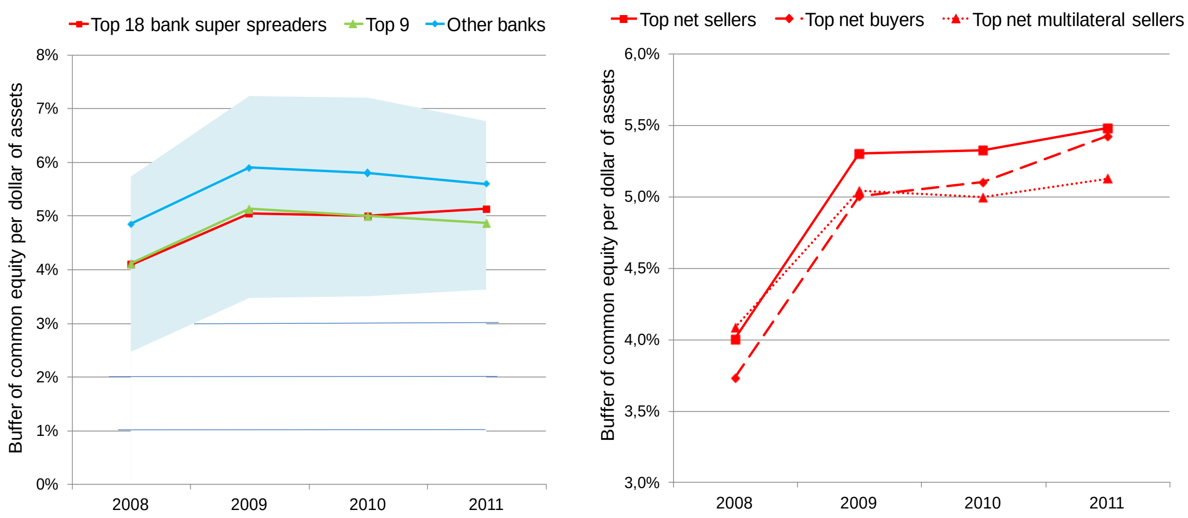

Fig. 14. Left: Leverage of the bank super spreaders identified *versus* other banks.

Right: Leverage of the top net bilateral sellers, top net bilateral buyers, and top net multilateral sellers. Leverage is computed as the ratio between banks' total common equity and total assets. The bank super spreaders in the left-hand side chart are the largest net multilateral sellers. The shaded area represents the interquartile range for the entire sample of banks.

6. Conclusions

The structural features revealed suggest that the network of CDS exposures would, in most cases, be resilient to failure. The likelihood of one of the most interconnected players being affected by a random shock is almost negligible; and even if a major player were hit, the network might possibly continue functioning thanks to the other highly interconnected hubs. However, were more than one major player to be affected simultaneously, the network would lose its connectedness – with potentially grave consequences. Ensuring their safety is thus potentially the best way to safeguard the system's resilience to failures. While, to the best of our knowledge, a similar study of the structural aspects of networks of CDS exposures is not yet available for reference entities of other geographical areas, a comparison with the structural features of other systems would certainly be of great interest.

The most common network centrality measures used in this paper point to the key role played in spreading contagion by *(i)* net sellers to a large number of counterparties which indirectly connect many participants not otherwise directly exposed to one another, and by *(ii)* large net buyers whose links to large net sellers pose a greater potential risk of a shock that hits one of the key players rapidly spreading to other major participants, thus endangering the connectedness of the whole network. In addition, while the analysis of these indicators confirms bank-type dealers' potential as super spreaders of financial contagion, it also pinpoints a variety of other non-bank/non-dealer market participants with super spreader potential, in particular some asset managers and hedge funds.

Our analysis confirms that all the institutions participating in the CDS market are interconnected by a complex liability structure that is highly concentrated among the largest bank-dealers. These large banks perform significantly more netting of their long and short contracts within their CDS portfolios. As a result of this intermediary role, the banks possess gross notional positions far in excess of their net notional holdings. For some of them, however, multilateral net exposures represent a significant amount relative to their core common equity. They also tend to hold, on average, a lower buffer of equity per dollar of assets than the other banks, i.e. they are highly leveraged.

Many of these large banks belong to the "G14 - G15" group of global derivatives dealers and have been identified by the Financial Stability Board as Global Systemically Important

Banks. As a result, they will be subject to additional capital requirements which may mitigate the risk of failure or contagion. However, we must emphasize that it is difficult to assess the scope for contagion by looking at CDS exposures alone. In effect, contagion depends on total exposures, resulting either directly or indirectly from correlated assets for instance, and not just from credit default swaps. In addition, financial institutions may take offsetting positions through other derivatives. Proper contagion analysis therefore requires a more comprehensive approach to counterparty and network risks.

Besides banks, another issue is proper monitoring of institutions such as asset managers and hedge funds, which are playing a growing systemic role in the CDS market. This is all the more important because their more prominent role may be partly due to regulatory arbitrage. While the links represented by some of these asset managers are not numerous, they are large, and there is no overlap between sellers and buyers. Ongoing regulatory initiatives may also attenuate or mitigate systemic risk.[20] For instance, widespread use of clearinghouses could mitigate counterparty credit risk inasmuch as most CDS are centrally clearable. This would certainly have a major impact on network structures and help reduce their complexity. However, increasing the role of central clearing counterparties places particular emphasis on the quality of their risk-bearing capacity and their collateral management. The scope for contagion might also be reduced by setting minimum liquid reserve requirements in respect of critical receivables or by limiting large exposures for nodes that act as counterparties to a large number of contracts. In this respect it is important accurately to factor in the network characteristics and properties of interbank exposures, since there might be critical side effects affecting both market intermediation and liquidity.

Finally, access to supervisory data and the exchange of information between key supervisors is of the utmost importance in this context, both to facilitate monitoring and to increase the transparency of the CDS market. Our results underline the importance of regularly monitoring outstanding positions.

[20] The main regulation covering CDS in Europe is the European Market Infrastructure Regulation (EMIR), which entered into force on 16 August 2012. EMIR establishes rules for the central clearing of OTC derivatives and for transaction record keeping. The proposal covers all types of OTC derivatives, including CDS. See Brunnermeier *et al.* (2013).

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Appendix A: Network theory – basic concepts, structural measures and network centrality

Basic concepts

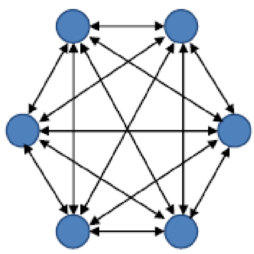
A network g_t at time t is defined by two sets: the set of *nodes* $N = \{1,\dots, n\}$ and the set L of unordered pairs of elements $(i\,, j)$ representing *edges* or *links* between them. More precisely, a CDS network $g_t \equiv g_t(N, L)$ is a directed graph where each link is a net exposure between two institutions at time t and is represented mathematically by the N-square adjacency matrix $G(g_t) = \{g_{ij,t}\}$ where $g_{ij,t} = 1$ if node i is a net buyer of protection from node j at time t, and $g_{ij,t} = 0$ otherwise (by convention $g_{ii,t} = 0$). If two institutions i and j are directly exposed, i.e. $g_{ij,t} = 1$, then i and j are *neighbours* or *adjacent*. For a given network g, even if i and j are not directly exposed (i.e. $g_{ij} = 0$), they may still be indirectly connected if there is a *path* from i to j. A path is a sequence of nodes $[i_0, i_1, \dots, i_k]$ starting from i and terminating at j (i.e. $i_0 = i$ and $i_k = j$) such that $g_{i,i+1} =1$ for all $0 \le s \le k\text{-}1$. Thus, a path is an ordered sequence where node i_s and node i_{s+1} are directly exposed. Finally, a weighted network can also be represented, next to $G(g_t)$, by the weighted adjacency matrix $W(g_t) = \{w_{ij,t}\}$, where each link between i and j is weighted by the net CDS position $w_{ij,t}$. In the following we omit the subscript t to make notation less cumbersome.

Structural network measures

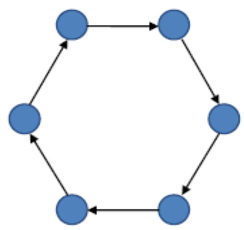
Connectivity. The most basic topological properties of a network are the number of nodes n (i.e. the cardinality of the set N), and the number of links m connecting the nodes. The ratio of actual to potential links between the nodes is known as the *density* or connectivity of the network. Formally:

$$p = \frac{m}{n(n-1)}$$

This ratio ranges from 0 to 1, with higher values denoting "denser" networks. In the limiting case in which every possible pair of nodes is connected by an edge, the graph is *complete*.



A. Complete network



B. Incomplete (cycle) network

Node degree. In a directed graph, both the *out*- and the *in*-degree of a node can be computed: the out-degree is the number of links originating from a node; the in-degree is the number of links terminating at it. The distribution of node degree is a key structural property of a network.

$$g_i^{in} = \sum\nolimits_{j \ne i} g_{ji}$$

$$\text{and } g_i^{out} = \sum\nolimits_{j \ne i} g_{ij}$$

In the CDS networks of this paper, the in-degree of participant i is the number of institutions to whom i sells CDS protection (meaning that in-degree is zero for net buyers), while the out-degree of i is the number of participants from whom it buys CDS.

Average shortest path length. There may be several different paths connecting two nodes in a network. The *distance* between any node i and any node j is the length of the shortest such paths (i.e. the minimum number of links) between them. The average shortest path is the mean distance separating a node from all other nodes within the same connected component.[21] That is:

$$\bar{d}_i = \frac{\sum_{j \neq i} d_{ij}}{n-1}$$

The average shortest path length of the whole network is then computed by taking the average of the $\bar{d}_i$ across all nodes i, and represents a measure for the average length of intermediation chains:

$$\bar{d} = \frac{\sum_{i=1}^{n} \bar{d}_i}{n}$$

Diameter. The diameter of a network is the maximum distance between any pair of nodes; it can thus range between 1, if every node is directly linked to each of the others, and *n-1*.

Assortative mixing or assortativity. This indicator measures the tendency of nodes to attach to similar nodes in the network based on certain values assigned to them. A high and positive coefficient indicates that participants linked to each other tend to have similar assigned values, whereas a negative coefficient indicates the opposite. In our analysis, we consider node degree in order to assess whether highly connected participants tend to associate with other highly connected institutions or not.

More specifically, we define a quantity e_{xy} which is the fraction of all exposures in the network that join together institutions with values x and y for their out-degree (i.e. the number of counterparties from which they buy CDS protection) and satisfies the following sum rules:

$$\sum_{xy} e_{xy} = 1, \quad \sum_{y} e_{xy} = a_x \quad , \qquad \sum_{x} e_{xy} = b_y$$

where a_x and b_y are, respectively, the fraction of CDS selling and buying positions of institutions with values x and y. Then, if there is no assortative mixing $e_{xy} = a_x b_y$. If there is assortative mixing it can be calculated via the standard Pearson correlation coefficient (see Newman, 2003):

$$assortativity = \frac{\sum_{xy} xy(e_{xy} - a_x b_y)}{s_a s_b}$$

where s_a and s_b are the standard deviations of the distributions a_x and b_y. The value of assortativity ranges from -1 to 1: a correlation coefficient equal to 1 indicates perfect assortativity, while a coefficient equal to -1 indicates perfect negative correlation between the number of counterparties of CDS buyers and CDS sellers.

Clustering. The clustering coefficient measures the probability that two nodes with a common neighbour will themselves be neighbours (i.e. themselves be directly exposed). Formally, the clustering coefficient measures the frequency of *transitive triads* in a graph, i.e. the frequency of groups of three nodes linked in such a way that whenever $i \rightarrow j$ and $j \rightarrow k$ then also $i \rightarrow k$ (i.e. whenever i buys CDS from j ,which in turn buys from k, then i and k are also directly exposed). In the CDS networks the clustering coefficient measures the average fraction of net sellers j and k selling CDS to the net buyer i that are counterparties of each other. In formulae:

[21] A component is a sub-network where all the nodes are directly or indirectly connected (i.e. reachable).

$$clustering_i = \frac{1}{g_i^{in}(g_i^{in}-1)} \sum_{j \neq i} \sum_{k \neq i} g_{jk} \text{ for each node and}$$

$$clustering = \frac{\sum_{j \neq i} clustering_i}{n-1} \text{ for the whole network.}$$

Measures of local centrality

The first centrality indicators we consider in the analysis are also known in literature as measures of *local* centrality because they take into account only a node's direct links, i.e. they measure a node centrality in its local neighbourhood. These are the *unweighted* and the *weighted degree*.

Node degree. In a directed graph the out-degree of a node is the number of links originating from it; the in-degree is the number of links terminating to it.

$$g_i^{in} = \sum_{j \neq i} g_{ji} \text{ and } g_i^{out} = \sum_{j \neq i} g_{ij}$$

In social network analysis both these indicators have been used to measure a node's importance in its neighbourhood of social acquaintances. In the CDS networks of this paper, the in-degree of participant i is the number of institutions to whom i sells CDS protection, while the out-degree of i is the number of participants from whom it buys CDS.

Possibly more suited to our purposes are the weighted versions of node in- and out-degree, which we call *in-strength* and *out-strength*. These are computed by weighting the links based on net bilateral exposures (w_{ij}). More specifically,

$$in-strength_i = \sum_{j \neq i} w_{ji}^{netsold}$$

represents the sum of the net *selling* positions of node i (i.e. the sum of all positions in which node i is a net seller); while

$$out-strength_i = \sum_{j \neq i} w_{ij}^{netbought}$$

represents the sum of the net *buying* positions of node i (i.e. the sum of all positions in which node i is a net buyer). Thus,

$$net-strength_i = \sum_{j \neq i} w_{ji}^{netsold} - \sum_{j \neq i} w_{ij}^{netbought}$$

represents the *net multilateral position* of node i.

Measures of global centrality

Global centrality metrics, taking into account both the direct and the indirect exposures of a node, are possibly more suited to capture the prominence of CDS participants in the network structure.

Betweenness centrality. A node with high betweenness is one that is often situated on the shortest paths connecting other nodes (Freeman, 1979). It is defined as the sum of the fraction of all shortest paths between any two nodes j and k that pass through node i, thus providing an indication of the exclusivity of the position of i in the overall network. In formulae:

$$betweenness_i = \frac{\sum_{j \neq i} \frac{a_{jk|i}}{a_{jk}}}{(n-1)(n-2)}$$

where $a_{jk|i}$ denotes the number of shortest paths between j and k that includes i and a_{jk} is the total number of shortest paths between j and k. The denominator represents the maximum number of pairs of nodes not including i, thus allowing for a normalized version of the indicator.

Eigenvector centrality. All the centrality indicators described so far are path-based, i.e. they rest on the premise that a given node (or a link) can appear only once in the sequence connecting two nodes; that is, nodes are connected via *paths*. This means that in the CDS networks of this paper all the centrality measures described identify the most central market players on the assumption that, for example, a shock could spread through net CDS exposures by passing each node (or link) only once.

However, other indicators developed in graph theory place no restrictions on the number of times that a node (or link) can appear in the sequence connecting two nodes; in this case, nodes are connected via *walks*. One of these measures is *eigenvector centrality* (Bonacich, 1972). In the context of assessing contagion stemming from CDS exposures, this measure could provide an indication of which nodes would be more important in the propagation of a shock when taking into account the knock-on effects that may follow a shock. Indeed, eigenvector centrality computes the relative influence of node i within the network by measuring the number of institutions that are directly exposed to it and also of all other participants that sell to node i through these immediate neighbours (sellers). Mathematically, eigenvector centrality is defined as the principal eigenvector of the adjacency matrix that represents the (internally connected) network. The defining equation is:

$$\lambda v = Gv$$

where G is the adjacency matrix of the graph with eigenvalues λ, and v is the eigenvector. Thus the eigenvector centrality of node i is:

$$eigenvector_i = \alpha \sum_{j \neq i} g_{ji} + 1$$

where $\alpha < 1/\lambda_{max}$ and represents an attenuation factor that allows to penalize exposures to distant sellers, i.e. to sellers of sellers...of node i. In its unweighted and undirected form, it represents an iterative version of degree centrality, according to which a node's global centrality depends iteratively on the interconnectedness of its counterparties.

To conclude, it is worth emphasizing that the formulas for the different centrality measures make implicit assumptions about the manner in which a given process of interest flows in a network. This means that the canonical interpretations we give to the measures are valid to the extent that "traffic" flows in certain ways in the system analysed (see Borgatti, 2005). In the graphs of our CDS analysis the most common centrality indices based on direct linkages between the nodes (i.e. degree and strength) seem well suited for the purpose of identifying potential super spreaders. More complex indicators, such as betweenness and eigenvector centrality, are very interesting to examine in view of the additional information they may provide compared to the former measures, but in evaluating them the main assumptions underlying their computation should be kept in mind.

Appendix B: Summary network statistics

The following tables report yearly summary statistics (average, minimum, maximum, and standard deviation) for the three sectoral sub-networks (i.e. Financials, Non-Financials, and Sovereigns) from 2008 to 2012.

Table 8
Summary statistics for the networks of CDS on *financial* reference entities

Year	2008	2009	2010	2011	2012[a]
Nodes (avg)	330	329	379	425	441
Min	289	310	327	405	438
Max	349	343	416	445	443
St. Dev.	12	9	27	11	-
Links (avg)	1571	1601	1770	1888	1900
Min	1334	1556	1657	1844	1876
Max	1679	1697	1862	1968	1916
St. Dev.	90	38	59	32	-
Density (avg)	1.45%	1.49%	1.25%	1.05%	0.98%
Min	1.38%	1.38%	1.07%	0.97%	0.97%
Max	1.60%	1.63%	1.56%	1.13%	0.99%
St. Dev.	0.05%	0.06%	0.15%	0.04%	-
Assortativity (avg)	-68.6%	-69.4%	-69.4%	-71.3%	-72.0%
Min	-70.3%	-71.2%	-70.4%	-73.1%	-72.4%
Max	-66.5%	-68.6%	-68.3%	-70.0%	-71.6%
St. Dev.	1.1%	0.6%	0.5%	0.9%	-
Average shortest distance (avg)	2.56	2.50	2.53	2.56	2.55
Min	2.50	2.46	2.46	2.54	2.54
Max	2.61	2.53	2.59	2.59	2.55
St. Dev.	0.03	0.02	0.03	0.01	-
Diameter (avg)	5	5	5	5	5
Min	5	4	5	4	4
Max	5	5	6	5	5
St. Dev.	0	0	0	0	-
Clustering coeff. (avg)	20.2%	20.3%	17.6%	14.6%	13.8%
Min	19.4%	19.0%	15.1%	13.8%	13.7%
Max	22.2%	21.4%	20.4%	15.2%	13.9%
St. Dev.	0.6%	0.7%	1.4%	0.4%	-

[a] The data for 2012 cover only the first four weeks of the year. This is why we do not report the standard deviation.

Table 9
Summary statistics for the networks of CDS on *non-financial* reference entities

Year	2008	2009	2010	2011	2012[a]
Nodes (avg)	374	399	453	480	486
Min	338	379	430	471	483
Max	396	437	484	493	490
St. Dev.	16	16	18	5	-
Links (avg)	2095	2199	2408	2408	2446
Min	1882	2068	2347	2355	2432
Max	2194	2399	2463	2448	2462
St. Dev.	74	86	31	23	-
Density (avg)	1.50%	1.38%	1.18%	1.05%	1.04%
Min	1.36%	1.25%	1.03%	1.00%	1.03%
Max	1.65%	1.48%	1.29%	1.09%	1.04%
St. Dev.	0.08%	0.06%	0.08%	0.02%	-
Assortativity (avg)	-70.6%	-68.6%	-69.0%	-71.8%	-70.8%
Min	-72.1%	-70.1%	-70.8%	-72.7%	-71.1%
Max	-68.4%	-67.3%	-67.9%	-70.5%	-70.6%
St. Dev.	0.8%	0.7%	0.9%	0.6%	-
Average shortest distance (avg)	2.51	2.47	2.49	2.53	2.53
Min	2.46	2.45	2.45	2.52	2.52
Max	2.53	2.51	2.53	2.55	2.53
St. Dev.	0.02	0.01	0.02	0.01	-
Diameter (avg)	5	5	5	5	5
Min	4	5	5	5	5
Max	5	5	5	5	6
St. Dev.	0	0	0	0	-
Clustering coeff. (avg)	19.0%	17.5%	16.1%	14.4%	13.8%
Min	17.8%	16.9%	14.5%	13.7%	13.7%
Max	20.9%	18.2%	17.1%	14.7%	13.9%
St. Dev.	0.8%	0.4%	0.8%	0.3%	-

Table 10
Summary statistics for the networks of CDS on *sovereign* reference entities

Year	2008	2009	2010	2011	2012[a]
Nodes (avg)	219	302	454	532	549
Min	150	255	364	501	545
Max	266	357	499	563	552
St. Dev.	29	24	37	17	-
Links (avg)	777	1105	1632	1951	1933
Min	519	936	1323	1826	1921
Max	962	1309	1831	2119	1940
St. Dev.	111	87	126	70	-
Density (avg)	1.66%	1.22%	0.80%	0.69%	0.64%
Min	1.33%	1.03%	0.72%	0.65%	0.63%
Max	2.36%	1.45%	1.02%	0.73%	0.65%
St. Dev.	0.23%	0.10%	0.08%	0.02%	0.01%
Assortativity (avg)	-62.4%	-65.2%	-67.6%	-69.2%	-67.6%
Min	-66.1%	-67.0%	-69.7%	-70.7%	-67.7%
Max	-52.5%	-63.1%	-64.9%	-67.4%	-67.4%
St. Dev.	3.3%	1.2%	1.2%	0.8%	0.2%
Average shortest distance (avg)	2.53	2.50	2.56	2.57	2.59
Min	2.49	2.46	2.51	2.54	2.59
Max	2.60	2.58	2.60	2.62	2.60
St. Dev.	0.03	0.02	0.02	0.02	-
Diameter (avg)	5	5	5	5	5
Min	4	4	5	5	5
Max	5	5	5	6	5
St. Dev.	0	0	0	0	-
Clustering coeff. (avg)	22.5%	16.7%	12.5%	10.8%	10.7%
Min	18.5%	14.7%	11.4%	9.9%	10.6%
Max	28.8%	18.9%	14.4%	11.5%	10.8%
St. Dev.	2.4%	0.8%	0.7%	0.4%	-

Appendix C: Scale-free systems and fit of CDS positions to a power-law distribution

A scale-free network is a network whose degree-distribution follows a power law, i.e. the percentage $P(k)$ of nodes in a network with k connections to other nodes is denoted for large values of k as:

$$P(k) \approx k^{-\alpha}$$

where α is a parameter whose value is typically in the range $2 < \alpha < 3$.

A power law distribution is heavy-tailed, with some nodes having many more connections than others (Fig. 10 provides an illustration of a simple scale-free network). The highest-degree nodes were called "hubs" by Barabási (2001), who mapped the topology of World Wide Web links. Subsequently, many other real-world networks were found (or claimed) to exhibit power-law degree distribution for various values of α and for large k. Albert and Barabási (2002) proposed a generative mechanism to explain the appearance of power-law distributions, which they called "preferential attachment"[22].

Table 10 reports the results of the Kolmogorov-Smirnov test that we performed to assess whether the (weighted) CDS links studied in this paper trace a power-law distribution in the tail, i.e. for net bilateral positions w_{ij} larger than a certain threshold value. We proceed as follows:

- First, as shown in Goldstein, Morris and Yen (2004) we fit our net bilateral positions (all net selling positions in the first week of each year) to a power-law distribution using maximum likelihood estimation (MLE). We estimate both the minimum net position $w_{ij}^{\min}$ and the value of α for which the positions are distributed, starting from that threshold, as a power law (α).
- Second, we perform the Kolmogorov-Smirnov test given in Clauset, Shalizi and Newman (2009) to evaluate the goodness-of-fit of our empirical distribution to a theoretical power law governed by the parameters estimated by MLE in the previous step.

22 "Scale-free" refers to the fact that the distribution remains (approximately) unchanged under a rescaling of node degree by a multiplicative factor (i.e., if x nodes have degree k in the network, then $\alpha \times x$ nodes will have degree $\beta \times k$ for some α, β<1). See among others Dorogovtsev and Mendes (2003).

Table 11
Results of the Kolgomorov and Smirnov test of goodness-of-fit to a theoretical power law (α)

	$w_{ij}^{\min}$ *(USD)*	α	*Kolmogorov-Smirnoff test statistics*	*Result*	*Size of the tail*	*Size in %*
Jan-08	460,000,000	1.60	0.0710	fail to reject	68/223	30%
Jan-09	884,718,544	1.62	0.1075	fail to reject	56/213	26%
Jan-10	513,575,000	1.55	0.0870	fail to reject	71/259	27%
Jan-11	123,024,009	1.48	0.0593	fail to reject	123/327	38%
Jan-12	163,500,000	1.53	0.0611	fail to reject	124/366	34%

The results show that, for every year, the test statistics computed on the empirical distribution do not permit rejection of the hypothesis that net multilateral exposures larger than the estimated threshold are distributed according to a power law with given α. Looking at the evolution over time in the number of net exposures forming the tail, we observe that 30% of the largest net positions belonged to the tail in the first week of 2008 against 38% in 2011, suggesting a higher concentration of net multilateral CDS positions in 2011 than in 2008. However, this concentration was somewhat reduced again in the first week of 2012.

Appendix D: Top-20 market participants in the CDS market for European reference entities

Table 12:
Top-20 market participants in the CDS market for European reference entities (by various network metrics, on average over 2008-2012). *In-degree* measures the number of counterparties to which a firm is a net seller of CDS; *in-strength* the total net amount sold; *out-degree* the number of counterparties from which a firm is a net buyer; *out-strength* the total net amount bought; net-strength the firm's net multilateral selling position; *eigenvector centrality* the interconnectedness of a firm based on the interconnectedness of its counterparties; betweenness the importance of a firm's intermediation role.

Rank 2008 - 2012	In-degree	In-strength	Out-degree	Out-strength	Net strength	Eigenvector centrality	Between-ness centrality
1	Bank 497*	Bank 622*	Bank 622*	Bank 497*	Bank 312*	Bank 497*	Bank 622*
2	Bank 622*	Bank 312*	Bank 356*	Bank 356*	Bank 622*	Bank 356*	Bank 148*
3	Bank 765*	Bank 765*	Bank 765*	Bank 317*	Bank 186*	Bank 276*	Bank 1172*
4	Bank 356*	Bank 497*	Bank 317*	Bank 765*	Bank 821	AM 1073	Bank 356*
5	Bank 148*	Bank 186*	Bank 497*	Bank 622*	HF 508	Bank 1045*	Bank 765*
6	Bank 317*	Bank 317*	Bank 148*	Bank 276*	Bank 656	Bank 954*	Bank 497*
7	Bank 1172*	Bank 1045*	Bank 276*	Bank 1172*	Bank 389	Bank 1172*	Bank 317*
8	Bank 276*	Bank 136*	Bank 1172*	Bank 1045*	AM 860	AM 873	Bank 276*
9	Bank 136*	Bank 148*	Bank 136*	Bank 148*	Bank 1176*	HF 304	HF 673
10	Bank 186*	Bank 356*	Bank 954*	Bank 136*	Bank 627	Bank 765*	Bank 136*
11	Bank 954*	Bank 1172*	Bank 186*	Bank 954*	Bank 1045*	Bank 317*	AM 541
12	Bank 1045*	HF 508	Bank 553*	Bank 553*	Bank 136*	Bank 136*	Bank 954*
13	Bank 553*	Bank 821	Bank 1045*	CCP 565	Bank 667	Bank 289	FS 373
14	Bank 667	CCP 565	Bank 289	Bank 289	Bank 765*	Bank 148*	Bank 186*
15	Bank 312*	Bank 954*	Bank 667	Bank 186*	FS 920	Bank 622*	AM 538
16	Bank 1176*	Bank 553*	Bank 804	Bank 782	AM 104	CCP 565	Bank 553*
17	Bank 804	Bank 1176*	Bank 1176*	AM 873	AM 345	Bank 782	Bank 1045*
18	Bank 389	Bank 389	Bank 312*	Bank 1176*	FS 1075	HF 182	AM 937
19	Bank 782	Bank 656	Bank 132*	Bank 304	Bank 659	HF 509	Bank 667
20	Bank 656	Bank 667	Bank 137	Bank 804	Bank 412	Bank 553*	Bank 118

AM stands for Asset Manager (in red in the table); HF for Hedge Fund (in blue); FS for Financial Service company (orange); CCP for_central clearing counterparty (green); N.A. for not available; * signals that the bank belongs to the G-SIBs identified by the Financial Stability Board.

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