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THE NETWORK STRUCTURE OF THE CDS MARKET AND ITS DETERMINANTS

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In 2013 all ECB publications feature a motif taken from the €5 banknote.

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Abstract

This paper analyses the network structure of the credit default swap (CDS) market, using a unique sample of counterparties' bilateral notional exposures to CDS on 642 sovereign and financial reference entities. We study the network structure, similarly to the literature on interbank and payment systems, by computing a variety of network metrics at the aggregated level and for several sub-networks. At a reference entity level, we analyse the determinants of some key network properties for large reference entities. Our main results, obtained on a sub-sample of 191 reference entities, are the following. First, the CDS network shows topological similarities with the interbank network, as we document a "small world" structure and a scale-free degree distribution for the CDS market. Second, there is considerable heterogeneity in the network structures across reference entities. In particular, the outstanding debt volume and its structure (maturity, collateralization), the riskiness, the type (sovereign/financial) and the location (European/non-European) of reference entities significantly influence the size, the activity and the concentration of the CDS exposure network. For instance, the network on a high-volatility reference entity is typically more active, larger in size and less concentrated.

JEL Codes: G15.

Keywords: Credit Default Swap (CDS), financial networks, network topology, network determinants.

Non-technical summary

Even though the CDS market has grown considerably over the last decade, its structure is still little described and understood. This paper uses a large and novel dataset to analyze the CDS exposures network from three different perspectives: (i) the aggregated CDS network, (ii) various sub-networks, such as the sovereign CDS network and (iii) networks for CDS reference entities. The dataset, obtained from the DTCC, comprises virtually all gross and net exposures worldwide on 642 reference entities, including 40 sovereign and 602 financial reference entities as of end-2011. Its coverage represents about 32.7% of the global single-name CDS market.

This paper provides two main contributions to the literature on CDS markets. First, it uses the tools of network analysis to provide a characterization of the topological properties of the aggregated CDS network and of several sub-networks with a lower level of aggregation (e.g. sovereign vs. financial, European vs. non-European reference entities). The first main result is that the CDS network shows topological similarities with the interbank network. In aggregate, active traders sell and less active traders buy (net) CDS protection, which parallels the finding that smaller banks tend to lend to bigger, 'money-center' banks. The aggregate CDS network also exhibits the so-called "small world" properties that have been documented for other financial networks, as well as a scale-free degree distribution. Such a result is found to be robust for various levels of aggregation. Finally, there is high(er) concentration among counterparties than among reference entities. The top-10 most active traders account for 73% of gross protection bought or sold and are active in more than 55% of sovereign and financial reference entities. So far, such a network description of the CDS market was inexistent.

Second, this paper goes to a more granular level and provides an econometric analysis of the determinants of the properties of the CDS network for individual reference entities. Whereas previous papers on financial networks have focused on descriptive analysis, our study investigates how various characteristics of the reference entity influence the corresponding CDS network properties. This analysis is conducted on a sub-sample of 191 reference entities representing 91% of the full dataset. Our findings therefore apply to large reference entities only. Using a generalized linear model (GLM), we focus on analysing the relationship between the size of the CDS network, its activity and concentration with variables related to the underlying debt characteristics, riskiness, as well as to the type (sovereign vs. financial) and location (European vs. non-European) of the reference entity.

In this respect, we document a significant impact of the characteristics of the underlying bond exposure (size, collateralization) and of the risk characteristics of the CDS (volatility, commonality in returns) on the CDS market size and activity. Whereas the distinction between sovereign and financial reference entities matters for the network structure, there are almost no significant differences in structural properties between European and non-European reference entities. Concentration, on the contrary, is largely explained by proxies for a CDS contract's activity and by its beta estimated with market returns.

1. Introduction

Despite its fast growth and significant size, there is very little research on the structure of the credit default swap (CDS) market. In December 2011, the gross notional amount of CDS contracts worldwide was about US$ 16,881 billion for single-name instruments, substantially higher than US$ 5,116 billion in 2004 (BIS, 2012). Even though important efforts have been made to standardise the contracts (especially with the so-called ISDA "big-bang" protocol in 2009 or the increasing use of central counterparties), CDS have typically been traded as over-the-counter derivative instruments. The prevalence of bilateral trading makes it difficult to analyse the market structure for market participants, researchers or even regulators.

Whereas many papers have studied the pricing of CDS, there is very little analysis of its market structure and its determinants. In fact, there is no research based on the network arising from actual bilateral exposure data, its characteristics and stability properties. Despite two recent studies on the determinants of the aggregate notional amounts exchanged in CDS markets (Oehmke and Zawadowski, 2012) and on the aggregate market liquidity and trading activity (Chen et al., 2011), a significant gap therefore remains in the current literature on derivatives. Regarding the stability of the CDS market, existing studies do not rely on true bilateral exposures but on maximum entropy estimations from aggregate exposures at a product level (Markose et al. 2012) or at a reference entity level (Vuillemey and Peltonen, 2013).

Analysing the network structure is crucial for understanding the functioning and potential sources of risks of the CDS market. In particular, the OTC nature of the trades implies that counterparty risk externalities are potentially large (see Acharya and Bisin, 2013) and that their assessment has to be based on the structure of bilateral exposures. For instance, if the CDS market is concentrated among a few major traders, market stability would differ from the case where market activity is widely dispersed across a large number of relatively smaller traders. The density of the network is also likely to be a determinant of its resilience to shocks. Such questions have been at the centre of attention for a long time in the context of interbank markets (see Acemoglu et al., 2013; Georg, 2011; Gai and Kapadia, 2010) but have not yet received widespread attention in the analysis of derivative markets.

Our paper analyses the structure of the CDS market from three different perspectives: (i) the aggregated CDS network; (ii) various sub-networks, such as the sovereign CDS network; and (iii) networks for individual CDS reference entities. We provide two main contributions to the literature on CDS markets. First, we characterise the topological properties of the aggregated CDS network and of several sub-networks with a lower level of aggregation using the tools of network analysis. We use a novel dataset of bilateral CDS exposures as of end-2011, representing about 32.7% of the global single-name CDS market. For 642 sovereign and financial reference entities, we have data on virtually all gross and net bilateral exposures between any two (anonymised) counterparties. In addition to the aggregated CDS network, our sample offers a full characterization of a large number of reference entity networks, which differ in size, structure and concentration. Even though network metrics have been widely used to describe payment systems and the interbank market, so far there is no description of the CDS network in the literature.

Second, we provide an econometric analysis of the determinants of the properties of the CDS network for individual reference entities. Whereas previous papers on financial networks have focused on descriptive analysis, our study goes one level deeper in investigating how various characteristics of the reference entity influence the corresponding CDS network properties. Using a generalized linear model (GLM), we focus on analysing the relationship between the size of the CDS network, its activity and concentration with variables related to the underlying debt characteristics, riskiness, as well as to the type and location of the reference entity.

Our first main result is that the CDS network topology shows some similarities to the interbank network. In aggregate, active traders sell and less active traders buy (net) CDS protection, which parallels the finding that smaller banks tend to lend to bigger, 'money-center' banks (for a recent study see Gabrieli, 2011). The aggregate CDS network also exhibits the so-called "small world" properties that have been documented for other financial networks, as well as a scale-free degree distribution. There is high(er) concentration among counterparties than among reference entities. The top-10 most active traders account for 73% of gross protection bought or sold and are active in more than 55% of sovereign and financial reference entities.

Second, regarding the determinants of the network structure, we find a significant impact of the characteristics of the underlying bond exposure (size, collateralization) and of the risk characteristics of the CDS (volatility, commonality in returns) on the market size and activity of a given CDS reference entity. Whereas the distinction between sovereign and financial reference entities matters for the network structure, there are almost no significant differences in structural properties between European and non-European reference entities. Concentration, on the contrary, is largely explained by proxies for a CDS contract's activity and its estimated beta with market return.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 describes the data used in the analysis and introduces potential determinants of the CDS network structure. Section 4 describes the aggregated CDS network as well as several CDS sub-networks. Section 5 presents the econometric methodology used to investigate the determinants of the CDS network structure, whereas Section 6 presents our results.

2. Related literature

In the literature on CDS, many papers have analysed CDS spreads. For example, the determinants of CDS spread changes have been extensively studied both for CDS *per se* (Berndt and Obreja, 2010) or jointly with other market data such as bond spreads (see

Fontana and Scheicher, 2010 and references therein). Moreover, CDS spreads have been used extensively to extract information on credit risk or on the impact of particular events on an entity's credit risk. Recent contributions on this issue are the study of the common and idiosyncratic components of sovereign credit risk (Longstaff et al., 2011), of contagion between sovereigns and banks (Ejsing and Lemke, 2011) or of intra-industry information transfers (Jorion and Zhang, 2007). The pricing of counterparty risk on the CDS market has been documented by Arora et al. (2012).

However, despite the large literature on CDS *spreads*, research on CDS *exposures* is very limited. There are only two papers on the macro- or micro-structure of the CDS market. Oehmke and Zawadowski (2012) use public data from DTCC to document the determinants both of the emergence of a CDS market for particular corporate bonds and of net credit protection bought or sold. Chen et al. (2011) use global CDS transaction data to describe the market composition, the trading dynamics and the level of standardisation in contract specifications. The present paper analyses a different question as it does not focus on transactions but rather on open exposures (i.e. the sum of all transactions that have not yet matured or been terminated) for a large number of reference entities. The question at the heart of our paper, on the relationship between the characteristics of a reference entity and the properties of the corresponding CDS market, has so far not been addressed in the literature.

The second important strand of the literature for our purposes is the one on financial networks, as surveyed by Allen and Babus (2009), Upper (2011) and Alves et al. (2013). A number of articles have already analysed the topological properties of payment systems (Bech and Atalay, 2010) of interbank networks (Boss et al., 2004, Iori et al., 2008) or of global banking (Minoiu and Reyes, 2013). They typically attempt to describe financial interconnections using network metrics either at one date or over time. Network topology has also been related in a growing strand of the literature to stability properties and to contagion conditional on a shock. Recent examples include Battiston et al. (2012a and 2012b) or Georg (2013).

3. Data

This section describes our data set. We distinguish the aggregated data set where all bilateral exposures are combined from a variety of sub-networks, e.g. the network of exposures to sovereign CDS. Furthermore, we also include a number of additional variables on the reference entities. These variables allow us to conduct a more granular analysis of the aggregated CDS network as well as to define a restricted sample on which we then conduct our econometric analysis.

3.1 The dataset on bilateral exposures

Our dataset on CDS exposures is provided by the Depository Trust and Clearing Corporation (DTCC) and is extracted from The Trade Information Warehouse (TIW). It is a snapshot of the world CDS market as of 30 December 2011 for a large number of reference entities. The TIW is a global trade repository, i.e. a database of transactions covering the vast majority of CDS trades worldwide, and virtually all recent CDS trades. It has several interesting features. First, whereas most regulators do have access to CDS transactions involving domestic counterparties or reference entities only, our dataset has a truly global coverage. Second, it covers both centrally cleared and bilateral OTC transactions, although we do not know which transactions are cleared or not. According to ISDA, about 8% of the single-name CDS transactions were cleared as of end-2011 (ISDA, 2012, p.7). Third, not only banks or dealers report their trades to DTCC, but all types of counterparties, so that our dataset encompasses all main non-bank institutions such as hedge funds, insurance companies, central counterparties (CCPs) and potentially some industrial corporations. Finally, this data set is a legal record of party-to-party transactions, as the Warehouse Trust Company (a subsidiary of DTCC which operates the Trade Information Warehouse) is supervised by US regulatory authorities.

Our sample covers 642 reference entities, including 18 G20 sovereigns, 22 European sovereigns and 602 global financial entities[5]. Overall, 946 counterparties have been active in these reference entities. Our dataset contains the names of reference entities, but the identity of the counterparties is anonymised. The total gross notional in our sample equals EUR 4.28 trillion. At the same date (30 December 2011) the total gross notional at a world level was – EUR 19.6 trillion (see ISDA, 2012). Therefore, our sample represents about 32.7% of the global single-name CDS market and 19.6% of the total CDS market (including multi-name instruments)[6].

For each reference entity, our dataset contains gross and net bilateral exposures between any two counterparties. The overall network consists of 57,642 bilateral exposures on individual reference entities. Any bilateral exposure may result from several separate transactions, so that the number of transactions covered by our dataset is 592,083. We do not have access to additional information at a transaction level. For example, we know neither the date at which a particular deal has been performed, nor the maturity (initial or remaining) of each position. However, a number of studies or market surveys found that most CDS deals have a 5 years maturity (see DTCC, 2010). The market value of open positions is not available either. All gross and net notional amounts are expressed both is euros and U.S. dollars for all bilateral exposures. In the following, all numerical amounts are expressed in euros.

We perform a number of standard data quality checks for our dataset. First, we control for the presence of outliers, i.e. notional exposures either unrealistically high or low. For each reference entity, we check that the maximum notional amount (gross and net) per transaction does not lie over five standard deviations from the mean transaction notional. We do not find such outliers. At the lower end of the distribution, the dataset includes 26 bilateral gross exposures below 1,000 euros (including some with notional between 2 and 100 euros). We

[5] Due to the DTCC definition of financials, the sample contains not only banks, but also insurance firms as well as industrial finance companies.
[6] The single-name reference entities we miss in our sample include essentially corporates (which represent about 56.6% of the global single-name CDS market) and sovereign CDS for non-G20 developing countries.

exclude these observations, which are not likely to reflect any genuine positions. Possible explanations for those transactions may include either misreporting or actual transactions aiming at testing the functioning of the trading system.

Finally, we observe 437 cases of bilateral exposure of a counterparty vis-à-vis itself. They involve 13 individual counterparties and most likely reflect aggregation inconsistencies at a bank level, i.e. an internal trade between two accounts or subsidiaries/legal entities of the same firm. These observations are barely relevant for our purposes, as we focus on the network properties (i.e. on genuine links between two different nodes), and may bias some network metrics. They are therefore dropped. Overall, the percentage of observations dropped is below 1%. For the remaining observations, no data is missing, so that we have the same full set of variables for all bilateral exposures on all 642 reference entities.

3.2 Restricted sample - the data set used in the analysis

In addition to the exposure data we use a number of additional variables to capture key reference entity characteristics. For each reference entity, DTCC data on exposures are matched, when available, with data on debt characteristics, CDS riskiness, and type and location of the reference entity. Both debt and price data are retrieved from Bloomberg. The definition of these variables is described below in more detail. We use these variables to define sub-networks (section 4) and they also serve as explanatory variables in our econometric analysis of the network structure (section 5).

Due to a gap with the data coverage of Bloomberg, matching the DTCC exposure data with these additional variables leads to a smaller sample, which we call as the *restricted sample*. This approach has the additional advantage that it removes reference entities where there is very little trading, i.e. where the information content of the related network properties is likely to be low.

Overall, the set of additional variables is available for 191 reference entities representing a gross notional amount of EUR 3.88 trillion, i.e. 91% of the total gross notional in our full dataset. Hence, our restricted sample covers a very large part of the information contained in the full sample of 642 reference entities.

3.2.1 Debt characteristics of the reference entity

As the main purpose of a CDS is to hedge credit risk, a first set of determinants of the CDS network properties is likely to be related to the characteristics of the underlying debt. We include the following debt characteristics using the data from Bloomberg[7]:

- **Bond outstanding:** For each reference entity, we retrieve the data for the total underlying bond outstanding as of December 2011. The data includes covered bonds but excludes repurchase agreements. All debt amounts are converted into euros using

[7] Given that our sample comprise both sovereign and financial reference entities, and given the heterogeneity among financial reference entities (banks, insurance companies, finance companies), we cannot include additional balance sheet variables at an entity level as potential determinants of the CDS network properties.

the end of December 2011 EUR/USD exchange rate (or the appropriate exchange rate from any other domestic currency).

- **Weighted average maturity:** For each reference entity, we retrieve the data for the weighted average maturity of the total bond volume outstanding.
- **Percentage of unsecured debt:** For each reference entity, we retrieve data for the percentage of the total bond outstanding that is unsecured.

3.2.2 Riskiness of the reference entity

Moreover, given the use of CDS as a risk management tool, individual CDS network structures are likely to be related to the risk characteristics of the underlying reference entities. For two reasons, we use risk variables related to CDS spreads rather than to the underlying reference entities. First, bond data are heterogeneous both in terms of quality and of maturity, and for corporates there is usually no benchmark bond. In contrast, CDS spreads are comparable between entities for a given maturity. Second, there are uses of CDS that are likely to be directly affected by the CDS riskiness but not by the bond riskiness. This includes uses of CDS for trading rather than hedging, e.g. relative value trading strategies on CDS.

We use time series of weekly data of CDS spreads spanning over 2010-11 retrieved from Bloomberg to define three risk-related variables:

- **Last CDS spread:** For each CDS reference entity, we use the spread of the contract with 5-year maturity as of end-December 2011. The CDS spread is taken as a proxy for the absolute level of riskiness of the underlying reference entity.
- **Volatility:** For each CDS reference entity i, the volatility of the CDS spread is computed using the time series of weekly data from 2010-11 as follows:

$$Volatility_i = std\left(d\log(p_i^{CDS})\right),$$

where p_i^{CDS} denotes the spread of CDS i, d the first difference and std the standard deviation.

- **Beta:** For each CDS reference entity, we estimate a one-factor model where the market return is defined as the simple (equally weighted) average of all individual CDS returns. The regression is computed with the weekly changes of the CDS spreads over the last two years. We then use the estimated factor loading as an estimate of the beta corresponding to a specific reference entity.

3.2.3 Type and location of the reference entity

In addition to the risk and debt characteristics, we add two dummy variables that can also determine the network structure:

- **Type:** The set of reference entities is partitioned into two subsets, one corresponding to sovereigns, and the other corresponding to financial reference entities.

- **Location:** Reference entities are distinguished according to their geographical location, being either European or non-European.

Descriptive statistics for the distribution of these variables are provided in table 1. The median CDS reference entity has bonds of EUR 14 billion outstanding, with a maturity of 6.2 years. The debt issued by the reference entities in the restricted sample is overwhelmingly unsecured. Hence, covered bonds do not play a large role among the financial institutions which we analyse. The median CDS spread is around 250 basis points (BP) and the median beta is 1.03. CDS spreads range from 42 BP to 5,924 BP. Betas range from 0.28 to 1.54, indicating that all 191 reference entities have a positive co-variation with the overall market.

4. Analysis of the network structure

This section describes the topological properties of the aggregated CDS market. It then defines a number of CDS sub-networks, i.e. alternative aggregation schemes where CDS networks are aggregated according to particular characteristics.

4.1. Definitions and notation

We first define the *aggregated CDS network*. There is a set Ω of n counterparties indexed by i and j. The gross CDS notional sold by an institution i to an institution j on a reference entity k is denoted A_{ij}^k. The aggregate gross notional sold by i to j is denoted $A_{ij} = \sum_k A_{ij}^k$. The aggregated gross CDS network is composed of the exposures A_{ij}, for all i and j in Ω. The aggregated net CDS network is then defined by a $n \times n$ unweighted adjacency matrix N whose elements N_{ij} are given by:

$$N_{ij} = \begin{cases} 1 \ if \ A_{ij} > A_{ji} \\ 0 \ otherwise. \end{cases}$$

We restrict our attention to the unweighted adjacency matrix, as some metrics (diameter, mean and maximum degree in particular) are more difficult to interpret for a weighted network. Even though they are not presented below, all results have been computed for the weighted network as well, and do not differ to a significant extent[8].

For the aggregated net CDS network defined by the unweighted adjacency matrix N, we compute a set of network metrics which have been commonly used in the network literature. Each trader is defined as a *node*, whereas each bilateral exposure is a *link* in the aggregated

[8] Such results are available upon request.

network. Links are directed and non-weighted[9]. Following Iori et al. (2008), we compute the following network metrics[10]:

- number of links
- density
- clustering coefficient
- diameter
- mean degree
- maximum degree
- degree distribution and its fitting to a power law.

Each of these metrics has been defined in the literature (Jackson, 2008, for example) and are interpreted below in the context of the CDS market (section 4.3).

4.2. Descriptive statistics for the aggregated network

Descriptive statistics for the aggregated CDS network are presented in table 2. As mentioned in the previous section, 946 counterparties trade on 642 reference entities, representing a total gross notional amount of EUR 4,280 billion. The net notional exposure at the aggregated level, however, is significantly smaller, equal to EUR 349 billion, leading to a net-over-gross notional ratio of 8.2%. One reason why net exposures are of significantly lower magnitude than gross exposures is that many CDS trades do not generate genuinely new exposures as they are designed to offset previously existing exposures. The average market participant is trading 18.7 reference entities and is linked to 9.6 counterparties, even though the distribution of links is highly skewed, as we will explain below. We observe 592,083 transactions that have an average notional value of EUR 7.2 million. There are virtually no transactions with a low notional amount, as standardised amounts (or multiples of them) are typically traded. Each exposure on a particular reference entity network on average results from 10.3 (potentially offsetting) transactions. The high number of transactions and the low net-over-gross notional ratio indicate that net CDS exposures between any two traders on a reference entity are frequently adjusted and that an exposure opened at some date is typically not kept unchanged until the maturity of the CDS contract (typically a five-year horizon).

Concentration among counterparties is quite high. In order to analyse the trading activity of groups of market participants we measure concentration of activity as the share of the gross CDS sold by the 10 most active institutions, relative to the total gross CDS market notional. The 10 most active traders account for 73% of the gross sales of CDS[11], implying that the

[9] We constrain each element of the adjacency matrix to be either 0 or 1. It is equal to 1 if $N_{ij} > 0$, and equal to 0 otherwise. Studying a weighted network would not change the results qualitatively, but would make most metrics (mean and maximum degree, diameter) more difficult to interpret.

[10] We also compute the largest strongly connected component (LSCC) of each network, presented in Bech and Atalay (2008). Results for this metrics are not presented as they have no straightforward interpretation and because the LSCC at a network level is highly positively correlated with the density (Pearson correlation of 0.91).

[11] The same 10 dealers also account for about 73% of gross CDS purchases.

CDS market is highly concentrated between a few major dealers, as also observed by Mengle (2010). At a more granular level, we investigate whether the aggregate net position of particular traders, either as a net buyer or as a net seller of CDS, depends on its level of activity. Given that counterparties are anonymised in the dataset, we can only distinguish them according to their overall level of activity (in percentiles).

We note that a large part of the active market participants acts as net protection buyers. In the aggregated CDS market, only 18% of the institutions are net CDS sellers overall (even though they may be net buyers of particular reference entities).

We compute the share of active institutions for three sub-groups: the 10 most active traders in the CDS market (ranked according to the total gross notional sold), the following 40 most active institutions (rank from 11 to 50) and all other active institutions. The percentage of net sellers among each group is presented in table 3. The observed pattern of trading behaviour shows that the proportion of net sellers is higher among the most active traders (50% of the top-10 traders are net sellers) and decreases with the level of trading activity. Only 17% of the less active market participants are net sellers of CDS, implying that small end-users of CDS (as opposed to dealers and market makers) are net buyers of protection to a significant extent. Even though the proportion of net sellers is the highest among the most active market participants, 50% of them are nevertheless net buyers.

Overall, we find that credit risk exposure transferred in the CDS market is ultimately born by only a small share of the market participants.

4.3. Network analysis for the aggregated system

The network metrics for the aggregated CDS network are presented in table 4. The network comprises 4428 links between the 946 counterparties, implying a low density (equal to 0.005), i.e. that only a small share of all possible links actually exists. Hence for the vast majority of counterparties, there are no direct bilateral links.

We find that the aggregated network exhibits the “small world properties” exposed in Watts and Strogatz (1998) or Jackson (2008). “Small world” networks are first characterized by a low diameter (here equal to 5), meaning that the average number of links separating any two nodes is short. Another property of these types of networks is that their clustering coefficient exceeds the level of an Erdös-Renyi random network of comparable density. The clustering coefficient is a measure of the tendency of some nodes in a graph to cluster together (see e.g. Iori et al., 2008). In financial networks, clustered nodes typically form a core of key intermediaries, dealers or market makers that are linked to a large number of other traders. In the aggregated CDS network, the clustering coefficient equals 0.07, which is several times higher than the density. In contrast, the clustering coefficient in an Erdös-Renyi random graph, i.e. a graph in which each link is formed with a probability p, is equal on expectation to the network density. The magnitude of the clustering coefficient, coupled with a low diameter, lead us to characterize the aggregated CDS network as a “small world” network. Moreover, the low diameter, together with the low density, show that the interconnectedness on the CDS market does not arise from the large number of bilateral links between any two counterparties, but because all traders are close to one another due to the existence of a few key intermediary traders.

We confirm that the aggregated CDS network is "scale-free". This property of the network relates to the shape of its degree distribution. The degree of a node is the number of links it has to other nodes, while the degree distribution is the probability distribution of these degrees over the whole network. The mean degree of a node in this network is 9.4, whereas the most-connected institution is linked to 470 counterparties. The degree distribution, however, is highly skewed; it is displayed in a log-log scale in figure 2. Most papers in the empirical literature on the interbank market or on payment systems fail to reject the hypothesis that their degree distribution follows a power law distribution, i.e. that the fraction of nodes $P(x)$ having a degree x is distributed, for values of x above some threshold x_{min}, as:

$$P(degree = x) = \frac{\alpha - 1}{x_{min}} \left(\frac{x}{x_{min}}\right)^{-\alpha}$$

The degree distribution of the aggregate CDS market is fitted to a power law distribution. Goldstein et al. (2004) show that the most robust procedure to do so is the use of a maximum likelihood estimator. We then compute the Kolmogorov-Smirnov statistics to test whether the hypothesis according to which the degree distribution follows a power law distribution can be rejected. Results are presented on table 5. We fail to reject the hypothesis, implying that the aggregate CDS network can be considered a scale-free network. In terms of stability and contagion, scale-free networks have been shown to be more robust than random networks to the disappearance of one node, but to be highly vulnerable in case one of the few highly-connected nodes disappears (Duan et al., 2005 and Georg, 2011). [12]

A number of papers, starting with Barabasi and Albert (1999), have provided theoretical underpinnings for explaining the emergence of scale-free networks. Dorogovtsev and Mendes (2003) provide a comprehensive overview of this class of models which, in order to generate scale-free degree distributions, feature characteristics such as "preferential attachment" mechanisms between nodes or "cumulative advantages". On OTC derivatives markets, "preferential attachment" can be linked to the role of a few major market participants who act as dealers, thereby trading large gross amounts but having a substantially smaller net exposure due to their intermediary role. One example here is the prime brokerage services offered by major banks to hedge funds.

Finally, we plot the aggregated CDS network (Figure 1). The chart illustrates the importance of a few major dealers compared to the rest of the market participants whose exposures are typically of a much smaller magnitude.

4.4. Descriptive statistics for the sub-networks

From the aggregated network we now move to lower levels of aggregation based on the characteristics of each individual reference entity introduced earlier. For each of the eight

[12] Mengle (2010) also shows that a few important dealers capture a large share of the CDS market activity.

characteristics, we split the sample into two subgroups and aggregate the corresponding CDS networks so as to obtain new networks with a lower level of aggregation. We later focus on explaining the structural properties of these sub-networks. By comparing pairwise the resulting networks, we aim to identify potential determinants of the CDS network structure. We define the following eight types of sub-networks:

1. **Sovereign vs. financial sub-networks:** All reference entities are categorised according to their type (sovereign/financial).
2. **European vs. non-European sub-networks:** All reference entities are categorised according to their geographical location.
3. **High- vs. low-spread sub-networks:** Reference entities are categorised according to the level of their CDS spread: “High-spread CDS” have a spread above 300 basis points whereas “low-spread CDS” have a spread below 300 basis points[13].
4. **High vs. low debt sub-networks:** Reference entities are categorised according to whether their outstanding debt is above or below the sample median.
5. **High vs. low maturity sub-networks:** Reference entities are categorised according to whether the maturity of their underlying debt is above or below the sample median.
6. **High vs. low unsecured debt sub-networks:** Reference entities are categorised according to whether their share of underlying unsecured debt is above or below the sample median.
7. **High vs. low volatility sub-networks** Reference entities are categorised according to whether the volatility of their CDS is above or below the sample median.
8. **High vs. low beta sub-network:** Reference entities are categorised according to whether the beta of their CDS spread is above or below the sample median.

Descriptive statistics for these sub-networks are presented in table 2 (due to the additional variables, the sample is 191 reference entities). We focus on identifying characteristics that may be important for understanding the drivers of the network structure.

We find that a number of reference entity characteristics have an important impact on the network properties. The number of active counterparties, as well as the gross and net CDS notional amounts exchanged in sub-networks are closely linked to one another and differ substantially when we consider the categorization based on the level of debt, the share of unsecured debt, CDS volatility and beta. For instance, whereas there are 850 active counterparties in the market for “high-debt” CDS (i.e. CDS whose underlying bond volume is above the sample median), there are only 504 active counterparties in the market for “low debt” CDS, therefore suggesting that the underlying debt volume is an important driver of the CDS market size and activity. Similarly, sub-networks for “high unsecured debt”, “low spread”, “high beta” and “high volatility” CDS are characterized by a larger number of active counterparties, as well as larger gross and net CDS exposures, even though those sub-networks are composed of roughly the same number of reference entities. In contrast, neither

[13] A cut-off CDS spread of 300 basis points is above the median (251 basis points). Choosing the median as a cut-off, however, would not alter the significance of the results presented below.

the sovereign vs. financial distinction, nor the European vs. non-European distinction strongly affect the characteristics of the sub-networks.

Turning to the net-over-gross ratio, we observe a range between 6.3% for the “low debt” CDS network to 9% for the sovereign CDS network. Even though this ratio does not vary importantly for most pairs of sub-networks, we observe that it is higher for the sovereign than for the financial CDS network (9% vs. 7.6%) and for the “low spread” than for the “high spread” CDS network (8.4% vs. 6.3%). Overall, this ratio is higher for sub-networks which are characterized by a larger number of active counterparties and by larger absolute (both gross and net) notional amounts, indicating that market participants tend to keep relatively larger net open positions on CDS that are more actively traded or whose market is larger in size.

The average transaction notional amount varies from one sub-network to the other, ranging between EUR 5.1 million (on the “low debt” CDS network) to EUR 11.6 million (on the sovereign CDS network). These figures are obtained for a large number of transactions, respectively 182,541 and 156,278. Several CDS characteristics are also found to be relevant for the average transaction notional amount when sub-networks are compared pairwise. It is larger for sovereign than for financial reference entities (11.6 vs. 5.7 million euros), suggesting that the standardized notional amounts traded depend on the reference entity type. To a large extent, it is larger for the European than for the non-European CDS network (8.3 vs. 6.5 million euros) and for the “high debt” than for the “low debt” CDS network (8.7 vs. 5.1 million euros).

The average number of counterparties per trader is remarkably stable from one type of network to the other, ranging from 7.9 (in the sovereign CDS network) to 9.5 (in the financial CDS network). Even though the average number of counterparties in the market may hide a highly skewed distribution of the links, as we shall see below, the stability of these metrics over different types of networks essentially reflects the fact that most market participants typically have only a small number of direct counterparties, for example their prime broker, irrespective of the number of reference entities they trade or their characteristics.

The average number of reference entities traded does not have a straightforward interpretation, as it is highly related both to the number of reference entities aggregated and to the size of the network (as measured by the number of active counterparties or by the gross notional exposure discussed earlier on). In contrast, the average number of transactions per reference entity per bilateral link, which shows how many transactions make up each bilateral exposure, is an indicator of how often positions on a subgroup of reference entities are adjusted. It ranges between 9.5 for European reference entities to 12.2 for sovereign reference entities. The difference between sovereign vs. financial reference entities is high, as bilateral exposures on sovereign CDS result from a larger number of trades (12.2 vs. 9.7), potentially indicating that sovereign exposures are adjusted more frequently on average. Furthermore, “high beta” and “high volatility” CDS exposures also result from a larger number of transactions, while most other characteristics do not seem to have a strong influence.

The concentration of the activity is high in all sub-networks. The share of the top-10 traders in the total gross notional sold ranges between 71% and 77% (for “high spread” and “low beta” sub-networks respectively). Focusing on a pairwise comparison of the sub-networks, most reference entity characteristics are not found to influence importantly the concentration in each sub-network. The sovereign CDS network is only slightly less concentrated than the financial CDS network (the share of top-10 traders being respectively 72% and 74%). Regarding risk characteristics, “high spread” and “low beta” CDS sub-networks are more concentrated than “low spread” and “high beta” networks.

The share of active counterparties who are net sellers of CDS is between 0.13 and 0.20 depending on the sub-network. In aggregate, a large majority of the market participants are therefore net buyers of CDS, corroborating the fact that the credit risk is ultimately born by a small fraction of the institutions. The share of net sellers among market participants is higher for the non-European than for the European CDS network (0.20 versus 0.15) and for the “high spread” than for the “low spread” CDS network (0.18 versus 0.13), implying that the ultimate credit risk is potentially better spread among market participants when it is higher. Regarding the share of institutions being net sellers depending on their level of activity (presented in table 3), the pattern documented for the aggregated network is observed in all sub-networks, with one exception. Overall, the proportion of net sellers increases with the level of activity. In most instances, between 30% and 60% of the institutions among the 10 most active traders are net sellers, whereas this proportion falls between 11% and 18% among the less active traders. One notable exception to this general pattern relates to the sovereign CDS network. On this market, only one out of 10 of the most active traders is a net CDS seller, implying that the vast majority of the most active dealers are net buyers of CDS on sovereign reference entities. The ultimate credit risk on this market is mostly born by institutions that have a medium level of activity (42% of them being net sellers).

4.5. Network analysis for the sub-networks

Structural properties of the sub-networks are presented in table 4. Focusing first on the number of links in each sub-network – or, equivalently, on the density of each sub-network (i.e. on the share of actual over possible links) – it is noticeable that the density is low in all sub-networks, ranging between 0.002 and 0.004. The number of links lies between 1,359 for the “high spread” network and 3,848 for the “high volatility” network. Significant differences are observed when the networks are compared pairwise. Whereas the difference between the sovereign and financial sub-networks is small, the “high debt”, “high beta” and “high volatility” networks are significantly denser than the “low debt”, “low beta” and “low volatility” networks. Furthermore, the network of non-European reference entities is denser than the network for European reference entities (3,343 versus 2,663 links).

Overall, the sub-networks exhibit the “small-world properties” documented earlier for the aggregated CDS network. The diameter is low for all sub-networks (consistently being either 4 or 5), whereas their clustering coefficient lies between 0.07 and 0.16. Such values are comparable to what has been documented for some national interbank networks. Boss et al. (2004), for example, find a clustering coefficient of 0.12 for the Austrian interbank market.

Moreover, these values for the clustering coefficient are significantly higher than the network density – an essential feature of "small-world" networks. Even though variations in the clustering coefficient are relatively limited, the clustering coefficient is overall higher in networks with a lower density. Hence, key institutions, which are at the core of the network play a larger role in those reference entities where the density is lower. This feature essentially reflects the fact that, when the notional volume on a CDS reference entity grows, new market participants who are not in the core group of traders account for a larger share of the links.

Differences in mean degree and in maximum degree are mainly explained by the density of the respective network. Additional insights are provided by the degree distribution of each sub-network, some of which are plotted on figure 2. Each of these distributions is fitted by maximum likelihood estimation to a power law distribution. The estimated shape parameter α as well as the number of links x_{min} above which the degree distribution follows a power law are given in table 4. In addition, p-values for the Kolmogorov-Smirnov test are provided. The null hypothesis according to which the degree distribution is drawn from a power law is rejected only once (for the "low unsecured" network), whereas we fail to reject it in all other instances. All CDS sub-networks but one can therefore be considered "scale-free" and can thus be expected to display the stability properties discussed above.

4.6. Additional results for reference entity networks

The final step in our descriptive analysis focuses on the level of reference entity networks. For this perspective, we calculate the network measures for the 191 reference entities which are also the basis for the sub-network discussion of the previous section. We observe that there is significant correlation among our network metrics. Table 6 reports the correlation coefficients for the network measures. By construction, the highest correlations are observed for Density, Mean degree and Max. degree. In addition, the shape of the distribution also shows high correlations with the degree-based variables.

For both the type and the location groups, we perform a two-sample t test to investigate differences in means for the dependent variables. Results are presented in table 7 for the sovereign/financial distinction and in table 8 for the European/non-European distinction. Differences in means between sovereign and financial reference entities are highly significant for all variables. Sovereign CDS networks have on average a larger size, are characterized by a more intense activity and their concentration is significantly lower. By contrast, the distinction between European and non-European reference entities is significant only when it comes to concentration (measured both by the Herfindahl index and by the share of top-10 traders) and to the share of daily traded volume (at a 10% significance level). Noticeably, non-European CDS networks are more concentrated than European CDS networks. No differences in group means are observed when the size of the network or the share of number of daily trades are considered.

4.7. Summary

In sum, we find that the CDS network displays properties of a scale free structure with a small-world characteristic. A key stylized fact is the existence of considerable heterogeneity in the structures of networks on the level of reference entities. In particular, entities categorised as “high debt”, “high beta” or “high volatility” have denser, more active and bigger networks. In contrast, the average number of counterparties per trader is remarkably stable across networks. In the next section, we analyse this heterogeneity in network structures in more detail by means of regression analysis.

5. Determinants of network structure: Methodology

Whereas the “small world” properties of a large number of real-world networks, including most financial networks, are well-documented in the literature, the determinants of the structure of financial networks have never been investigated empirically. This section describes our econometric strategy and discusses the hypotheses.

5.1. Dependent variables

Our dependent variables are designed to represent structural properties of the CDS network. There are two reasons why we do not choose the pure network metrics discussed in the previous section as dependent variables. First, most of them are highly correlated, as already discussed in the context of table 6. Second, most of these measures have no straightforward economic interpretation. We define instead three broad categories of network characteristics we aim to explain, related to the *size*, to the *activity* and to the *concentration* on particular markets.

5.1.1. Size characteristics

An important characteristic of the trading on a given reference entity is its overall size. Its size can be first measured in relative terms, i.e. by comparing it with the size of the aggregated CDS market. Second, it can be captured by reference entity-specific metrics.

Share of the net notional to the total market net notional

For each reference entity, the aggregate net notional amount of CDS sold is computed. The relative importance of a reference entity on the market is computed as the share of the net notional exposure over the total net market notional exposure.

Share of traders/ links involved

We analyse how many traders are active in a given reference entity as well as the share of links. The share of nodes (i.e. of traders) for a given reference entity is equal to the number of market participants actually active (both on the buy and on the sell side) over the total number of participants in the CDS market as a whole.

Density of the network

The density of the reference entity network is the ratio of the number of actual links over the total number of possible links in the network.

5.1.2. Activity characteristics

Given a particular size, CDS markets for individual reference entities may differ with respect to their activity. Namely, given a certain density and a certain number of market participants, CDS may be more or less actively traded, and the notional amounts traded on a daily basis may differ across entities. These activity factors are captured through two variables.

Average share of trades per day

Public data on the average number of trades per day for each reference entity is retrieved from the DTCC's website. The average is computed over the period starting in September 2011 and ending in December 2011. For each reference entity, we then compute the average share of trades per day, relative to the total number of trades per day.

Average share of gross daily notional

From the same public dataset, we retrieve information about the average daily gross notional amount traded for each reference entity. For each reference entity, we compute the average share of gross daily notional over the total daily notional, where the total is computed over all reference entities in the sample.

5.1.3. Concentration characteristics

Finally, given the size and the activity of a CDS contract, the exposures in this network may be more or less concentrated. Concentration is captured through two variables.

Herfindahl index

We use the Herfindahl index, a traditional measure of concentration in industrial organization or competition economics. As the simple Herfindahl index ranges between $1/n$ and 1 (where n is the number of firms), we normalise it to a range between 0 and 1. It is computed as:

$$H = \frac{\sum_{i=1}^{n} s_i^2 - 1/n}{1 - 1/n},$$

where s_i is the market share of trader i on the gross sell side of the market.

Share of the top-10

For each reference entity, we compute the share of the top-10 traders in the aggregate gross notional sold. The main difference between the share of top-10 traders and the Herfindahl index is that the latter takes the whole distribution of market shares into account, whereas the former focuses on key traders only, disregarding the overall number of market participants and their distribution.

5.2. Specification of the regression

All our dependent variables are constructed as proportions, i.e. they take on values between 0 and 1. A methodology to estimate regressions with such fractional response variables as dependent variables has been proposed by Papke and Wooldridge (1996). It uses the generalized linear model (GLM) developed by Nelder and Wedderburn (1972) and McCullagh and Nelder (1989).

In a GLM model, the dependent variable Y is assumed to be generated from a distribution from the exponential family, whose mean μ depends on the independent variables X through:

$$E(Y) = \mu = g^{-1}(X\beta)$$

, where β is a vector of unknown parameters and g the so-called link function. The variance of Y is then typically a function of the mean:

$$Var(Y) = Var(\mu) = Var\left(g^{-1}(X\beta)\right)$$

In order to model proportions, a usual specification is to assume that the dependent variable can be modelled by a binomial distribution, in combination with a logit link function. We therefore have:

$$E(Y) = \frac{1}{1 + e^{-X\beta}}$$

The vector of parameters β is estimated by maximum likelihood.

5.3. Expected signs of the explanatory variables

Our econometric specification aims at explaining (i) the relative impact of various reference entity characteristics on the corresponding CDS network structure and at examining (ii) whether the membership to sub-groups significantly impacts the CDS network structure. A variety of characteristics likely to influence the CDS network structure for particular reference entities have been described earlier and will now be used as our independent variables. In this sub-section, we apply results from theoretical research on the motives for CDS use to discuss the role of each explanatory variable and its expected impact on size, activity and concentration variables.

Three key applications of CDS contracts have so far been analysed in the literature. CDS' first purpose is to hedge credit exposures. Duffee and Zhou (2001), for example, show how CDS may be used to meet the hedging demand of banks or investors. Second, Zawadowski (2013) provides theoretical underpinnings for the use of CDS as tools to hedge counterparty risk. In this approach, financial institutions hedge the counterparty risk arising e.g. from derivatives positions with other financial institutions or sovereigns. Third, CDS may be used for outright trading rather than hedging purposes. Two examples of this practice are insider trading of CDS (Acharya and Johnson, 2007) or trading CDS vs. the underlying bonds (Fontana and Scheicher, 2010). Our set of explanatory variables is designed to capture the use of CDS for all three purposes. Expected signs are summarized in table 9.

As the primary purpose of CDS is to hedge credit exposures, the size and activity of CDS markets is likely to be influenced by the underlying debt characteristics. *Ceteris paribus*, size and activity variables are expected to be positively related to the volume of underlying debt, as the exposure to be potentially hedged is larger. In contrast, the expected relation between the average maturity of the underlying debt and the size and activity on the CDS market is not straightforward. Everything else being kept equal, the probability that a reference entity defaults increases with the maturity of its debt. However, heavy reliance on short-term debt increases the roll-over risk which, in times of funding strains, may significantly increase the probability of default of an entity. The empirical motivation for this hypothesis is the inverted term structure of credit spreads for the high-yield category (see e.g. Lando and Mortensen, 2005). Depending on which effect dominates, one may expect either a positive or a negative impact of the average debt maturity on the CDS network size. We expect activity on the CDS market to be negatively related to the average debt maturity, as CDS positions need to be adjusted more frequently if the nature of the underlying debt exposure changes more frequently. The last characteristic of the CDS' underlying debt is its level of collateralization. If a large share of the debt is secured, then the need for using CDS is reduced, as the creditor is already (partially or totally) hedged through the assets pledged as collateral. Therefore the size and activity variables are expected to be positively linked to the percentage of unsecured debt. Moreover, the magnitude of the coefficient is expected to be greater if CDS are used for hedging purposes, rather than for trading purposes, to a larger extent.

Turning to the CDS risk characteristics, one might expect a positive relation between CDS spreads and the network size and activity if CDS are mainly used for hedging purposes. Indeed, the need for a portfolio manager to hedge riskier credit exposures is therefore, *ceteris paribus*, higher. The volatility of the CDS spread is likely to matter both for traders engaged in hedging and for those engaged in trading activities. On the one hand, for traders using CDS for hedging purposes, high volatility signals potentially large changes in the underlying reference entity's perceived creditworthiness. Thus, the incentive to hedge more volatile exposures is *ceteris paribus* higher. On the other hand, market participants who use CDS for active trading could only expect small profits if the spread remains constant over time. A more volatile CDS spread therefore potentially generates higher trading profits. In a combination of those two factors, we expect a positive effect of CDS spread volatility on size and activity variables. Regarding the coefficient on the beta of CDS spreads, the existing literature does not offer clear guidance on the expected sign.

The sectoral type (sovereign vs. financial) of a reference entity is likely to matter for the CDS network structure because sovereign CDS can be used for "macro hedging" purposes whereas financial CDS typically are only used for a reference-entity specific purpose. Macro hedging occurs when a CDS on a reference entity i is bought to hedge an exposure on a credit exposure for which there is no CDS. An example is the credit exposure to public railway companies for which no CDS exist but whose creditworthiness is highly correlated with the domestic sovereign. If macro hedging is implemented using sovereign CDS only, then we may expect a positive impact of the sovereign dummy on the size variables.

Finally, one reason why the European/non-European distinction may matter is because our dataset dates back to the height of the European sovereign debt crisis (a few weeks before the Greek credit event, which was declared in March 2012). Therefore the structure of the CDS market for European reference entity is possibly affected by a higher riskiness overall, or by the potential for more important creditworthiness spillovers from one reference entity to the other (as documented, for example, by Ejsing and Lemke, 2011).

Theoretical determinants of concentration on financial markets have so far not received a lot of attention in the literature, even though models for the emergence of highly concentrated scale-free networks have been developed (see references earlier). Hence, our analysis of the determinants of concentration is mainly of an exploratory nature. We would expect that concentration is negatively related to a CDS activity. Smaller traders are indeed likely to enter more easily a CDS contract where activity is denser, i.e. where there is a larger choice of counterparties, where transaction costs are potentially lower and where novation is easier. Furthermore, concentration is likely to be related to the risk characteristics of the CDS contract. For example, activity is likely to be better shared, therefore concentration to be lower, for CDS with high spread or high volatility, as the risk-bearing capacity of the net sellers is necessarily limited.

6. Determinants of network structure: Results

This section presents our results. It begins with a statistical description of differences in group means for the dependent variables. It then presents our baseline results and exposes group differences in both intercepts and effects. Finally, it focuses more on explaining the concentration of CDS markets.

6.1. Baseline results

Our baseline regression is estimated on the restricted sample of reference entities (i.e. 191 reference entities) and does not include either dummy variables (by type or location) or interaction dummies, which are introduced later on.

Denote Y_i a particular network characteristic to be explained for reference entity i. We estimate:

$$Y_i = g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i) + \varepsilon_i$$

This equation is estimated for Y_i being successively $Density_i$, $Share\ nodes_i$, $Share\ net_i$, $Share\ trades_i$, $Share\ notional_i$, $Herfindhal_i$ and $Share\ top10_i$. Results are presented in table 10. Variables related to risk characteristics and to the properties of the underlying debt are highly significant. Regarding debt characteristics, there is a strongly positive impact of a reference entity's bond outstanding volume on the size and activity variables. More underlying bonds are therefore associated with a more extensive trading of credit risk, which tends to confirm the use of CDS for hedging credit risk. In addition, the larger the percentage of unsecured debt, the higher the size and the activity of the corresponding CDS market, which is consistent with theoretical explanations. Collateralizing debt exposures reduces the need to trade credit risk. Furthermore, the impact of debt maturity is either negative or insignificant. A potential explanation for the negative impact of debt maturity lies in the funding strains environment that both financial institutions and sovereign entities faced at the time our sample was collected. Whereas longer maturities are traditionally associated with higher probabilities of default, a heavy reliance on short-term debt that has to be rolled over may turn out to increase the probability of default of an entity in case of liquidity crisis. Shorter debt maturities may therefore be associated with larger CDS hedging needs, i.e. larger CDS market size. In addition, shorter underlying debt maturities may entail the need to adjust CDS position more frequently, therefore implying a higher activity on the CDS market.

Concerning the price variables, it is noticeable that the absolute level of the CDS spread is insignificant in most instances, whereas the volatility of the CDS spreads and the commonality in CDS returns (as measured by the beta coefficient) are positively highly significant for the size and activity dependent variables. What therefore matters mostly for the CDS network structure is not the perception of a higher credit risk *per se* (as measured by the CDS spread), but the change in the market perception of this credit risk, i.e. its volatility. Market participants seem to be willing to hedge against potential jumps in perceived creditworthiness. Finally, the strong importance of the CDS beta for size and activity characteristics signals that market participants are typically hedging reference entities bearing a high systematic risk as captured by the CDS beta.

Regarding the estimates for concentration, there is no clear pattern of explanation. Only the commonality in CDS returns (beta) has a significantly negative impact on both concentration variables, which is discussed below in more detail. In the remaining part of this section, concentration variables will be treated separately. Whereas no variables pertaining to a CDS' activity have been introduced on the right-hand side of the equations for size variables (as endogeneity would have been created), they are later introduced to explain concentration. In the next sub-section they are temporarily omitted.

6.2. Introducing interaction effects

Up to now, we did not introduce any dummy variables or dummy interactions for the reference entity type (sovereign vs. financial) or location. In this section, we add both dummy variables to test for the impact of CDS reference entity type on the intercept and interaction dummy variables to test for differences in effects, i.e. differences in slopes for all relevant explanatory variables. We focus first on the impact of the reference entity type and then on its location. In this section, we restrict our attention to size and activity dependent variables. A deeper study of the concentration variables is left for the next section.

6.2.1. Reference entity type: sovereign vs. financial

We test both the impact of a sovereign dummy on the intercept and on the effect of each of the variables. To do so, we estimate the two following regressions, where Y_i denotes all size and activity dependent variables:

$$Y_i = g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Sov) + \varepsilon_i$$

$$Y_i = g^{-1}\big(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Sov + \beta_8 \cdot Price_i \cdot Sov + \beta_9 \cdot Volatility_i \cdot Sov + \beta_{10} \cdot Beta_i \cdot Sov + \beta_{11} \cdot Bonds_i \cdot Sov + \beta_{12} \cdot Maturity_i \cdot Sov + \beta_{13} \cdot Unsecured_i \cdot Sov\big) + \varepsilon_i$$

Results are presented in table 11. Overall, they show both higher differences in average size and activity and significantly different marginal effects of the explanatory variables for sovereign reference entities. The effect of the CDS spread and of the CDS beta on the size variables is significantly higher for sovereigns, whereas the impact of the underlying bonds outstanding is significantly lower. One possible explanation for this result lies in the use of CDS for “macro hedging”. If sovereign CDS are used not only to hedge direct bond holdings but also a larger set of credit claims within a country, then the relationship between the volume of bonds outstanding and the CDS market size may be looser for sovereign CDS, while risk-related variables (for example, the credit risk of firms within a country) still remain highly relevant.

6.2.2. Reference entity location: European vs. non-European

We test both the impact of a sovereign dummy on the intercept and on the effects of each of the variables. To do so, we estimate the two following regressions, where Y_i denotes all size and activity dependent variables:

$$Y_i = g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Eu) + \varepsilon_i$$

$$Y_i = g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Eu + \beta_8 \cdot Price_i \cdot Eu + \beta_9 \cdot Volatility_i \cdot Eu + \beta_{10} \cdot Beta_i \cdot Eu + \beta_{11} \cdot Bonds_i \cdot Eu + \beta_{12} \cdot Maturity_i \cdot Eu + \beta_{13} \cdot Unsecured_i \cdot Eu) + \varepsilon_i$$

Results are presented in table 12. It is noticeable that no significant differences in constants between European and non-European reference entities are observed, implying that, *ceteris paribus*, being a European reference entity does not affect the size and activity properties of a CDS network. Moreover, no differences are to be observed between European and non-European reference entities for the effect of the risk-related variables. On the contrary, there are locational differences in effects for the variables related to the characteristics of the underlying debt. In particular, the effect of the debt size is significantly higher for European reference entities.

Overall, for the structural properties of the CDS network the European/non-European distinction seems much less relevant than the sovereign/financial distinction.

6.3. Concentration of the market

We estimate the following equation, where two explanatory variables pertaining to activity have been added ($Activity_i$ being successively $Share\ trades_i$ and $Share\ notional_i$). Those variables could not be introduced in the two previous sections to explain the size dependent variables, as they would have been potentially endogenous regressors (a network's size is likely to affect its trading activity).

$$Y_i = g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Activity_i) + \varepsilon_i$$

Baseline results on concentration are presented in table 13. It is noticeable that the two newly-introduced variables have a significantly negative effect on concentration, implying that a higher activity on the market leads to reduced concentration. This implies that credit risk can better be shared among traders when particular CDS markets are important in size and activity. This result also conveys a view on the development of particular CDS markets. As long as trading on a given CDS contract remains small, most of the trades are concentrated between a few major dealers and a handful of less active end-users.

We find that some risk characteristics significantly affect the concentration in the network. The level of the CDS spread has a significantly positive impact on the concentration, implying that fewer traders are willing to sell credit risk protection when the absolute riskiness of the underlying credit exposure is higher. In addition, the CDS beta has a significantly negative impact on the concentration (measured both by the Herfindahl index and by the share of the top-10 traders), showing that the number of traders willing to bear systematic risk is lower. In contrast, no coefficients on the volatility are significant.

We then focus on type and locational differences in concentration. Results are presented on tables 14 and 15 respectively. No differences in intercept are observed between sovereign and financial reference entities. Regarding differences in effects, it is noticeable that the effect of the CDS spread level on concentration is lower for sovereign than for financial reference entities. Moreover, when concentration is measured as the share of top-10 traders, the effect of the activity explanatory variables is significantly reduced.

Locational differences in intercept and effect are limited. First, when concentration is measured with the Herfindahl index, differences in intercept are significant and European references entities appear less concentrated. Moreover, the impact of activity variables (especially $Share\ notional_i$) is higher for European than for non-European reference entities, disregarding the concentration metrics on which one focuses.

In sum, we find that activity as well as some risk characteristics are significant drivers of the concentration in the network at the reference entity level. For instance, trading on reference entities with a higher beta is less concentrated.

7. Conclusions

This paper describes the network structure of the aggregated CDS market. Our focus is on the determinants of network properties such as the size, activity and concentration of CDS networks on the level of reference entities. We find that the aggregated CDS network resembles the interbank market in several aspects. Its density is low and it exhibits "small world" properties. Such features signal that the interconnectedness in the CDS market does not exist because of the large number of bilateral links between any two counterparties, but because virtually any trader in linked to or close to one of the key core institutions (dubbed "14 families" by the Federal Reserve Bank of New York[14]). In addition, we document a scale-free degree distribution for the CDS network, implying both a high concentration of the links among a few traders, and a high vulnerability in case one of these key traders fails.

On the level of individual reference entities we observe considerable heterogeneity in the size, activity and concentration of the network structures. Regarding the determinants of the CDS network properties, we document a significant impact of the variables related to the underlying debt characteristics and to the risk-characteristics of each CDS. Our findings are consistent with theoretical results in the literature on the use of CDS by financial institutions. First, a higher pool of underlying bonds outstanding, together with a higher proportion of unsecured funding, increases both the size and the activity on the CDS market. Second, higher debt maturity, decreases both the CDS network size and activity, indicating that roll-over risk by underlying reference entities is an important concern for CDS traders. Third, regarding the risk characteristics, we find that CDS volatility and beta have a larger influence on the size and activity than the absolute level of the CDS spread. Traders are more numerous and more active on reference entities, whose perceived changes in creditworthiness can be larger and whose systematic component is higher. Fourth, concentration, is largely explained by variables pertaining to a CDS' activity, and is negatively related with its beta. Therefore, fewer traders are willing to bear a large share of systematic risk when it is relatively higher. Fifth, concerning differences due to CDS reference type, we document significant differences in intercepts and in effects due to type differences (sovereign vs. financial reference entities). On the contrary, locational differences only influence the effects of the debt-related variables, not of the risk-related explanatory variables. European reference entities resemble non-European reference entities in that respect.

[14] See Federal Reserve Bank of New York, OTC Derivatives Supervisors Group, http://www.newyorkfed.org/markets/otc_derivatives_supervisors_group.html.

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Appendix. Tables and figures.

	Bonds outstanding	Average maturity	Unsecured debt (%)	CDS price	CDS volatility	CDS beta
Min.	0	0.46	0	42.6	0.4	0.28
25 pctile.	2748	4.35	79.8	161.1	0.9	0.79
Median	14317	6.19	99.4	254.4	0.11	1.03
75 pctile.	83692	8.75	100	367.1	0.12	1.21
Max.	890330	57.4	100	5924.5	0.219	1.54

Table 1. Descriptive statistics for the explanatory variables. Bonds outstanding are expressed in million euros. Average debt maturities are expressed in years. CDS prices are expressed in basis points.

Statistics	Aggregated network	Sovereign	Financial	EU	Non-EU	Spread <300	Spread >300	High debt	Low debt	High maturity	Low maturity	High unsecured	Low unsecured	High beta	Low beta	High volatility	Low volatility
Number of reference entities	642	40	602	200	442	118	75	97	96	96	95	96	95	97	96	97	96
Number of counterparties	946	687	722	705	795	818	672	850	504	784	749	814	670	834	599	851	582
Gross notional (Bn EUR)	4 280	1 810	2474	1953	2332	2188	1699	2958	929	2274	1601	2082	1793	2973	915	2969	918
Net notional (Bn EUR)	349	162	187	168	181	195	111	248	58	185	121	185	1199	228	78	234	71
Net over gross notional ratio	8.20%	9.00%	7.60%	8.60%	7.80%	8.90%	6.50%	8.40%	6.30%	8.10%	7.60%	8.90%	6.70%	7.70%	8.50%	7.90%	7.80%
Number of bilateral observations	115 283	25647	89636	49162	66121	54062	37973	59099	32936	50059	41414	43643	47830	60503	31532	60164	31871
Number of transactions	592 083	156278	435805	234555	357528	297908	223111	338478	182541	296737	221793	245079	273451	363595	157424	365280	155739
Average transaction notional (Mn EUR)	7.2	11.6	5.7	8.3	6.5	7.3	7.6	8.7	5.1	7.7	7.2	8.5	6.6	8.2	5.8	8.1	5.9
Average number of counterparties per trader	9.6	7.9	9.5	8.5	8.7	8.7	8.8	9.1	8.2	8.9	8.5	8.3	9.2	9.1	8.1	9.2	8.6
Average number of reference entities traded	18.7	5.6	19.2	10.6	12.9	9.4	7.8	10.1	8.7	9	7.7	7.7	9.8	10.3	7.3	10	7.6
Average number of transactions per reference entity per bilateral link	10.3	12.2	9.7	9.5	10.8	11	11.8	11.5	11.1	11.9	10.7	11.2	11.4	12	10	12.1	9.8
Share of top-10 traders	0.73	0.72	0.74	0.72	0.73	0.71	0.76	0.72	0.76	0.73	0.73	0.74	0.72	0.72	0.77	0.72	0.75
Share of net sellers	0.18	0.16	0.18	0.15	0.20	0.13	0.18	0.17	0.19	0.18	0.17	0.19	0.20	0.18	0.17	0.19	0.19

Table 2. Descriptive statistics, aggregated CDS network.

	Aggregated network	Sovereign	Financial	EU	Non-EU	Spread <300	Spread >300	High debt	Low debt
Top-10 traders	0.5	0.1	0.5	0.4	0.4	0.3	0.3	0.3	0.4
10-50 traders	0.4	0.42	0.37	0.4	0.42	0.4	0.32	0.4	0.4
50-end traders	0.17	0.14	0.16	0.12	0.18	0.15	0.11	0.16	0.16

		High maturity	Low maturity	High unsecured	Low unsecured	High beta	Low beta	High volatility	Low volatility
Top-10 traders		0.3	0.6	0.5	0.6	0.5	0.5	0.4	0.5
10-50 traders		0.42	0.45	0.47	0.37	0.42	0.3	0.45	0.35
50-end traders		0.16	0.15	0.16	0.17	0.16	0.15	0.17	0.17

Table 3. Percentage of CDS net sellers by percentiles. The definition of the three groups (or "percentiles") is based on the total gross notional bought and sold by each counterparty within the sub-network.

	Aggregated	Sovereign	Financial	EU	Non-EU	Spread <300	Spread >300	High debt	Low debt	High maturity	Low maturity	High unsecured	Low unsecured	High beta	Low beta	High volatility	Low volatility
Number of edges	4428	2951	3395	2663	3343	2105	1359	3816	2014	3421	3118	3318	3016	3723	2362	3848	2323
Mean degree	9.4	6.2	7.2	5.6	7.1	4.5	2.9	8.1	4.3	7.2	6.6	7	6.4	7.9	5	8.1	4.9
Max. degree	470	336	367	312	371	265	165	415	236	393	343	390	340	410	277	420	264
Density	0.005	0.003	0.004	0.003	0.004	0.002	0.002	0.004	0.002	0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.003
Clustering coefficient	0.07	0.09	0.08	0.09	0.09	0.1	0.16	0.08	0.12	0.08	0.09	0.08	0.1	0.08	0.1	0.07	0.11
Diameter	5	5	4	5	5	5	5	4	4	4	4	5	4	4	5	5	4

Table 4. Network statistics for the unweighted aggregated network and the sub-networks.

	Aggregate	Sovereign	Financial	EU	Non EU	CDS >300	CDS <300	High debt	Low debt
xmin	4	3	2	4	2	2	3	2	3
alpha	1.66	1.63	1.5	1.77	1.51	1.68	1.75	1.51	1.75
p value	0***	0.001***	0***	0***	0.005***	0.01**	0.007***	0.004***	0.012**

		High maturity	Low maturity	High unsecured	Low unsecured	High beta	Low beta	High volatility	Low volatility
xmin		2	4	3	4	3	4	4	2
alpha		1.56	1.61	1.7	1.71	1.76	1.75	1.65	1.51
p value		0.02**	0***	0.009***	0.107	0.001***	0.002***	0.005***	0***

Table 5. Power law distribution of the degree distributions. "xmin" is the value of the degree above which the degree distribution is fitted to a power law. "alpha" is the shape parameter of this power law. "p value" is the probability that the degree distribution is not drawn from the fitted power law distribution (i.e. rejection of the null hypothesis by the Kolmogorov-Smirnov test). *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Density	Mean degree	Max. degree	Clustering	Diameter	Power law shape
Density	1					
Mean degree	1	1				
Max. degree	0.96	0.96	1			
Clustering	-0.75	-0.75	-0.82	1		
Diameter	0.06	0.06	0.1	-0.27	1	
Power law shape	-0.96	-0.96	0.92	0.77	0.14	1

Table 6. Correlation coefficients for the network metrics. Pearson correlation is used.

	Density	Share nodes	Share net	Share trades	Share notional	Herfindahl	Share top 10
Sovereign	0.0005	0.108	0.013	0.013	0.017	0.075	0.536
	(0.000)	(0.01)	(0.002)	(0.003)	(0.000)	(0.002)	(0.01)
Financial	0.0003	0.063	0.003	0.004	0.003	0.082	0.587
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)
All	0.0004	0.071	0.005	0.005	0.0005	0.08	0.578
	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.0009)	(0.005)
Diff. (Fin. - Sov.)	-0.0002	-0.045	-0.01	-0.009	-0.014	0.007	0.051
Pr(Diff=0)	0	0	0	0	0	0.002	0.0001
Pr(Diff≠0)	1***	1***	1***	1***	1***	0.998***	0.9999***

Table 7. Two-sample t test, Sovereign vs. Financial CDS. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Density	Share nodes	Share net	Share trades	Share notional	Herfindahl	Share top 10
Non-European	0.0004	0.066	0.004	0.005	0.004	0.083	0.585
	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)
European	0.0004	0.076	0.005	0.006	0.007	0.077	0.568
	(0.000)	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)	(0.008)
All	0.0004	0.071	0.005	0.005	0.005	0.008	0.578
	(0.000)	0.003	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
Diff. (Non-EU. - EU.)	0	-0.01	-0.001	-0.001	-0.003	0.006	0.017
Pr(Diff=0)	0.45	0.1	0.18	0.29	0.07	0.0005	0.1
Pr(Diff≠0)	0.55	0.9	0.82	0.71	0.93*	0.9995***	0.9*

Table 8. Two-sample t test, European vs. Non-European CDS. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Size	Activity	Concentration
Bonds outstanding	+	+	-
Maturity	~	~	~
Unsecured debt	+	+	-
CDS price	+	+	-
Volatility	+	+	-
Beta	~	~	~
Sovereign	+	+	-
European	+	+	-

Table 9. Expected signs. A “+” and a “-“ denote respectively an expected positive and negative sign. A “~” denotes the absence of theoretical prior regarding the expected sign of the regression coefficient.

	Density	Share of active traders	Share of net notional	Share of number of trades	Share of traded volume	Herfindahl index	Share top 10
CDS price	0.433	0.376	-0.279	2.626**	2.069	0.354**	-0.199
	(0.75)	(0.55)	(-0.25)	(2.17)	(1.45)	(2.10)	(-0.57)
CDS volatility	2.886*	3.613*	9.333***	7.401**	11.02***	-0.958	-1.473
	(1.75)	(1.82)	(2.72)	(1.99)	(2.61)	(-1.19)	(-1.25)
CDS beta	1.026***	1.266***	2.006***	2.404***	2.784***	-0.231***	-0.634***
	(7.57)	(7.58)	(5.56)	(6.95)	(6.40)	(-3.25)	(-6.42)
Bonds outstanding	0.0713***	0.142***	0.269***	0.248***	0.295***	-0.00541	-0.0380***
	(3.36)	(4.07)	(4.66)	(4.93)	(4.28)	(-1.34)	(-4.70)
Average debt maturity	-0.00537	-0.0100**	-0.0183*	-0.0161	-0.0237*	0.00138	0.00278
	(-1.37)	(-2.05)	(-1.68)	(-1.41)	(-1.80)	(1.15)	(0.98)
Unsecured debt (%)	0.376***	0.426***	1.899***	1.448***	2.509***	-0.0670	-0.174***
	(3.03)	(2.94)	(4.36)	(2.66)	(3.32)	(-1.57)	(-2.58)
Constant	-9.540***	-4.635***	-10.29***	-10.09***	-11.90***	-2.074***	1.251***
	(-63.67)	(-24.94)	(-17.15)	(-14.69)	(-11.99)	(-43.70)	(15.12)
Observations	191	191	191	190	190	191	191

Table 10. Baseline regression results. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Density	Density	Share of active traders	Share of active traders	Share of net notional	Share of net notional	Share of number of trades	Share of number of trades
CDS price	0.453	0.681	0.422	0.997*	-0.278	0.807	2.789**	3.480***
	(0.79)	(1.32)	(0.62)	(1.65)	(-0.26)	(0.87)	(2.13)	(2.68)
CDS volatility	2.643	3.407**	3.037	3.200*	6.306*	6.071**	4.347	4.803
	(1.58)	(2.29)	(1.54)	(1.94)	(1.88)	(2.23)	(1.04)	(1.17)
CDS beta	1.005***	0.599***	1.217***	0.676***	1.760***	0.878***	2.274***	1.373***
	(7.38)	(4.15)	(7.54)	(4.44)	(5.14)	(2.79)	(6.61)	(4.30)
Bonds outstanding	0.0574***	3.41***	0.113***	4.69***	0.183***	6.81***	0.173***	5.90***
	(2.74)	(7.11)	(3.59)	(9.05)	(3.60)	(6.57)	(4.02)	(7.06)
Average debt maturity	-0.00409	0.00226	-0.00693	0.00162	-0.00109	0.0108	-0.00142	0.0124
	(-1.03)	(0.52)	(-1.45)	(0.34)	(-0.12)	(1.44)	(-0.14)	(1.14)
Unsecured debt (%)	0.310**	0.415***	0.267**	0.418***	0.757**	0.910***	0.548	0.587
	(2.48)	(3.39)	(1.96)	(3.50)	(2.39)	(3.39)	(1.19)	(1.38)
Sov.	0.114	-3.074*	0.261**	-7.996***	0.993***	-15.51***	0.849***	-11.17*
	(1.31)	(-1.79)	(2.30)	(-3.74)	(4.67)	(-2.80)	(4.15)	(-1.81)
Sov. * CDS price		6.637***		5.395**		2.905		6.772
		(3.25)		(2.05)		(0.53)		(1.11)
Sov. * CDS volatility		-22.19**		-14.92		-8.025		-14.23
		(-2.53)		(-1.57)		(-0.40)		(-0.86)
Sov. * CDS beta		1.794***		1.460**		1.098		1.987
		(2.79)		(2.03)		(0.73)		(1.44)
Sov. * Bonds outstanding		-3.35***		-4.58***		-6.64***		-5.71***
		(-6.96)		(-8.82)		(-6.40)		(-6.83)
Sov. * Debt maturity		0.0339**		0.0661***		0.0999**		0.0642
		(2.27)		(3.48)		(2.10)		(1.26)
Sov. * Unsecured		3.592**		8.138***		16.05***		11.27*
		(1.98)		(3.71)		(2.87)		(1.81)
Constant	-9.464***	-9.439***	-4.455***	-4.355***	-9.054***	-8.726***	-9.135***	-8.702***
	(-59.99)	(-60.12)	(-24.61)	(-27.78)	(-19.75)	(-29.65)	(-16.76)	(-18.73)
Observations	191	191	191	191	191	191	190	190

Table 11. Type differences in intercepts and in effects. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Density	Density	Share of active traders	Share of active traders	Share of net notional	Share of net notional	Share of number of trades	Share of number of trades
CDS price	0.438	0.566	0.421	1.088	-0.219	0.476	2.725**	3.843***
	(0.76)	(1.03)	(0.61)	(1.63)	(-0.19)	(0.43)	(2.23)	(3.24)
CDS volatility	2.949*	3.078	4.193**	2.123	10.83***	4.352	8.508**	2.590
	(1.76)	(1.59)	(1.99)	(0.81)	(2.68)	(1.05)	(1.97)	(0.51)
CDS beta	1.017***	0.867***	1.186***	1.240***	1.766***	1.995***	2.242***	2.301***
	(7.00)	(4.91)	(6.66)	(5.53)	(4.24)	(3.97)	(5.84)	(4.97)
Bonds outstanding	0.0714***	0.0440***	0.144***	0.103***	0.279***	0.220***	0.254***	0.181***
	(3.39)	(4.74)	(4.30)	(10.12)	(4.92)	(7.64)	(5.05)	(9.92)
Average debt maturity	-0.00529	-0.00940*	-0.00932*	-0.0139**	-0.0163	-0.0256*	-0.0147	-0.0142
	(-1.36)	(-1.91)	(-1.94)	(-2.29)	(-1.50)	(-1.76)	(-1.32)	(-0.94)
Unsecured debt (%)	0.383***	0.642***	0.488***	0.823***	2.078***	1.621***	1.555***	1.833**
	(2.96)	(2.86)	(3.11)	(3.14)	(4.49)	(2.68)	(2.67)	(2.19)
EU.	0.0120	0.0461	0.110	0.512	0.341	0.564	0.210	0.567
	(0.20)	(0.14)	(1.35)	(1.34)	(1.53)	(0.73)	(1.00)	(0.48)
EU. * CDS price		1.219		-1.065		-3.547		-1.802
		(1.08)		(-0.69)		(-0.87)		(-0.54)
EU. * CDS volatility		-0.407		3.067		6.304		9.640
		(-0.12)		(0.78)		(0.86)		(1.20)
EU. * CDS beta		0.251		-0.250		-0.779		-0.342
		(0.88)		(-0.73)		(-1.02)		(-0.43)
EU. * Bonds outstanding		0.386***		0.765***		1.38***		1.31***
		(5.00)		(5.15)		(9.76)		(6.37)
EU. * Debt maturity		0.0148**		0.0148*		0.0236		0.00620
		(2.19)		(1.78)		(1.38)		(0.33)
EU. * Unsecured		-0.564**		-0.814***		-0.787		-1.768*
		(-2.09)		(-2.69)		(-1.13)		(-1.83)
Constant	-9.550***	-9.611***	-4.727***	-4.833***	-10.54***	-9.495***	-10.25***	-9.872***
	(-61.41)	(-33.13)	(-23.14)	(-13.78)	(-16.34)	(-13.79)	(-13.49)	(-9.29)
Observations	191	191	191	191	191	191	190	190

Table 12. Location differences in intercepts and in effects. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Herfindahl	Herfindahl	Share top 10	Share top 10
CDS price	0.426**	0.373**	-0.0169	-0.169
	(2.57)	(2.29)	(-0.06)	(-0.54)
CDS volatility	-0.858	-0.892	-0.980	-1.130
	(-1.10)	(-1.13)	(-0.89)	(-0.99)
CDS beta	-0.196***	-0.206***	-0.544***	-0.582***
	(-2.76)	(-2.91)	(-5.45)	(-5.84)
Bonds outstanding	0.00248	0.00183	-0.0134	-0.0190***
	(0.81)	(0.79)	(-1.59)	(-3.35)
Average debt maturity	0.00109	0.00113	0.00215	0.00237
	(0.89)	(0.94)	(0.81)	(0.87)
Unsecured debt (%)	-0.0531	-0.0546	-0.135**	-0.145**
	(-1.25)	(-1.28)	(-2.13)	(-2.20)
Share of number of trades	-3.614***		-9.927***	
	(-2.63)		(-2.92)	
Share of traded volume		-2.316***		-5.337***
		(-2.72)		(-2.66)
Constant	-2.114***	-2.104***	1.118***	1.161***
	(-42.66)	(-42.94)	(12.87)	(13.58)
Observations	190	190	190	190

Table 13. Concentration – Baseline regression. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Herfindahl	Herfindahl	Herfindahl	Herfindahl	Share top 10	Share top 10	Share top 10	Share top 10
CDS price	0.368**	0.416**	0.418**	0.403**	-0.169	-0.0129	0.309	0.452
	(2.26)	(2.51)	(2.54)	(2.10)	(-0.54)	(-0.04)	(1.30)	(1.60)
CDS volatility	-0.870	-0.836	-0.943	-0.970	-1.130	-0.989	-0.885	-0.812
	(-1.11)	(-1.07)	(-1.22)	(-1.24)	(-0.99)	(-0.90)	(-0.93)	(-0.83)
CDS beta	-0.205***	-0.195***	-0.104	-0.117	-0.582***	-0.544***	-0.364***	-0.397***
	(-2.89)	(-2.75)	(-1.46)	(-1.61)	(-5.84)	(-5.45)	(-3.56)	(-3.88)
Bonds outstanding	0.00369	0.00454	-0.722***	-0.852***	-0.0191***	-0.0143	-0.150	-0.433
	(0.99)	(1.09)	(-2.60)	(-3.16)	(-2.98)	(-1.61)	(-0.41)	(-1.23)
Average debt maturity	0.000981	0.000937	0.000182	-0.0000238	0.00238	0.00222	0.00202	0.00136
	(0.80)	(0.76)	(0.15)	(-0.02)	(0.86)	(0.83)	(0.82)	(0.52)
Unsecured debt (%)	-0.0484	-0.0466	-0.0689	-0.0785*	-0.145**	-0.138**	-0.107*	-0.129**
	(-1.11)	(-1.07)	(-1.59)	(-1.78)	(-2.16)	(-2.13)	(-1.89)	(-2.22)
Share of traded notional	-2.028**		-9.788		-5.345**		-42.97***	
	(-2.30)		(-1.56)		(-2.40)		(-4.27)	
Share of number of trades		-3.267**		-5.002		-10.07***		-30.66***
		(-2.35)		(-0.95)		(-2.78)		(-3.90)
Sov.	-0.0211	-0.0215	-0.216	-0.199	0.000586	0.00922	0.901	0.728
	(-0.66)	(-0.70)	(-0.26)	(-0.24)	(0.01)	(0.22)	(0.85)	(0.70)
Sov. * CDS price			-1.611*	-1.564*			-3.446***	-3.286***
			(-1.91)	(-1.77)			(-3.31)	(-3.07)
Sov. * CDS volatility			0.724***	0.854***			0.133	0.418
			(2.61)	(3.17)			(0.36)	(1.19)
Sov. * CDS beta			5.182	5.089			9.255*	8.650*
			(1.47)	(1.44)			(1.72)	(1.65)
Sov. * Bonds outstanding			-0.379	-0.363			-0.626	-0.525
			(-1.39)	(-1.30)			(-1.63)	(-1.39)
Sov. * Debt maturity			-0.00933	-0.00943			-0.0104	-0.00933
			(-1.30)	(-1.33)			(-1.62)	(-1.55)
Sov. * Unsecured			0.0422	0.0235			-1.325	-1.185
			(0.05)	(0.03)			(-1.12)	(-1.03)
Sov. * Share traded notional			8.648				39.65***	
			(1.37)				(3.91)	
Sov. * Share trades				3.662				25.24***
				(0.68)				(3.11)
Constant	-2.110***	-2.120***	-2.131***	-2.109***	1.162***	1.120***	0.985***	1.028***
	(-42.20)	(-41.85)	(-37.65)	(-36.13)	(13.71)	(13.06)	(11.08)	(11.61)
Observations	190	190	190	190	190	190	190	190

Table 14. Concentration – Difference in reference entity type. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

	Herfindahl	Herfindahl	Herfindahl	Herfindahl	Share top 10	Share top 10	Share top 10	Share top 10
CDS price	0.329**	0.377**	0.468***	0.554***	-0.190	-0.0430	-0.0803	0.201
	(2.03)	(2.31)	(3.03)	(3.36)	(-0.60)	(-0.14)	(-0.35)	(0.87)
CDS volatility	-1.296	-1.262	-1.776*	-1.706*	-1.337	-1.206	-1.574	-1.331
	(-1.58)	(-1.55)	(-1.87)	(-1.78)	(-1.16)	(-1.09)	(-1.46)	(-1.28)
CDS beta	-0.161**	-0.148**	0.00659	0.00951	-0.559***	-0.517***	-0.353***	-0.316***
	(-2.27)	(-2.09)	(0.08)	(0.11)	(-5.58)	(-5.13)	(-3.25)	(-3.03)
Bonds outstanding	-0.000424	0.00107	0.0104**	0.00777*	-0.0202***	-0.0142*	-0.000146	-0.00151
	(-0.16)	(0.34)	(2.56)	(1.68)	(-3.53)	(-1.67)	(-0.01)	(-0.12)
Average debt maturity	0.000669	0.000597	0.00132	0.00133	0.00215	0.00189	0.00301	0.00285
	(0.60)	(0.52)	(1.01)	(0.96)	(0.79)	(0.72)	(1.05)	(1.03)
Unsecured debt (%)	-0.0976**	-0.0956**	-0.139*	-0.142**	-0.168**	-0.160**	-0.267**	-0.259**
	(-2.16)	(-2.15)	(-1.94)	(-2.00)	(-2.35)	(-2.34)	(-2.30)	(-2.34)
Share of traded notional	-1.775*		-7.975***		-5.058**		-18.45***	
	(-1.84)		(-3.55)		(-2.48)		(-3.43)	
Share of number of trades		-3.241**		-8.066**		-9.697***		-22.13***
		(-2.07)		(-2.52)		(-2.78)		(-5.23)
EU.	-0.0751***	-0.0768***	0.0845	0.0770	-0.0384	-0.0429	0.0875	0.104
	(-3.54)	(-3.73)	(0.78)	(0.71)	(-1.22)	(-1.42)	(0.44)	(0.54)
EU. * CDS price			-0.668	-0.704			-0.494	-0.645
			(-1.25)	(-1.28)			(-0.69)	(-0.90)
EU. * CDS volatility			0.0204	0.0505			0.0313	0.0989
			(0.61)	(1.21)			(0.27)	(0.75)
EU. * CDS beta			0.717	0.694			-0.288	-0.422
			(0.40)	(0.39)			(-0.11)	(-0.17)
EU. * Bonds outstanding			-0.301**	-0.294**			-0.287	-0.292
			(-2.05)	(-2.01)			(-1.37)	(-1.42)
EU. * Debt maturity			-0.00323	-0.00332			-0.00480	-0.00481
			(-1.05)	(-1.07)			(-0.89)	(-0.90)
EU. * Unsecured			0.0953	0.0989			0.209	0.199
			(1.05)	(1.10)			(1.41)	(1.41)
EU. * Share traded notional			6.893***				14.77**	
			(2.93)				(2.47)	
EU. * Share trades				5.259				13.77**
				(1.49)				(2.25)
Constant	-2.033***	-2.045***	-2.096***	-2.100***	1.198***	1.157***	1.151***	1.103***
	(-35.36)	(-35.67)	(-23.60)	(-23.60)	(12.96)	(12.60)	(7.36)	(7.43)
Observations	190	190	190	190	190	190	190	190

Table 15. Concentration – Differences in reference entity location. *, ** and *** respectively indicate that we fail to reject the null hypothesis at a 10%, 5% and 1% significance level.

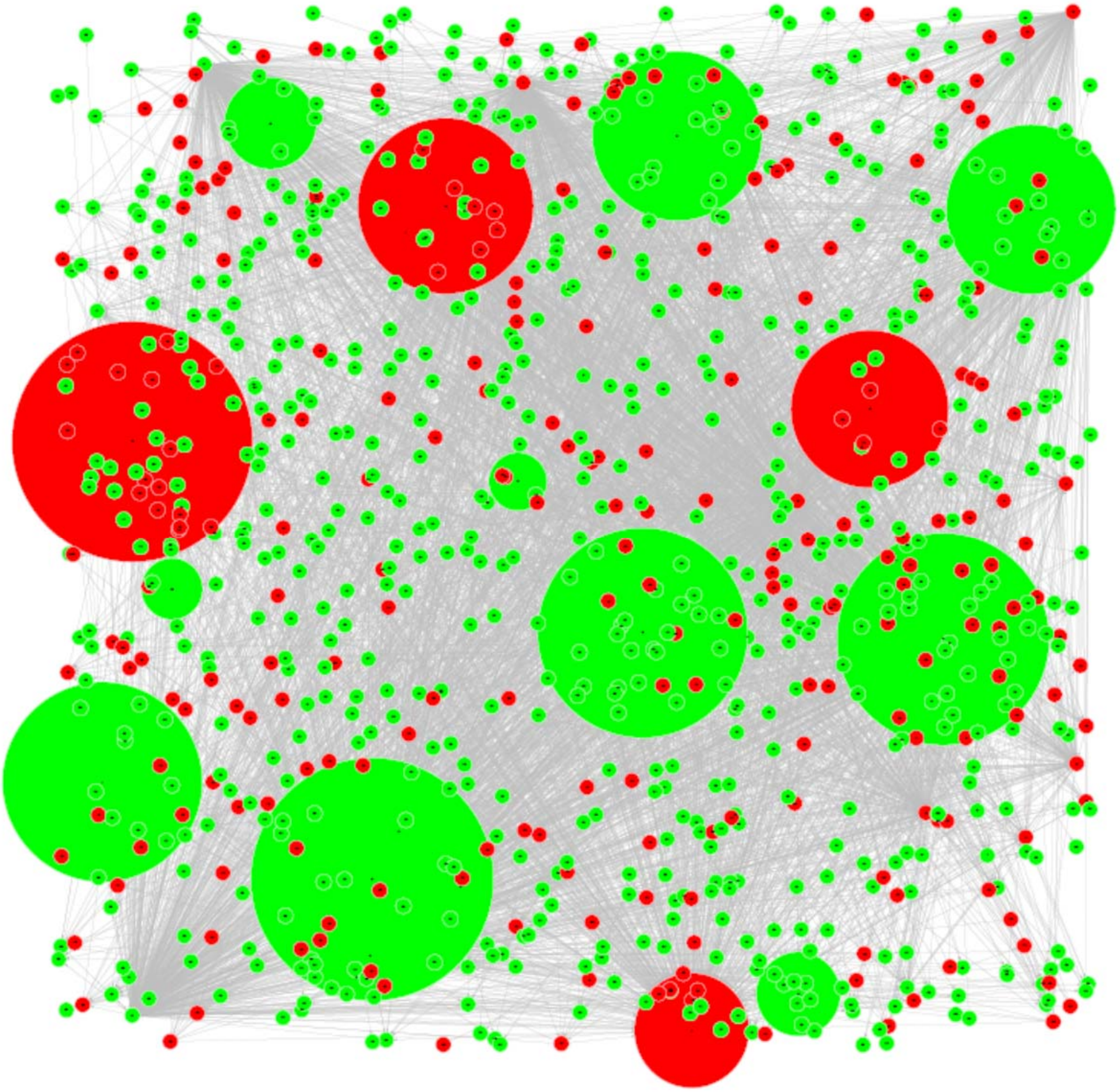

Figure 1. The aggregated CDS network. Red nodes are net sellers of CDS. Green nodes are net buyers of CDS. The size of each node is proportional to its gross activity on the CDS market.

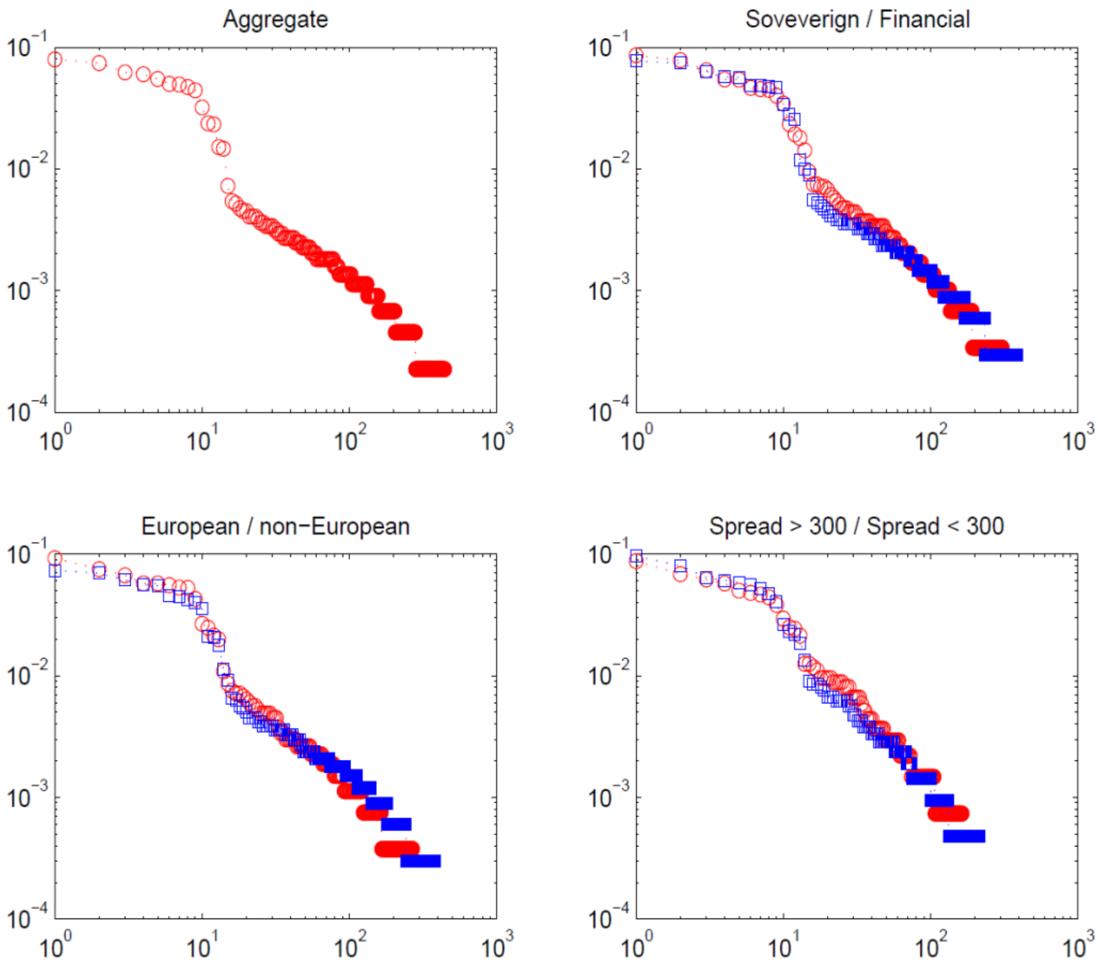

Figure 2. Degree distributions. On the top right side, the blue distribution refers to the sovereign and the red distribution to the financial CDS network. On the bottom left, the blue distribution refers to the European and the red distribution to the non-European CDS network. On the bottom right, the blue distribution refers to the "high spread" and the red distribution to the "low spread" CDS network.