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A Network Analysis of the Evolution of the German Interbank Market

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Abstract

In this paper, we report a descriptive investigation of the structural evolution of two of the most important over-the-counter markets for liquidity in Germany: the interbank market for credit and for derivatives. We use end-of-quarter data from the German large credit register between 2002 and 2012 and characterize the underlying networks. Surprisingly, the data show little or no impact of the 2008 crisis on the structure of credit market. The derivative market however exhibits a peak of concentration in the run up to the crisis. Globally, both markets exhibit high stability for most of the networks metrics and high correlation amongst them.

Keywords: financial networks, interbank market, credit default swaps, liquidity
JEL classification: G2, G21, D85

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1 Introduction

Over-the-counter (OTC) markets are particularly difficult to study empirically because of their opacity. One possibility to study their structure is to use supervisory data. In this descriptive paper we use data on individual exposures between all German banks available at Deutsche Bundesbank. We use quarterly data from the German large credit register from 2002 to 2012 to study the joint structure of two of the most important OTC markets in Germany: the market for interbank liquidity and the market for credit default swaps (CDS). In both markets, banks engage in OTC transactions with other banks in order to manage their liquidity positions. While the German interbank market has been studied in isolation and for shorter time periods before, this paper is the first to analyze the network structure of the German CDS network. To the best of our knowledge, this paper is the first that studies the *joint structural evolution* of two OTC markets simultaneously.

Studying the network structure of OTC markets is important for a number of reasons. First, there is growing consensus around the idea that financial inter-linkages play an important role in the emergence of financial instabilities and that the mathematical formulation of systemic risk can greatly benefit from a network approach (see, for example, Haldane (2009)). Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000) are among the first to study contagion in financial networks. A large and growing number of recent papers study contagion via interbank markets. See, for example, Stiglitz (2008), Gai and Kapadia (2010), Beale, Rand, Battey, Croxson, May, and Nowak (2011), Haldane and May (2011), Cont, Moussa, and Santos (2011), Gai, Haldane, and Kapadia (2011), Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2012), Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2012), Georg (2013), Roukny, Bersini, Pirotte, Caldarelli, and Battiston (2013), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013), Elliott, Golub, and Jackson (2014).

Second, the network structure of OTC markets can be used to identify prevalent market mechanisms. Because OTC markets are opaque, they are potentially characterized by asymmetric information. Heider, Hoerova, and Holthausen (2009) stress the importance of asymmetric information in the interbank market as a possible cause for a market freeze, i.e. a substantial reduction in interbank lending activity. Other authors stress the importance of liquidity hoarding as a potential mechanism for a market freeze (see, for example Acharya and Skeie (2011), Gale and Yorulmazer (2013), Acharya, Gale, and Yorulmazer (2011)). If a market freeze is caused by precautionary liquidity hoarding, the decision which bank is being cut-off lending should be independent of the borrower characteristics.

If a market freeze is caused by counterparty risk, lenders are sensitive to borrower characteristics. Glode and Opp (2013) explain the existence of intermediation chains in OTC markets with the fact that asymmetric information can be overcome if spread along a set of less asymmetrically informed intermediaries. One important prediction of their paper is that the average length of intermediation chains is longer with increased asymmetric information. We provide a test for this hypothesis. However, we find that the average length of intermediation chains is only little affected by the amount of asymmetric information in the market (as proxied by the LIBOR-OIS spread). This result holds both for the interbank as well as for the derivative network. While our result should be taken as indicative only, this finding shows the relevance of our structural analysis of the German interbank and CDS network.

Third, a new literature analyzes welfare impacts of OTC networks. Gofman (2013) introduces a bargaining friction in sparse OTC networks and studies the inefficiencies arising from it. Neklyudov (2013) studies competition amongst dealers in an OTC network and shows that more efficient central dealers provide intermediation services to peripheral dealers. Bargaining in stationary networks is analyzed in Manea (2011) who shows that the fraction an agent in a network of buyers/sellers can capture from gains from trade are determined by network structure. The relationship between network efficiency and connectivity is addressed in Galeotti and Condorelli (2012) who point out the existence of two types of inefficiencies: either networks in equilibrium underconnected when compared to efficient networks, or multiple equilibria exist and agents may fail to coordinate on the efficient equilibrium network.

Fourth, the network structure of OTC markets is an important subject of analysis in dynamic models of network formation. Cohen-Cole, Patacchini, and Zenou (2012) develop a model of banking behaviour with endogenous (interbank) network formation and, using data from the e-MID electronic exchange, show that their model can be matched with empirical data on the degree distribution (diversification) of banks on the interbank market. van der Leij, in 't Veld, and Hommes (2013) show that the existence of a core-periphery structure - which is typically found in interbank markets (see, for example, Craig and Von Peter (2010)) can only be explained if agents are heterogenous.

And fifth, a set of models analyzes a bank's incentive to gain systemical importance by becoming increasingly interconnected e.g. on the interbank market. Acharya (2009) models the endogenous choice of banks asset correlations. When bank resolution mechanisms focus on the insolvency of individual banks, banks endogenously correlate their assets more than is socially optimal. A network perspective is taken by Leitner (2005) who shows that financial linkages not only spread contagion, but that the threat of contagion also induces private sector bailouts by connected banks. Eisert and Eufinger (2013) develop a model of the interbank market where banks increase their interconnectedness by engaging in cyclical lending. This effectively increases their systemic importance and the probability of a bailout. Cyclical lending thus provides uninsured creditors with a mechanism to benefit from an implicit bailout guarantee.

One of the most studied type of financial network is arguably the interbank market where banks are nodes and links between them represent loans or payments. While some analysis focus on macroscopic measures (Boss, Elsinger, Summer, and Thurner, 2004; Soramäki, Bech, Arnold, Glass, and Beyeler, 2007; Iori, De Masi, Precup, Gabbi, and Caldarelli, 2008; Cajueiro and Tabak, 2008; De Masi, Fujiwara, Gallegati, Greenwald, and Stiglitz, 2009; Cont et al., 2011), others put the emphasis on micro- and mesoscopic levels Craig and Von Peter (2010), Fricke and Lux (2012), van Lelyveld (2012). The former approach reports high heterogeneity in the number of counterparties and flows that different banks can have in the same market. The latter approach provides evidence of core-periphery structures where banks in the core act as intermediaries while banks in the periphery only interact with these core banks and not with each other. While interbank networks have been extensively analyzed, CDS networks are much less studied (Markose, Giansante, Gatkowski, and Shaghaghi (2012), and Peltonen, Scheicher, and Vuillemey (2013) are notable exceptions).

Our paper contributes to this literature not only by providing a complete account of the evolution of the German interbank market, but also by combining it with an analysis of the network of CDS contracts. This enables us to study the correlation of the two network structures over a long period of time. Furthermore and in contrast to most of the literature, our networks take the amounts of contracts and (when possible) directions into account.

We report a number of interesting findings about the structural evolution of the German credit and derivative market. The data, however, shows surprisingly little variation over time. Neither the financial crisis of 2007/2008, nor the eurocrisis, or the business cycle have a substantial and visible effect on the credit market. The market for derivative becomes more concentrated and more important in terms of aggregated volumes in the run-up to the crisis, but remains structurally (as measured by degree distributions and higher order moments of the network) fairly constant. The structure rather evolves slowly over time which indicates that the interbank network structure is not as volatile as one might think.

We also analyze the evolution of structural roles in terms of network centralities and the correlation between banking activities. On the one hand, correlation between lending and borrowing activities both in terms of number of counterparties and of volumes are remarkably high and stable over time for the credit market while correlation in the derivative deteriorates with the increase of volume concentration. On the other hand, correlation between banking activities and structural roles in both markets (i.e., the correlation between a bank's properties in the credit and the derivative market) is remarkably high for most of the variables except the clustering coefficient.

The paper is organized as follows. After this introduction we describe the dataset and the methods in Section 2. In Section 3 we report the results obtained and in Section 4 we discuss the results.

2 Methods

2.1 Data

We use data present at the Deutsche Bundesbank containing banking exposures reports. By German law, all domestic banks have to report all bilateral liability exposures each quarter if related the exposure was larger then 1.5 kEUR at any point during the quarter. We have such information for the period spanning from January 2002 to August 2012, which results in 43 time periods.

From this dataset, we extract only bank-related exposures, that is, we exclude all kinds of other information with regards to banks reporting exposures to other types of firms. We then map the lending and borrowing activity of each bank by combining the identifiers that reported when they lend to or borrow from other banks in the dataset. We also take care of multiple reporting of bank holding corporation through several legal entities by aggregating all the information at the holding corporation level. Note that, we also take bank mergers into account but, contrary to other works, not in a backward fashion: if two banks merge during a given quarter Q_t, all information will be aggregated under the acquirer bank for each further quarter $Q_{t'>t}$ but not for the quarters prior to Q_t, $Q_{t^p<t}$. This enables us to have a clearcut view of the market evolution over time, period by period. Also, forcing the aggregation allows to deal with potential legal effects

which, in some cases, still force some acquired banks to still report independently for some periods.

The term exposure here stands both for credit relationship and derivative contracts. The reported credit relationship contains the lender identifier and the borrower identifier, the notional value of the credit. The derivative contracts represent securities taken by a bank from another depending on a credit relationship between the former bank and a third bank and the value of the underlying credit is reported. Such contracts can be of several forms (e.g., Credit Default Swap, Total Return Swap, Credit Linked Note). Due to the complex nature of some of the contracts and the related reporting requirements, it is difficult to have a clear view on the exposure dependencies. We will therefore not consider directionality for the case of derivative contracts (see next Section).

Finally, the data used in this paper is highly confidential. As a result, constrains exist on the granularity level of the disclosed results. More precisely, individual information on banks cannot be disclosed. Therefore, the results presented are aggregated either at the system level or at the percentile level and ensure that each result is the aggregation of ten banks at least. Distributions are thus proxied via the use of information of a series of percentiles (see next Section).

2.2 Network Analysis

A network is a set of nodes that are connected to each other via links. When the network is said to be *directed* and *weighted*, the links have a direction (from one node to another) and an associated value. In our context, the network consists of banks that are connected whenever an exposure is reported in the data. We distinguish between two kinds of exposures: *credit exposure* and *derivative exposure*. In the credit exposure case, the network is directed: a link goes from the lender to the borrower. Hence, a bank having at least one outgoing (resp. incoming) link in a given period is considered lender (resp.borrower) in that period. Obviously, a bank can act as a borrower and lender in the same period. The weight of a link corresponds to the total amount of money currently being lent by the lender to the borrower.In the derivative case, the directionality is more subtle as it depends on the type of contract (see previous Section). In the following, we thus consider undirected networks when we analyze the derivative market.

Density. We compute the density d of the network as the the ratio between the number of realized loans and the number of all possible loans as defined in the following formula:

$$d = \frac{\sum_i \sum_j \delta_{ij}}{(n(n-1))}$$

where $\delta_{ij} = 1$ if there is an existing loans between the bank i and the bank j and $\delta_{ij} = 0$ otherwise. The parameter n is the total number of banks in the network. For example, a complete network (i.e. where all banks are connected to each other) has a density of 1 while a star network (i.e. where one bank is connected to all the others) has a density of $\frac{1}{(n-1)}$.

Degree. In a network, the degree k_i of a bank i is the number of counterparties that the bank has. When the network is directed, we distinguish between two sides. The in-degree, k_i^{in}, is the number of banks that have a loan to the bank i. It corresponds to the number of lenders of bank i and, hence, is a measure of the bank's liability side diversification. Correspondingly, the out-degree, k_i^{out}, is the number of banks that receive a loan from the bank i. It corresponds to the number of borrowers of bank i and, hence, it is a measure of the bank's asset side diversification.

Formally, the degree can be defined as follows in the directed case:

$$k_i = k_i^{out} + k_i^{in}$$

Where $k_i^{out} = \sum_j \delta_{ij}$ and $k_i^{in} = \sum_j \delta_{ji}$. In the undirected case, k_i^{out} and k_i^{in} are equal and k_i takes the same value. The average degree $\overline{k}$ is the average number of connections that banks have in the network irrespective of the direction:

$$\overline{k} = \frac{\sum_i k_i}{n}$$

Average Shortest Path Length. In a network, a path is a set of links that allow two banks to reach each other. The number of links (i.e., loans) needed to define a path corresponds to the length of this path which can be seen as the length of intermediation chain between two banks. The shortest path length, d_{ij}, between two banks i and j is thus the minimal amount of intermediary connections needed to go from one bank to the other. The average shortest path length of a network is the average minimal number of links that are needed to connect 2 banks in the network:

$$l = \frac{\sum_i \sum_{j \neq i} d_{ij}}{n(n-1)}$$

In our study, we consider two types of networks. The credit network transfers liquidity amongst counterparties. A path in the credit network is a set of loans that transfer liquidity from one bank to another. Derivative contracts also provide liquidity exchange between two counterparties. In contrast to the credit network, however, derivative contracts provide liquidity conditional on an underlying event.

Diameter. The diameter is the maximum length of all shortest paths in the network. Hence, it is the number of links present in the longest intermediation chain present in the network. Note that the diameter must be computed on a *connected* network, that is, a network in which, for every pair of banks, there exists a least one path connecting the two banks. In fact, if ever two banks cannot not reach each other, the diameter of the corresponding network is infinite.

Volume. The volume v_i is the aggregated value of all the loans associated with a node. In economic terms, it amounts to the size of a bank interbank assets and liabilities. When the network is directed, we distinguish between the volume of interbank assets, v_i^{out}, and the volume of interbank liabilities v_i^{in}. Similar to the degree, we formally define the total volume of a bank in a directed network as follows :

$$v_i = v_i^{out} + v_i^{in}$$

where $v_i^{out} = \sum_j w_{ij}$ and $v_i^{in} = \sum_j w_{ji}$. In the undirected case, v_i^{out} and v_i^{in} are equal and v_i takes the same value. Where w_{ij} is the value of the loan from i to j.

Herfindhal Hirschman Index (HHI). The HHI index is a measure of market concentration. We use this measure to compute the level of concentration in terms of both degree and volume, that is, we analyze how concentrated the system is in terms of share of connections and of share of money involvement. The formula is expressed as:

$$HHI_x = s_{1_x}^2 + s_{2_x}^2 + s_{3_x}^2 + ... + s_{n_x}^2$$

where s_{i_x} is the share of the i-th firm. The index x indicates if the analysis is on the degree share ($x = k$) or on the volume share ($x = v$). The higher the HHI value, the more concentration there is in the system.

Clustering coefficient. The clustering coefficient measures the probability for a bank to have counterparties that are also connected to each other. Here, we do not account for directionality nor weights. Furthermore, this measure can be seen as a proxy for the size of counterparty risk externality (e.g., Acharya and Bisin (2013)) which exists whenever two related banks share a common third counterparty. Another way to define the clustering coefficient of a bank is to compute the number of triangles that can be formed within the set of the bank's counterparties and the bank itself:

$$C_i = \frac{\sum_{j \neq i} \sum_{h \neq (i,j)} \delta_{ij} \delta_{ih} \delta_{jh}}{k_i(k_i - 1)}$$

where $\delta_{ij}\delta_{ih}\delta_{jh} = 1$ whenever there exists a triangle linking banks i, j and h. The average clustering coefficient $\overline{C}$ is the average value of this coefficient for each bank in the network:

$$\overline{C} = \frac{\sum_i C_i}{n}$$

Betweenness.The betweenness is a network centrality measure allowing to partially characterize the structural role of a bank in the market. The betweenness of a bank i computes the number of shortest paths in the network that pass through the bank i. Banks with higher betweenness belong to a larger amount of chains of intermediation.

$$b_i = \sum_j \sum_{h \neq j} \frac{s_{jh}(i)}{s_{jh}}$$

where $s_{jh}(i)$ is the number of shortest paths between the bank j and h in which the bank i is found and s_{jh} is the total number of shortest paths between the bank j and h. The average betweenness $\overline{b}$ is the average value related to each bank in the network

$$\overline{b} = \frac{\sum_i b_i}{n}$$

Closeness.The closeness is another centrality measure allowing to compute the average shortest distance (in terms of links) to all the other banks in the network. Let l_i be the average shortest path length from i to all the other banks in the network:

$$l_i = \frac{\sum_j d_{ij}}{n - 1}$$

Where d_{ij} is the length of the shortest path between i and j. The closeness of i is then defined as the inverse of the former value:

$$cl_i = \frac{1}{l_i} = \frac{n-1}{\sum_j d_{ij}}$$

The average closeness $\overline{cl}$ is the average value related to each node in the network

$$\overline{cl} = \frac{\sum_i cl_i}{n}$$

Eigenvector The eigenvector centrality is computed from the adjacency matrix A in which $a_{ij} = 1$ if the banks i and j are connected and $a_{ij} = 0$ otherwise. The eigenvector centrality is the vector e satisfying the following relationship :

$$\lambda e = Ae$$

where λ is the largest eigenvalue. The eigenvector centrality of a bank i is thus defined by:

$$e_i = \frac{1}{\lambda} \sum a_{ij} e_j$$

The resulting centrality vector thus takes into account the centrality of the neighbors to compute the centrality of each bank. This measure retrieves the level of centrality of a bank with respect to the number of its counterparties and the of number of counterparties its counterparties have, etc.

Percentiles.A percentile $i\%$ is a statistical measure retrieving the threshold beyond which i% of the population can be found. We use this measure to analyze the state and evolution degrees and volumes distributions among the banks in the network, i.e. to explore the cross-sectional dimension of our measures. In other words, through a set of 10 percentiles $(90\%, 80\%, ..., 10\%,\ 5\%$ and $1\%)$, we assess the heterogeneity of banking activities both in terms of lending/borrowing relationships (degree) and liquidity flows (volume). Contrary to the usual use, we use percentiles as values above which one can find the dedicated population. For example, if the percentile 10% of the degree distribution is 15, it means that in order to belong to the 10% of most connected banks, one has to have more than 15 counterparties. To compute it, it suffices to order values of the distribution and determine the value beyond which $i\%$ (or more) of the population is addressed.

Correlation In order to assess the existence of correlations between networks features, we compute the Pearson product-moment correlation coefficient, between 2 sets of results X and Y.

$$r = \frac{\sum_i^n((X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_i^n(X_i - \overline{X})^2}\sqrt{\sum_i^n(Y_i - \overline{Y})^2}}$$

This measure retrieves the level of linear correlation between the two sets of values with a certain inverval of confidence (p-value). Resulting values are between -1 and $+1$, where $+1$ (resp. -1) corresponds to a total positive (resp. negative) correlation. If the value is 0, then the two sets are not correlated.

Furthermore, this metric is used in two different contexts. On the one hand, we use it to analyse the degree of correlation between banks' features within a market (i.e. credit or derivative): (i) *In-Out degree* (i.e., The level of correlation between the in and out degree offers an information about the extent to which a bank having many lenders will also have many borrowers), (ii) *In-Out volume* (i.e., the extent to which a bank acting as a large creditor (in absolute amounts of money) is also likely to act as a large borrower) and (iii) *Degree-Volume* (i.e., The level of correlation between the degree of a bank and its volume is useful to assert wether largely connected banks tend to significantly be highly active in terms of flows of fund).

Additionally, we also use the Pearson correlation to compute the degree assortativity and link reciprocity in each network. The former is obtained by assessing for each link the correlation between the degrees of the nodes . This measure can be seen as the likelihood that large banks lend to large, and small banks lend to small banks. When it is negative, the network is said to be dissassortative: large banks tend to interact more with small banks. The former measures was introduced in Garlaschelli and Loffredo (2004) and assesses the tendency for the connected nodes in a directed graph to have links in the two directions (i.e., mutual connections):

$$\rho = \frac{\sum_{i \neq j}(a_{ij} - d)(a_{ji} - d)}{\sum_{i \neq j}(a_{ij} - d)^2}$$

where d is the density presented above.

On the other hand, we also compute correlations in order to assess how banks behave in the credit market given their activity in the derivative market. This is achieved by comparing the sets of relative values (i.e., divided by the maximum value in the given market) of (i) degree, (ii) volume, (iii) clustering coefficient, (iv) betweennes and (v) closeness for each bank in the derivative market and the corresponding values in the credit market.

Reciprocity Component Analysis. A directed network can be decomposed onto four different sets. The Largest Strongly Connected Component (LSCC) is the largest subset of the network in which for every pair of banks there exists a path connecting the

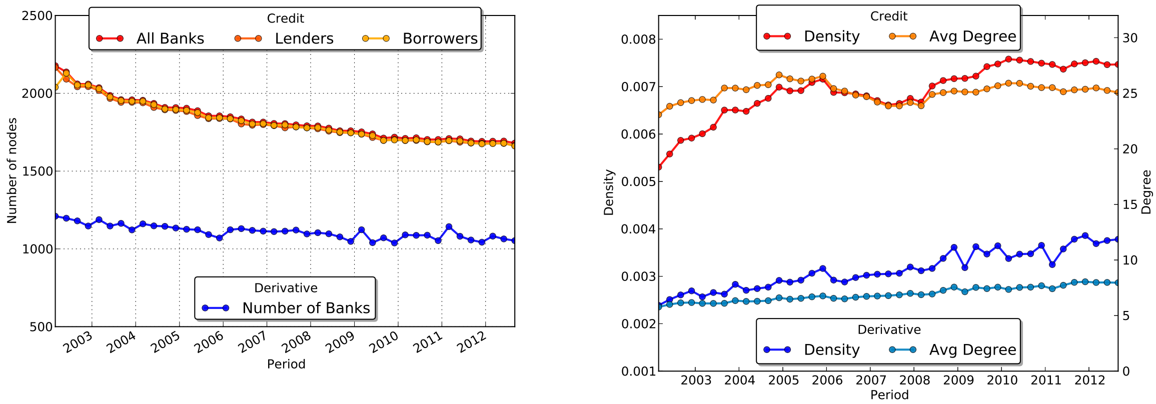

Figure 1: (Left) Evolution of the number of banks in the market from 2002 to 2012. The curves in tones of red show the evolution of the market of credit ties while the blue line shows the results of the market of derivatives. The former being directed, three values are reported: total number of banks, total number of banks acting at least once as lender and total number of banks acting as borrower. (Right) Evolution of the connectivity from 2002 to 2012. The density values are read on the left y-axis. The degree values are read on the right y-axis.

two bank: every bank can reach any other bank within the LSCC. The OUT component (OUT) is the set of banks not belonging to the LSCC but that can be reached from banks in the LSCC, directly or indirectly. The IN component (IN) is the set of banks not belonging to the LSCC but that can reach nodes in the LSCC, directly or indirectly. The Tubes and Tendrils are banks that do not belong to the LSCC and cannot either be reached by nor reach any bank from the LSCC.

3 Results

In this section we report the results of our empirical analyses. We start from the simplest measures, such as size and density of the network and proceed to more sophisticated measures like correlations. As much as possible we try to compare the results for the interbank credit network to the results for the derivative network.

3.1 Size and Density

As Figure 1 (left) shows, the number of banks in the credit network (red tones) decreases slowly but steadily over the years from about 2200 to about 1700. We can distinguish between banks lending to at least one other bank, i.e. with at least one outgoing link, $k_i^{out} > 0$, denoted as "lenders", and banks borrowing from at least one other bank, i.e. with at least one incoming link, $k_i^{in} > 0$, denoted as "borrowers". Their number is approximately the same as the total over time, meaning that all banks act at the same time as lenders and borrowers in at least one relation. Note, that the number of borrowers and lenders is not trivially equal, as we only require $k^{in/out} > 0$ for a bank to be a lender/borrower. The total in-degree (the number of incoming links in all nodes), however, is trivially equal to the total out-degree (number of outgoing links from all nodes) because of simple accounting. Later, we analyse the extent to which banks' activities are related in terms of lending and borrowing in more detail.

The same figure shows also how the number of banks in the derivative network (in blue) is remarkably stable over time. Notice, however, that this figure only provides the number of banks participating in the market even with just one contract and, hence, does not account neither for the density of the network nor the volumes involved.

Figure 1 (right) shows the average degree and the density both for the credit and the derivative networks. The average degree of the credit network increases over time from 23.075 to 25.08 (a +8.68% change). The average degree of the derivative network increases over time from 5.77 to 7.95 (a +37.85% change). The density of the credit network increases over the time span of the data by +49.85% while the one of the derivative network increases by +58.42%. This suggests that the relative amount of ties in both markets has significantly increased over time. Nevertheless, while the density increase of the credit network can be seen as a mere consequence of the continuous shrinking in the number of market participants, the increase of density in the derivative is important as the total size of that market remained rather stable over time. In any cases, density values remain at a low level (i.e., smaller than 0.008 for the credit market and smaller than 0.004 for the derivative market). Hence, those networks are very sparse.

When we move to analyse aggregate volumes and concentration, Figure 2 (left) shows that the volume of the contracts in the credit network contains several cycles providing 4 peaks: 2003Q3, 2005Q2, 2008Q2, 2010Q2. The highest peak (i.e., 2008Q2) accounts for an increase of more than 13% (i.e., an increase of $\approx$ 182 billion euros) with respect to the initial amount in 2002Q1. After the peak of 2010Q2, the market reaches levels similar to the initial values from 2002Q1. Interestingly, those peaks do not coincide with the business cycle. The biggest peak directly before the height of the crisis in 2008Q3 indicates substantially heightened market activity in the run-up to the Lehman insolvency.

In contrast, the volume of contracts in the derivative network has a much larger volatility, it peaks in 2008 and 2009 at more than two times the value it had in 2002, then in

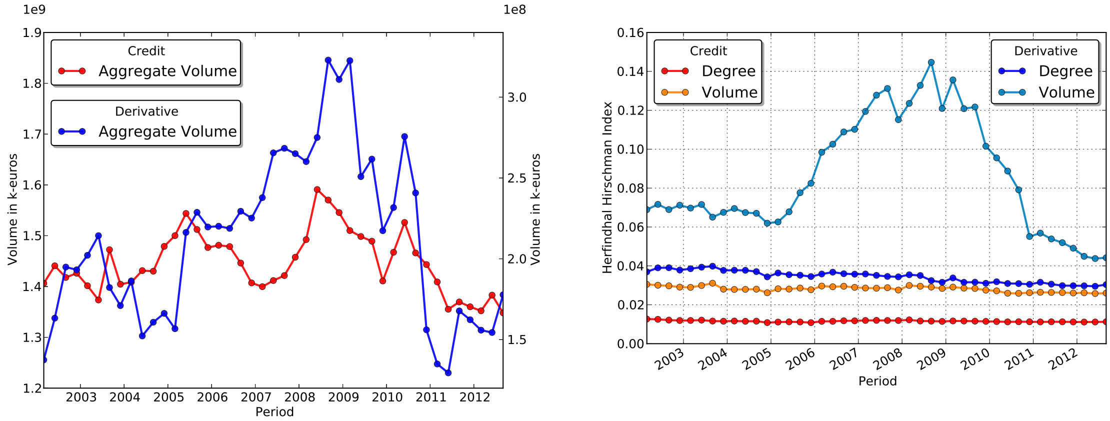

Figure 2: (Left) Evolution of the aggregate volume in the credit (red) and derivative (blue) interbank market from 2002 to 2012. Results for the credit market are reported on the left-axis. Results for the derivative market are reported on the righ-axis. (Right) Evolution of the HHI for degrees and volume in the system from 2002 to 2012 for the credit (red tones) and derivative (blue tones) interbank market.

2011 it bounces back at the values of 2002 to start increasing at the end of 2011. The highest peak of the CDS market is in 2008Q3, almost coincident with the highest peak in the credit market.

Complementary to the information on volumes is the measure of how much the volume and number of contracts are concentrated across banks in the market. To this end, we measure concentration by means of the Herfindhal index (HHI) of both the number of contracts (degree) and the volumes. Higher values of HHI in the degree imply that contracts are established with a smaller number of banks that act as hubs. Higher values of HHI in the volumes imply that a smaller number of banks handles a larger fraction of the contracts in terms of volumes. Figure 2 (right) shows that the concentration in the credit network of both degree and volume was stable or at most slightly decreasing. In the derivative network, however, concentration of volumes increase to more than double its initial values (i.e., a change of +109.9% between 2002Q1 and 2008Q3) and then drops again.

The inverse of the HHI gives a proxy of the number of leading actors in the market. Thus, the number of contracts for the credit market tends to be concentrated in a subset of a bit more than 80 leading banks (i.e., average: 86.45 ± 3.017) while, in the derivative market, this subset contains among 30 leading banks (i.e., average: 29.5 ± 2.68).

In terms of volume concentration, the credit market contains a subset of about 35 leading banks (i.e., average: 35.64 ± 1.845). For the case of the derivative market, it starts with approximately 14 banks in 2002Q1. At the highest point, the number of leading banks falls around 7 before reaching a bigger set of 22 banks by the end of 2012.

3.2 Clustering and Centrality

The clustering coefficient is a measure of the fraction of triangles present in the network out of all the possible triangles that could be formed. Triangles are considered here as undirected and thus can correspond to several configurations involving three banks. In general, the intuition is that the higher the clustering coefficient the higher chances that the counterparties of a given bank are also engaging in a contract together. The clustering coefficient is thus a measure of the counterparty risk externality introduced by Acharya and Bisin (2013). Betweenness measures the probability that a given bank is found on the shortest path of liquidity transfer between two other banks. Closeness gives a measure of proximity between all banks in the network by computing the average distance between a bank and all the other banks. Finally, the eigenvector centrality measures how important a bank is in terms of connectivity taking into account the importance of its neighbors in a recursive way.

As shown in Figure 3 (Top Left), we observe that the clustering coefficient of the credit network remains stable over time while the one of the derivative network increases steadily over time to levels that are twice as large as those in 2002. The initial value of the coefficient in 2002 is very high for the credit network, $c \approx 0.87$ (the coefficient has to be smaller than one by definition, see more details in Methods), meaning that the majority of the triangles are in fact present. In contrast, the initial value for the derivative network is much lower, $c \approx 0.17$.

The average betweenness centrality of banks increases over time for both networks (see Figure 3, Top Left). While the slope for the credit network is higher (i.e., 30% change in the whole time period) and steady, the derivative network is more volatile and increases less (i.e., a 10% change in the whole time period). This is in line with the increase in link density that we observed in Figure 1 but contrasts with the behaviour of the clustering coefficient for the credit network (Figure 3, Top Left). The absolute betweenness values for both networks are very small, especially in the credit case, which is in line with having a highly heterogenous structure. The derivative case is less pronounced but shares same characteristics as the credit case.

In contrast to the betweenness, the closeness centrality for both networks is remarkably stable over time and absolute values are high. This indicates an important proximity between banks in both markets. The fact that this proximity almost did not change over time is also interesting.

The average eigenvector centrality was small and very similar for both networks at the beginning of our timeframe. While the derivative network oscillate around the same value over time, the credit network' average eigenvector centrality continuously increased over time (increase of 64.9% between the first and the last quarter). On average, banks thus significantly increased their average connectivity importance in the credit market.

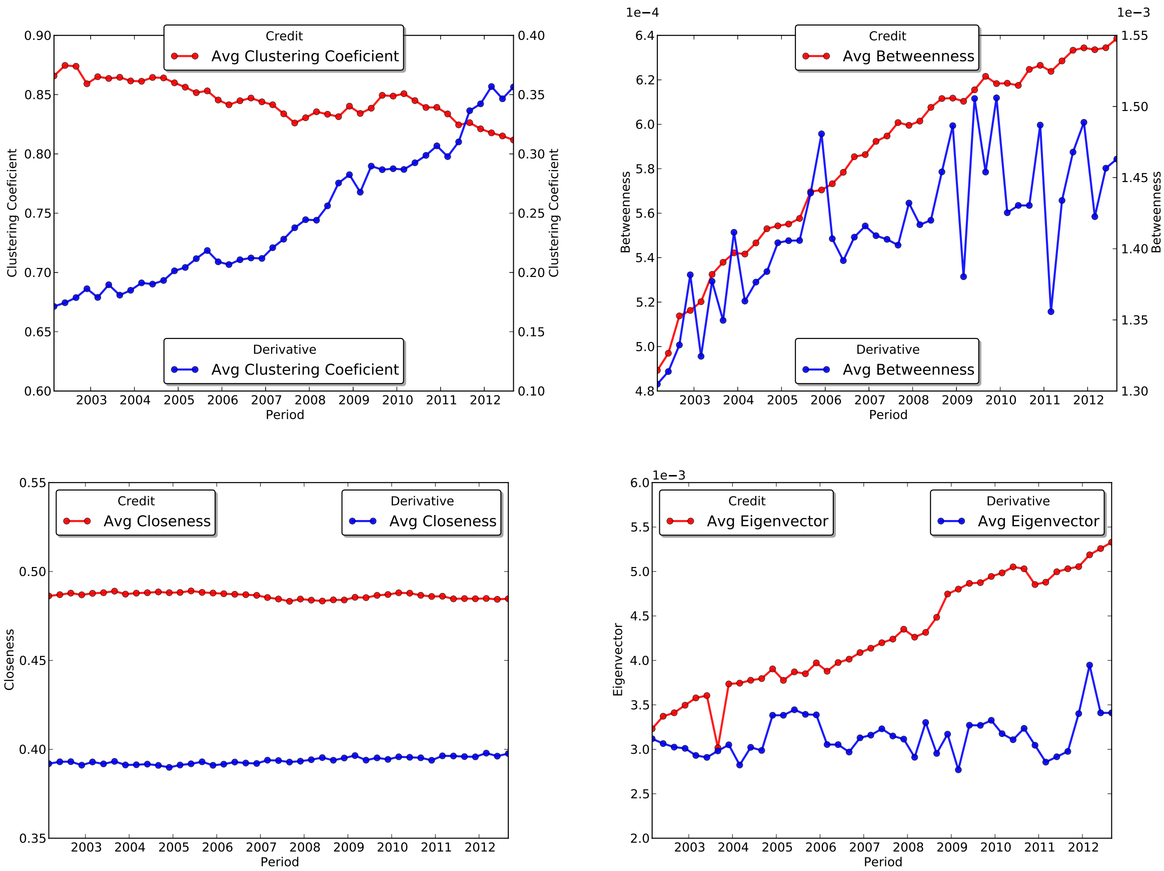

Figure 3: (Top Left) Evolution of the average clustering coefficient from 2002 to 2012. Values for the credit network are reported on the left axis while values for the derivative network are reported on the right axis. (Top Right) Evolution of the average betweenness centrality from 2002 to 2012. Values for the credit network are reported on the left axis while values for the derivative network are reported on the right axis. (Bottom Left) Evolution of the average closeness centrality from 2002 to 2012. (Bottom Right) Evolution of the average eigenvector centrality from 2002 to 2012.

3.3 Degree and Volume Distributions

Next, we report the distributions of the number of contracts (degree) across banks and the distributions of volumes of contracts across banks. The second quantity refers, for each bank, to the total value of all the contracts in which the bank is involved as lender or borrower. From the data, we construct a degree distribution for each quarter. In order to characterize the distributions we performed a Kolmogoroff-Smirnoff test to confirm/reject the hypothesis that the tail of the distribution is power law using the method of Clauset, Shalizi, and Newman (2009). The hypothesis was rejected systematically in all analyzed quarters.

Figure 4 reports the average values of the percentiles over time. Due to the high heterogeneity (i.e., several orders of magnitude), each case is reported in normal with an horizontal bar indicating the confidence interval of one standard deviation and semi-logarithmic scales. Each plot can be read as follows. For a given point on the curve, the y-axis coordinate of the point gives the percentage of banks with a degree larger than or equal to the value of the x-axis coordinate of the point. Thus for instance, in the credit network (left panel) only 50% of the banks have a degree larger than 10. Compared to all other percentiles, the $1-$st percentile is further in the tail by more than one order of magnitude (i.e., 519.97 ± 34.6 for the $1-$st percentile compared to the $5-$th percentile which has an average degree of 33.765 ± 1.46). This shows a high heterogeneity in the degree distribution of the credit network even if the tail overall cannot be fitted with a power-law.

We notice that the distribution in the derivative network exhibits an almost vertical line from the $80-$th to the $30-$th percentile, suggesting an important break between a large set of banks (more than 70% of the market) being only interacting with a couple of other banks and a smaller set of much more connected banks. Furthermore, the latter set also shows a high inner heterogeneity as the $1-$st percentile (i.e., 128.61 ± 25.2) is almost 10 times superior to the $5-$th percentile (i.e., 13.85 ± 2.42).

As a second representation, Figure 5 shows the evolution over time of the various percentiles. We can read the plot as follows. Consider for instance the curve corresponding to the $1-$st percentile (pale cyan) in the credit network (top-left panel). In order to be in the top $1-$st percentile of the degree distribution, a bank needs to have a degree larger than 450. Most curves in Figure 5 (Top) are stable over time meaning that the distribution of degree in the credit network does not change much across the years. The top $1-$st percentile curve increases sensibly in 2008 (i.e., an increase of 22%), implying that in order to remain in the same percentile a bank would have needed to increase its total

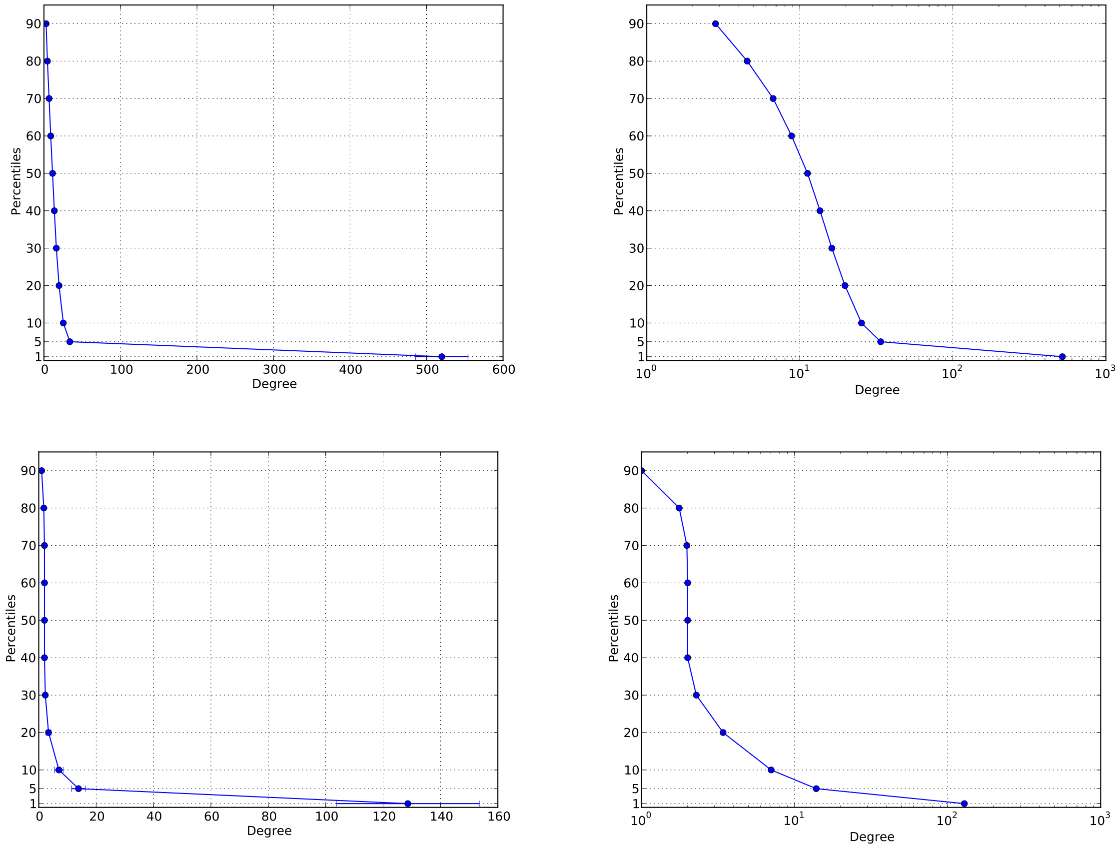

Figure 4: (Top) Average percentiles value and standard deviation in normal scale (Left) and average percentiles value in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the credit network (Bottom) Average percentiles value and standard deviation in normal scale (Left) and average percentiles value in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the derivative network.

number of contracts by one fifth. This number then decreases back to previous values. This behaviour of the top 1% of banks could result from a flight to quality. An alternative interpretation could be that banks in the core of the financial system, i.e. large, internationally connected and therefore potentially susceptible to foreign shocks, trying to gain systemic importance by becoming more interconnected (see Eisert and Eufinger (2013) for a theoretical model of this mechanism).

The situation for the derivative network is shown in Figure 5 (Bottom) where we notice two things. First, the curves for percentiles that are below the top 5-th percentile and 10-th percentile are packed at the bottom of the plot, meaning that the banks in those percentiles have smaller degree as compared to the case of the credit network. This is simply another way of looking at the same effect that was shown in Figure 4. Second, the

	Degree (Credit)	***Degree (Derivative)***
Skewness	13.08 ± 1.006	19.67 ± 2.22
Kurtosis	227.88 ± 40.41	485.28 ± 99.84

Table 1: Average skewness and kurtosis of degree distribution between 2002Q1 and 2012Q3 for both credit and derivative networks.

	Volume (Credit)	***Volume (Derivative)***
Skewness	13.37 ± 0.45	14.78 ± 2.44
Kurtosis	213.14 ± 16.99	251.62 ± 77.79

Table 2: Average skewness and kurtosis of volume distribution between 2002Q1 and 2012Q3 for both credit and derivative networks.

curves for top 5-th percentile, 10-th percentile and, most importantly, the 1−st percentile, increase over time by almost a factor of two. This means that it takes higher degree (twice as high to be precise) to remain in the same percentile, implying the distribution becomes substantially more skewed over time.

Table 1 reports the average skewness and kurtosis value over the whole time period of both credit and derivative degree distributions. Reported resulted show that the degree distribution of the derivative is comparatively more skewed and has a more then two times higher kurtosis.

In addition, we carried out the same analysis just described for volumes. Figure 6 reports the average values of the percentiles over time, with horizontal bars indicating the confidence interval of one standard deviation for the plots with normal axis. The plots can be read similar to the one in Figure 4. For instance, in the credit network (top panel) only 1% of the banks have, on average, an aggregate volume larger than 30 billion euros (the scale is in thousand euros). Again, we notice that the distribution is steeper in the derivative network than in the credit network, implying that the tail of the distribution is broader.

As a second representation, similar to Figure 5, Figure 7 shows the evolution over time of the various percentiles of the volume distribution. Consider the curve corresponding to the 1-st percentile (pale cyan) in the credit network (top-left panel). It shows the evolution of the minimum volume that a bank needs in order to belong to the 1% banks with the highest volume in the market. It increases over time and it is characterized by 3 sequences of boom-and-bust periods: (i) from 2004Q3 to 2005Q4, (ii) from 2007Q3 to 2009Q1 and (iii) from 2009Q1 to 2011Q1. The latter time period is the most important

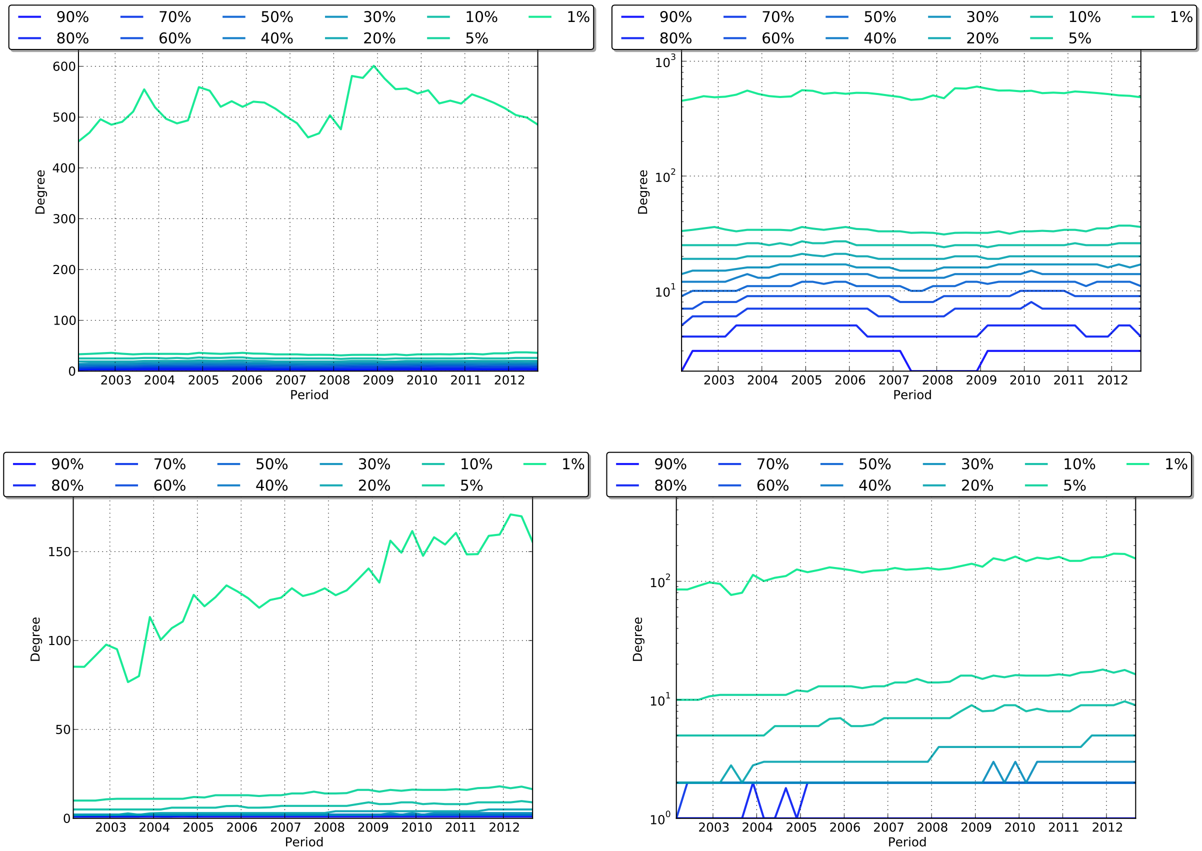

Figure 5: (Top) Evolution of percentiles in normal scale (Left) and in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the credit network (Bottom) Evolution of percentiles in normal scale (Left) and in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the derivative network.

change (+52.3% between 2010Q3 and 2011Q1). Again, the semi-log presentation in the top-right panel suggests that the market did not structurally change through the analyzed time period as the distances between the curves stay similar over time.

In the derivative case (Bottom), the 1st percentile is even more volatile with four boom-and-bust periods but does not point towards a general trend. Nevertheless, the results from Figure 2 on the evolution of the total volume and the HHI of the volume concentration presented a trend peaking in 2008 and decreasing back to previous values. The present result suggests that the increase between 2005 and 2010 occurs mainly because of a smaller subset of banks comprised in the 1st percentile. Also notice that the lower percentiles are closer to zero meaning that the distribution of volumes in the derivative network is more skewed than the one in the credit network.

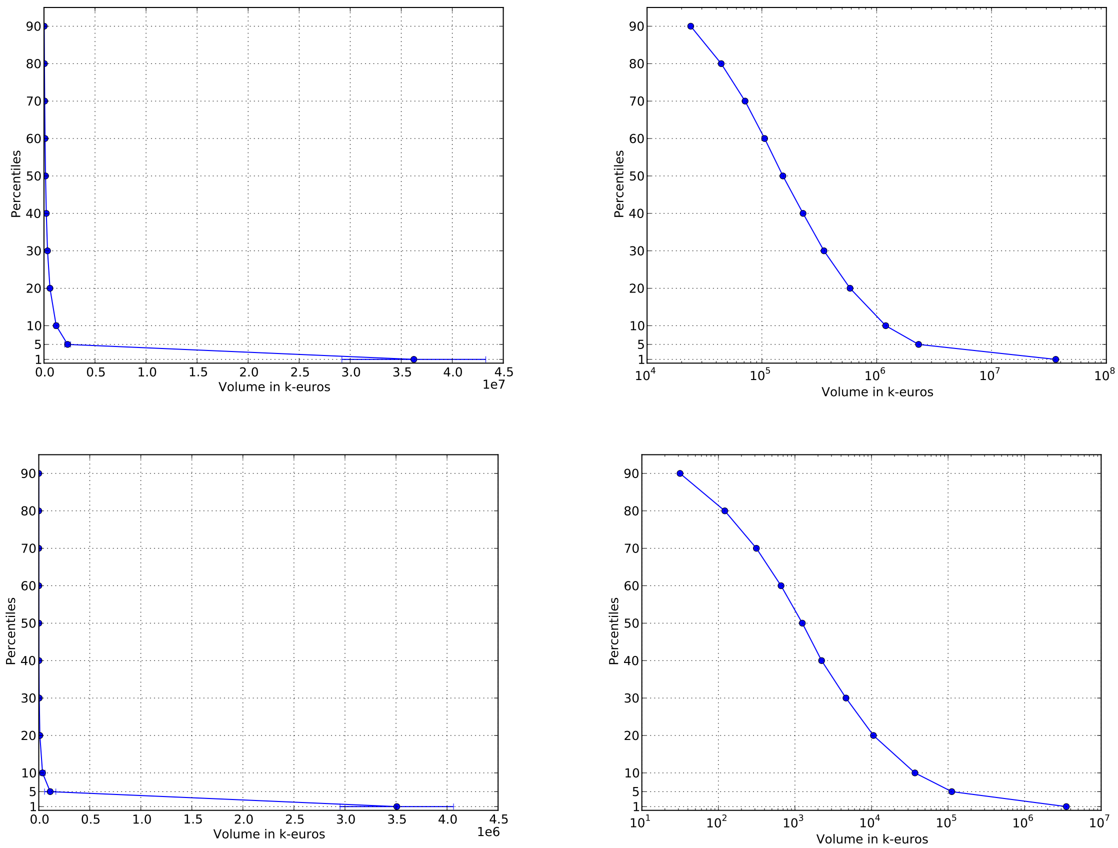

Figure 6: (Top) Average percentiles value and standard deviation in normal scale (Left) and average percentiles value in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the volume distribution in the credit network (Bottom) Average percentiles value and standard deviation in normal scale (Left) and average percentiles value in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the volume distribution in the derivative network.

Table 2 reports the average skewness and kurtosis value over the whole time period of both credit and derivative volume distributions. Interestingly, results are very similar between both distributions even though the derivative network exhibits higher deviation in both cases.

3.4 Correlations

We now turn to the correlation between the quantities investigated so far (see Figure 3.4 Top-Left). We look at three combinations of quantities. The first is the correlation between the number of contracts in which a bank is involved as a borrower versus those in which it appears as a lender, i.e. between in-degree and out-degree. The second is the correlation between the volume of the contracts in which a bank appears as a borrower

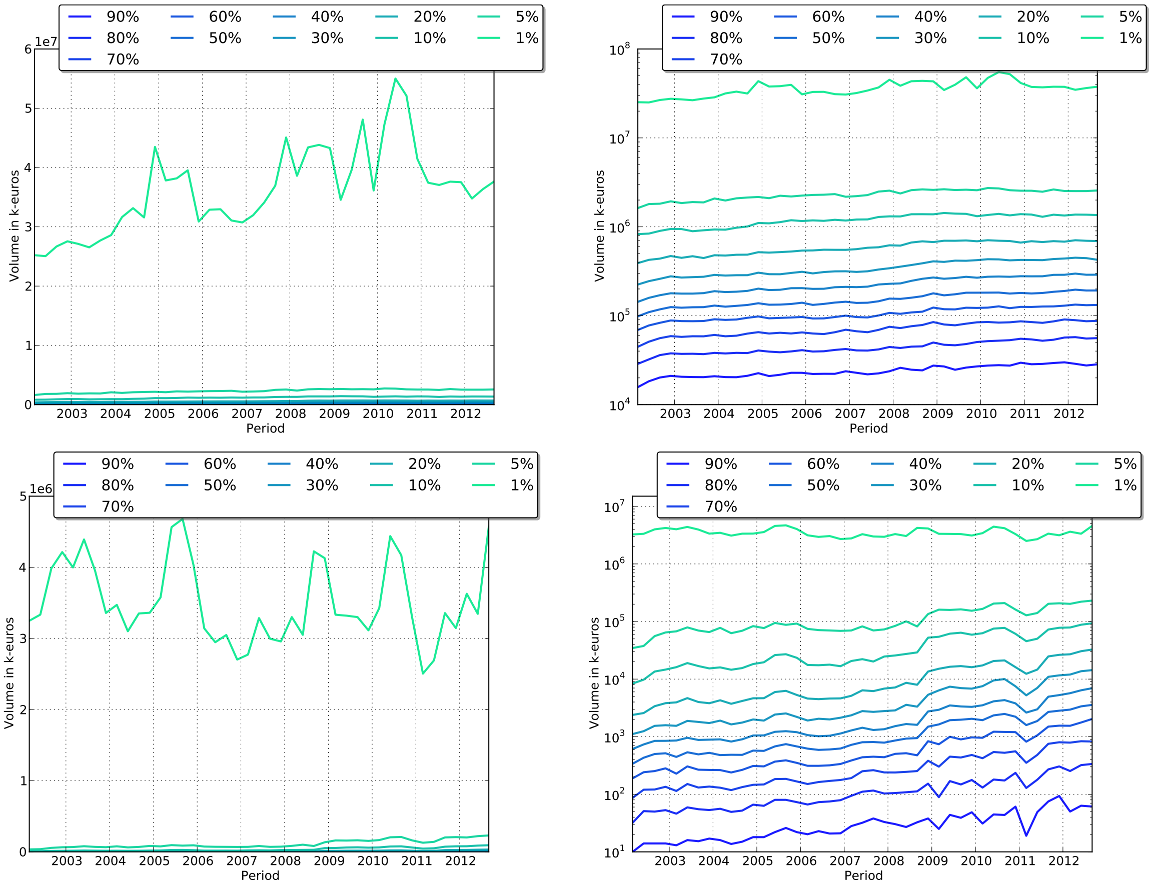

Figure 7: (Top) Evolution of percentiles in normal scale (Left) and in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the credit network (Bottom) Evolution of percentiles in normal scale (Left) and in semi-logarithmic scale (Right) between 2002Q1 and 2012Q3 for the degree distribution in the derivative network.

versus those where it appears as lender. The third combination is the correlation between number of contracts in which a bank is involved in either role (total degree) an the total volume of those contracts. For the network of derivatives, we do not look at the direction of the links and thus we only consider the correlation degree-volume.

The correlations between variables in the credit network (degree in-out, volume in-out, degree-volume) are remarkably high, and remarkably constant over time, as can be seen from Figure 3.4 (Top, Left). This implies that banks the lending and borrowing activities are highly correlated both in terms of number of counterparties and in terms of levels of total contracts volumes. In contrast, the degree-volume correlation of the derivative network starts with a significant correlation (> 0.5), decreases between 2005 and 2008 and then increases back to high values (> 0.7). This U-shaped evolution is in line with the previous results from Figure 2 showing the evolution of the concentration of volumes and

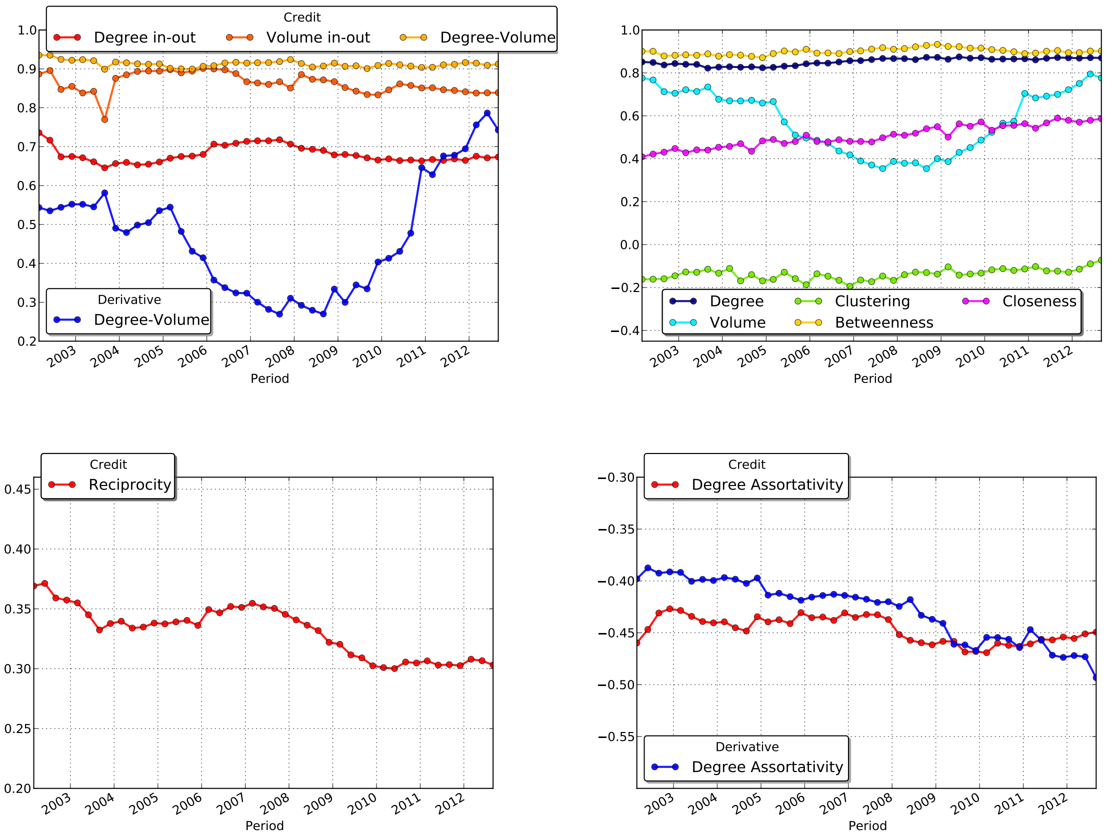

Figure 8: (Top Left) Evolution of correlations between 2002Q1 and 2012Q3 inside the credit and the derivative networks. (Top Right) Evolution of correlations between 2002Q1 and 2012Q3 between the credit and the derivative networks for nodes present in both networks. (Bottom Left) Evolution of link reciprocity between 2002Q1 and 2012Q3 for the credit network. (Bottom Left) Evolution of the degree assortativity between 2002Q1 and 2012Q3 for the credit and the derivative network.

degrees. As a result of the increasing volume and its concentration and relatively constant average degree, the correlation between the degree and the volumes drops between 2010.

We then analyze quantity correlation between the two markets by comparing quantities related to nodes present in the two networks. We thus assess the extent to which banking activity and structural roles are correlated between the credit and the derivative market. Figure (Top-Right) retrieves the results of such comparison for the following metrics: total degree, total volume, clustering coefficient, betweenness centrality and closeness centrality. The degree-degree and betweenness-betweenness correlation between the credit and the derivative network are also remarkably large and remarkably constant over time. The volume-volume correlation takes a dip due to the volume dynamics in the derivatives market mentioned above. Finally, closeness-closeness correlation is largely positive (start-

Measure	***Average***	***Std Error***
Share of nodes in the LSCC	98.23%	0.0085
Share of nodes in the IN	0.8%	0.0089
Share of nodes in the OUT	0.97%	0.0031
Share of volume in the LSCC	99.66%	0.002
Share of volume in the IN	0.2%	0.0014
Share of volume in the OUT	0.09%	0.00165
Diameter	4.49	0.59
Average Shortest Path	2.241	0.0176

Table 3: Shares of components and analysis of the LSCC

ing from around 0.4 in 2002Q1) and increasing (up to 0.6 in 2012Q3). Interestingly, the clustering-clustering correlation is constantly negative and stable.

A related analysis concerns the so-called reciprocity of the links, that is the fraction of links that exist in both directions out of the total number of links. The reciprocity can only be computed for the the credit network. Figure 3.4 (Bottom-Left) shows that reciprocity is positive but slightly decreasing over time (from around 0.4 to 0.3). Note that our data contains end-of-quarter exposures between banks, which means that lending can still be driven by liquidity demand as long as banks also engage in interbank lending with maturity larger than the end of quarter.

Finally, assortativity in both networks is negative and increasingly so as shown in Figure 3.4(Bottom-Right): both networks are thus dissassortative. This implies that small banks have a tendency to lend to and borrow from large banks and vice versa. Negative assortativity is to be expected in highly heterogenous networks (e.g. core-periphery).

3.5 Topological Structure

A strongly connected component (SCC) is a subgraph in which every node can reach any other node along some path in the subgraph. Many empirical networks display a non-trivial bow-tie structure (e.g.Vitali, Glattfelder, and Battiston (2011)), in the sense that they can be decomposed into a largest strongly connected component (LSCC) and into non-empty in and out components. The former consist of all the nodes that can reach the LSCC but cannot be reached from the node in there. The latter consists of the nodes that can be reached from the nodes in the LSCC but cannot reach the LSCC.

Since the derivative network is undirected this analysis only makes sense for the credit network. From Table 3, we find that the in- and out- component are very small and the LSCC makes up almost the entire network. The fraction of banks in the LSCC is $98.23\% \pm 0.0085\%$, where the standard deviation is computed across the values over time. In principle it would be possible that the banks in the tiny in- or out-component are important in terms of volume. It turns out that they aren't. Almost all the volume is located at the banks in the LSCC and this remains stable over time ($99.66\% \pm 0.002\%$). Also the average shortest path length, is stable over time ($2.141\% \pm 0.0176\%$).

4 Conclusion

In this paper we analyse the network of the German interbank credit and derivative market from 2002 to 2012. Our data provides a unique view on the joint structure of two of the most important OTC markets in Germany and covers over two thousand banks. The German interbank market is large in size compared to other countries and thus exhibits potentially rich dynamics.

We report a number of interesting findings about the structural evolution of the German credit and derivative market. Even though the credit market is much bigger than the derivative market, its size steadily decreases over time while the size of the derivative market remains stable. Both markets are very sparse (i.e., their density of connection is low). Nevertheless, the average number of counterparties in each case increases over the period. It is worth noting that the derivative market followed increases more than four times more than the credit market. The connectivity distributions of both markets, while not following a power-law, show substantial heterogeneity and fat tails. Much of the change of both markets occurs in the tail. While the distribution structure remains similar between the different quarters for the credit market, the derivative market becomes increasingly and continuously more skewed over time.

In terms of volumes, the derivative market more then doubled in terms aggregated level and concentration in the pre-crises period and then decreased to reach back initial values at the end of 2012. The volume levels of the credit market are comparatively more important by more than one order. The evolution of the aggregated level over time of the latter market is much less volatile and characterized by four smaller boom-and-busts periods. The concentration is smaller and stable over time. The distribution of volumes in both markets is highly heterogenous. Again, much of the change occurs in the tail where the one percent of most active banks continuously and importantly increased their level of volume activity.

In terms of network metrics, we find that the two market have an opposite profile in terms of clustering. The credit market has a very high average clustering coefficient while the derivative market has a substantially smaller value. The former is stable over time while the latter steadily increases. Betweenness in both markets is small and slowly increases throughout the period. Closeness is surprisingly similar in both markets and its evolution is almost flat. Finally, the average eigenvector centrality increased over time in the credit market while, in the derivative case, it remains around the same level.

Correlations between various network measures in each market are remarkably high and stable in the credit market except the correlation between the aggregated volume and aggregated number of counterparties per bank in the derivative network which has a U-shaped profile over time. Correlations across markets are similarly high and stable except the volume correlation, which follows a U-shape as well, and the clustering coefficient, which is negative. The credit market also is also characterized by a high level of reciprocity between banks. The structure of the credit network, as measured by the relative size and volumes of the strongly connected component is stable over time.

The results of this paper are relevant for policy makers, though, as they show a remarkable resilience of both studied OTC networks to endogenous and exogenous shocks. One could argue that banks will unwind existing positions and distance themselves from the market when there is a shock somewhere in the system. The resilience of the network structure, however, indicates that banks are either unwilling or unable to do so, thus highlighting the necessity of interbank network and contagion analyses.

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