Network Analysis of European Financial Institutions CDS Market

Veronika Kajurová, Oleg Deev
Masaryk University
Faculty of Economics and Administration
Department of Finance
Lipová 41a
Brno, 602 00
Czech Republic
e-mail: vkajurova@mail.muni.cz

Abstract
The aim of the study is to examine network structures of credit default swaps (CDS) market, with focus on the most liquid CDS issued by the biggest European financial institutions. Correlation-based procedure is employed in order to identify links between CDS spreads. Correlation based networks allow us to comprehend and forecast the dynamics in the CDS market with reduction of complexity of dependencies. Network modeling of CDS spreads can be useful and powerful tool, which can provide much insight and understanding on mutual dependence of CDS spreads behavior. The results show that CDS spreads are homogeneous with respect to their economic sector, rather than country's origin. The increasing correlations between spreads in the second phase of the financial crisis can provide an evidence that there could have been created more suitable conditions for dispersion of systemic risk. Results can be beneficial for both investors and regulators as an indication of channels of financial contagion, particularly, if networks are observed continuously over time.

Keywords: financial contagion, correlation network, CDS market, network analysis, systemic risk
JEL codes: G01, G15

1. Introduction

Both economic and financial integration within Europe have led to an increasing connectedness of financial markets. To explore interconnections among financial markets or institutions and to identify possible channels of financial contagion, network analysis is a considerably powerful tool, which recently has become very popular in finance. Such analysis is very important for understanding the nature of systemic risk that could be triggered by certain events, e. g. a sudden market disruption or bank failure. According to the European Central Bank (2010), the repercussions of systemic risk depend considerably on the collective behavior of financial institutions and their interconnectedness, as well as on the interaction between financial markets and macroeconomics.

Network modeling can be a powerful tool which can help us discover channels of contagion and build a notion whether the system is resilient to contagion. This type of analysis aims at representing the interconnections of a large multivariate system as a network, and then the network representation is used to study the properties of the system (Barigozzi and Brownlees, 2013). Indisputable advantage of correlation based networks is that they enable us to comprehend the dynamics in the system with reduction of complexity of dependencies.

The aim of our study is to examine network structures of the European financial institutions CDS market with respect to changing characteristics of correlation-based network in the period before, during and after the financial crisis. Network modeling of CDS spreads is employed in order to provide much insight and understanding on mutual dependence of CDS spreads behavior.

2. Credit Default Swaps and Network Analysis Application

Because of the previous limited availability of data, the majority of published empirical studies are focused primarily on the mathematics of credit default swaps. The mechanism of CDS market functioning were investigated on the data obtained directly from banks or other financial institutions. In recent years the CDS market dynamics has been represented by the credit default swap indices, which allow the investigation of such markets by the means of the time series analysis.

Blanco, Brennan, Marsh (2003) is the first study which explores credit default swap prices with time series application. Since CDS can be perceived as an indicator of credit risk, many studies try to find the determinants of CDS prices. However, before the global financial crisis CDS markets were not examined with apparatus of the network analysis. Historically, stock markets are in the spotlight of network applications in finance. The number of contributions devoted to network analysis of stock markets has gone hand in hand with stock market globalization and integration. Studies deal with either stock indices or with individual stocks, for instance see Tse et al. (2010), Roy and Sarkar (2011), Cupal et al. (2012), Liu and Tse (2012) or Lyócsa et al. (2012).

The number of papers on networks in CDS markets has been increasing since the latest financial crisis. Authors pay attention particularly to CDS with respect to systemic risk, contagion and financial stability. Heise and Kühn (2012) propose a model which can analyze contagion dynamics and systemic risk in networks of financial dependencies which include exposures created by CDS contracts considered to be an additional contagion channel. They state that CDS help to reduce losses under normal or favorable conditions, but they cannot completely eliminate the tail risk of very large losses. Markose et al. (2012) deal with the notion of "too interconnected to fail" in the framework of the network analysis. Their study investigates the systemic risk posed by the topological fragility of the CDS market between 25 highly connected US banks. They apply agent-based modeling to a financial network and use simulation results to devise an operational measure of systemic risk. Trapp and Wewel (2010) study the systemic risk for the US and Europe. They measure systemic risk applying a copula approach to specify a downside risk. Their results imply that regulators and supervisors should first address international bank dependencies arising from common risk factors, while recessions in real sectors due to bank defaults should be a secondary concern. Network modeling of systemic risk is also in the spotlight of the European Central Bank (2010) or other international financial institutions, e. g. see Markose (2012).

3. Data and Methodology

In our study, we pay attention to CDS of the financial institutions which are included in the Markit iTraxx Europe Senior Financial index. This index comprises 25 credit default swaps with 5-year maturity on European investment entities. Daily observations were obtained from Bloomberg. 5-year maturity is chosen in accordance with Mayordomo's et al. (2013) contribution which shows that this maturity-provider combination reflects new information more rapidly than CDS of other maturities.

CDS spreads were used to investigate network structure. In general, CDS premium represents creditworthiness of the reference entity. The use of CDS spreads instead of stock returns has its advantages and disadvantages. Trapp and Wewel (2012) suggest that it has a closer link to a firm's probability of default than stock returns. But it might also reflect factors other than the default risk of underlying entity. All observed financial institutions are described in Table 1 alongside with their country of origin and industry.

The total sample period (November 2003 – April 2013) is divided into three sub-periods according to trends in development of the Markit iTraxx Europe Senior Financial index:

a) pre-crisis period (11/01/2003 – 05/31/2007),
b) financial crisis period (06/01/2007 – 10/31/2009),
c) debt crisis period (11/01/2009 – 04/30/2013).

The financial crisis period is taken as a period of the biggest turmoil in financial markets. Then the crisis has been transformed into a sovereign debt crisis, therefore the period after the financial crisis is denoted as the debt crisis period. The entire period of the financial crisis is divided into two sub-periods because of significant changes in the correlation network:

a) first sub-period (06/01/2007 - 06/17/2008),
b) second sub-period (06/18/2008 – 10/31/2009).

Table 1: Observed financial institutions

Institution	Country	Industry
Aegon NV	Netherlands	Life Insurance
Allianz SE	Germany	Property and Casualty
Assicurazioni Generali SpA	Italy	Life Insurance
Aviva PLC	United Kingdom	Life Insurance
AXA SA	France	Life Insurance
Banco Santander SA	Spain	Banking
Barclays Bank PLC	United Kingdom	Banking
BNP Paribas SA	France	Banking
Commerzbank AG	Germany	Banking
Credit Agricole SA	France	Banking
Credit Suisse Group AG	Switzerland	Financial Services
Deutsche Bank AG	Germany	Financial Services
Hannover Rueckversicherung SE	Germany	Insurance
HSBC Bank PLC	United Kingdom	Banking
ING Bank NV	Netherlands	Banking
Intesa Sanpaolo SpA	Italy	Banking
Lloyds TSB Bank PLC	United Kingdom	Banking
Muenchener Rueckversicherungs AG	Germany	Property and Casualty
Royal Bank of Scotland PLC	United Kingdom	Banking
Societe Generale SA	France	Banking
Standard Chartered Bank	United Kingdom	Banking
Swiss Reinsurance Co Ltd	Switzerland	Property and Casualty
UBS AG	Germany	Financial Services
UniCredit SpA	Italy	Banking
Zurich Insurance Co Ltd	Switzerland	Life Insurance

Source: Bloomberg

Correlation-based procedure is employed in order to identify links between CDS spreads. The mere correlation analysis, usually reported in every study of financial markets in a form of the table of pair cross-correlation coefficients, does not give us a full picture of connectivity between assets, but if represented in the form of graph, could give us an interactive and deep understanding of the data for further consideration. In networks, each asset is represented by a node and correlations between assets are represented by links. Researchers are interested in choosing the most important correlations, which enable us to understand them easier. Benefit of correlation networks is that they allow us to find which of the pair-wise relations among the observed variables are the most important.

To build a network of chosen assets, first, we calculate pair-wise correlations to quantify the degree of synchronization between assets and, second, we employ filtering techniques to determine the most important links from the correlation matrix as well as layout algorithms to choose the best way to illustrate the results.

The correlation coefficient for each pair of assets is defined by:

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}} \tag{1}$$

where *i* and *j* are CDS labels, and *r* are CDS spreads.

Next step is to define a metric that clarifies the distance between CDS spreads synchronously evolving in time: $d_{i,j} = \sqrt{2(1-\rho_{ij})}$ (formula's derivation might be found in Prim, 1957). The following three properties (or axioms) must hold:

1) $d_{i,j}$ = 0 if and only if *i=j;*
2) $d_{i,j}$ = $d_{j,i}$;
3) $d_{i,j} \leq d_{i,k} + d_{k,j}$.

A unique way of connection between assets is specified from the obtained distance matrix by employing the graph theory's concept of minimum spanning tree (MST). In a connected graph *G = (V, E)*, each edge *e* is given a weight *w(e)* represented by the calculated metric distance $d_{i,j}$, and weight of a whole graph, which is needed to be minimized, is a sum of weights of edges. Hence, MST is a tree having *n-1* edges that minimize the sum of the edge distances. The problem is how to compute a minimal weighted tree, whose edges cover the entire set of vertices *V*. MST problem is one of the most studied problems in graph theory, for which several solutions or algorithms are known, namely the algorithms of Prim (1957), Kruskal (1956) and Borůvka (1926). Different filtering procedures could provide different aspects of the time series information. Several studies, e. g. Bonnano et al. (2004) and Broutin et al. (2006), propose that the filtering procedure based on Kruskal's algorithm is a straightforward choice.

The MST associated with the subdominant ultrametric distance matrix *D* can be obtained as follows (here described in spirit of Kruskal, 2003). Let assume that the given connected graph *G = (V, E)* is complete, which means that every pair of vertices is connected by an edge. If any edge of *G* is "missing", an edge of greater length may be inserted, and this does not alter the graph in any way relevant to our purpose. Also, it is possible and intuitively appealing to think of missing edges as edges of infinite length. Among the edges of *G* not yet chosen, we pick the shortest edge, which does not form any loops with those edges already chosen. This procedure is performed as many times as possible. Clearly the set of edges eventually chosen must form a spanning tree of *G*, and in fact it forms a shortest spanning tree.

For programming purposes Kruskal's algorithm should be presented as the following procedure:

Step 1: Create an edgeless graph *T = (V, 0)* which vertices correspond with those of *G*.

Step 2: Choose an edge *e* of *G* such that (1) adding *e* to *T* would not make a cycle in *T* and (ii) *e* has the minimum weight *w(e)* of all the edges remaining in *G* that fulfill the previous condition.

Step 3: Add the chosen edge *e* to graph *T*.

Step 4: If *T* spans *G*, procedure is terminated; otherwise, the procedure is repeated from Step 2.

Obtained scale-free graph *T = (V, E')* in a form of a hierarchical tree represents the network of most important correlation-based connections of assets. Vertices or nodes symbolize different time series (or, in our case, CDS spreads).

4. Results

We built correlation networks in accordance with the above mentioned procedure to discover changing structure of the European financial institutions CDS Market. The minimum spanning tree is provided for each period. A correlation of 1 is mapped to a low distance and the correlation of 0 to a high distance.

The important nodes in the MST are determined by calculating centrality measures. Nodes with higher degree are connected to more other nodes, therefore they can be considered more important within the network. Onnela et al. (2003) suggest that if the asset is a central node, it means it is important in the sense that any change in its price strongly affects the course of events in the market as a whole.

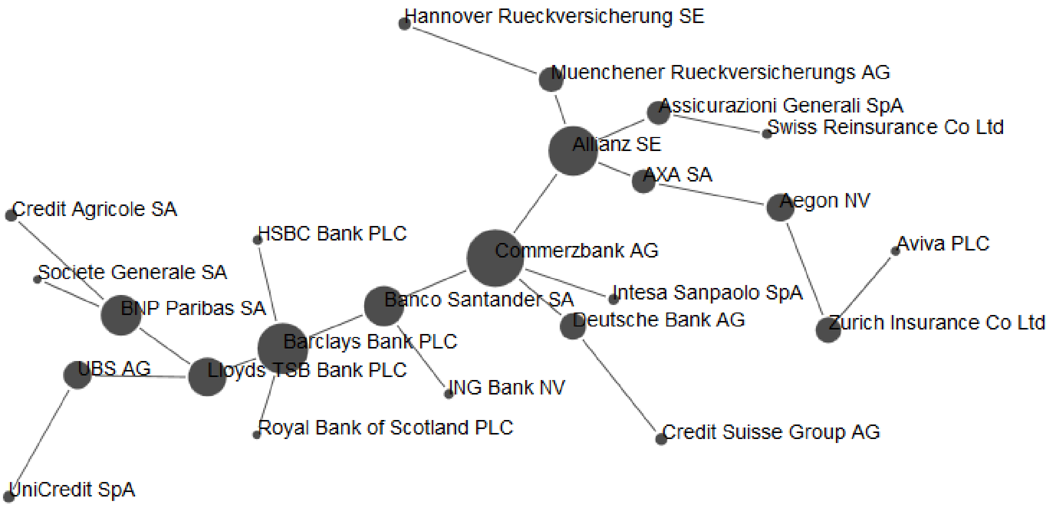
Although it is possible to create an interactive visualization of networks, we have simplified the final networks in our research. We have assumed that each network is represented by the exactly specified period of calendar days. The choice of time interval for network creation is certainly a main limitation of network analysis (for discussion, see Bonnano et al., 2004), however, this limitation can also be seen as a method of illustrating the complex process of the price formation occurring in financial markets in certain time spans.

4.1 Pre-crisis Period

A pre-crisis network represents a period of 1308 calendar days. As seen in Figure 1, two industries of our study, namely banking and insurance, are separated into two clearly observed clusters. In the cluster of insurance companies, Allianz SE had the highest degree of connection to other nodes. In the bank cluster, several nodes with higher degree of connection to other nodes –

Commerzbank AG, Barclays Bank PLC, Banco Santander SA, Lloyds TSB Bank PLC and BNP Paribas – play a prominent role in the network. Correlations between credit spreads were not very high, which could have lowered the possibility of systemic risk spreading during the pre-crisis period.

Figure 1: Minimum spanning tree in the pre-crisis period

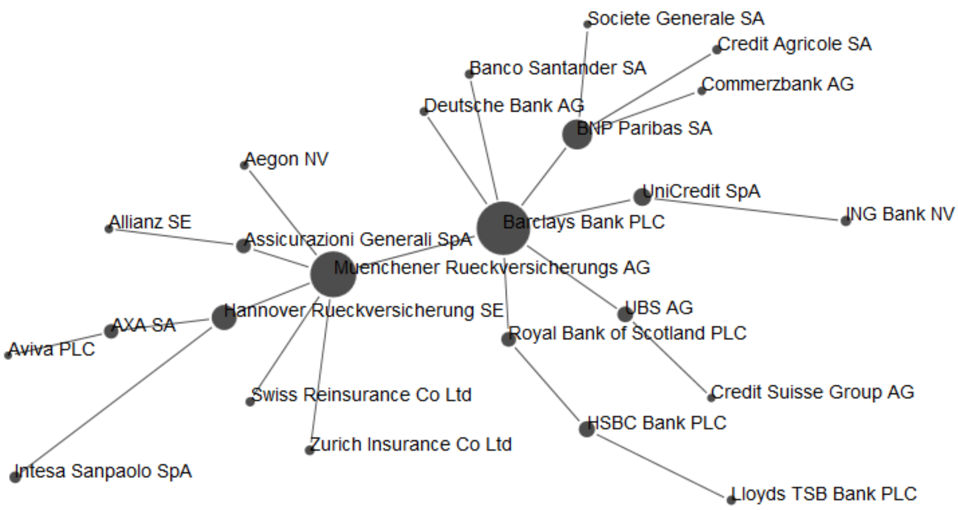


Source: Authors' processing

4.2. Financial Crisis Period

The financial crisis period is divided into two sub-periods. The correlation network in the first phase of the financial crisis is represented by a period of 383 days, and in the second phase of the financial crisis is represented by a period of 501 days. Final network for the first phase is illustrated in Figure 2, and for the second phase can be seen in Figure 3.

Figure 2: Minimum spanning tree during the financial crisis period (first phase)

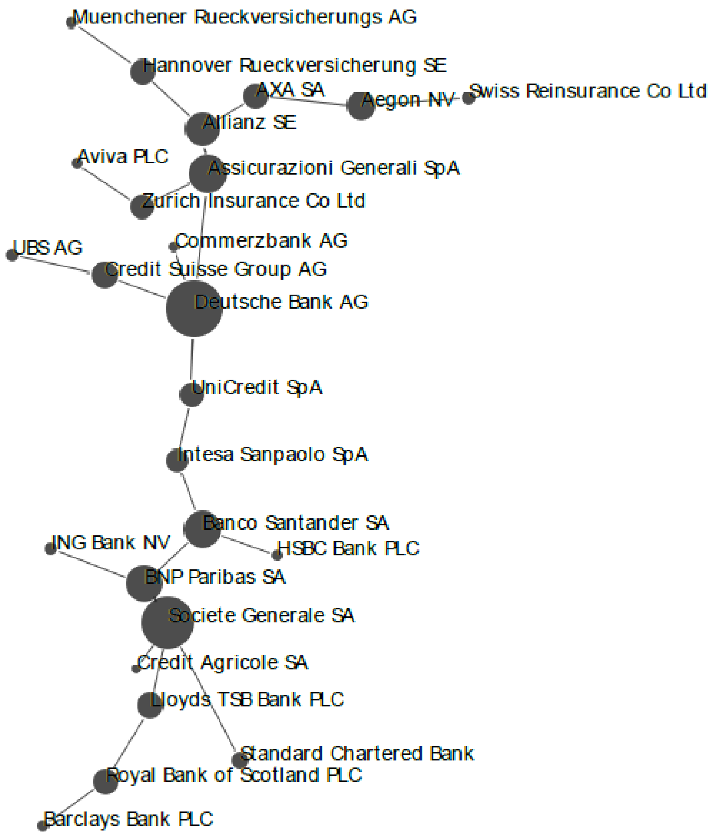


Source: Authors' processing

The MSTs in both sub-periods again indicate that the vertices in the particular sectors form sub-trees similar to what was observed during the pre-crisis period. During the first phase of the financial crisis, the central node in the insurance cluster is occupied by Muenchener Rueckversicherungs instead of AG Allianz SE. In the bank cluster, only Barclays Bank PLC kept its central place with the higher degree of connections to other nodes. In this phase of the crisis, we did not find any significant correlations among CDS spreads of the European entities, and the circumstances for contagion spread did not seem to be suitable.

The MST in the second phase of the financial crisis considerably changed compared to the first phase. None of insurance companies were significantly connected to other nodes as in the previous periods. In the bank cluster, Barclays Bank PLC was substituted by Deutsche Bank AG and Societe Generale SA. In this phase of the financial crisis, increasing correlations among CDS spreads were observed, which could be interpreted as that more suitable conditions were created for dispersion of systemic risk.

Figure 3: Minimum spanning tree during the financial crisis period (second phase)



Source: Authors' processing

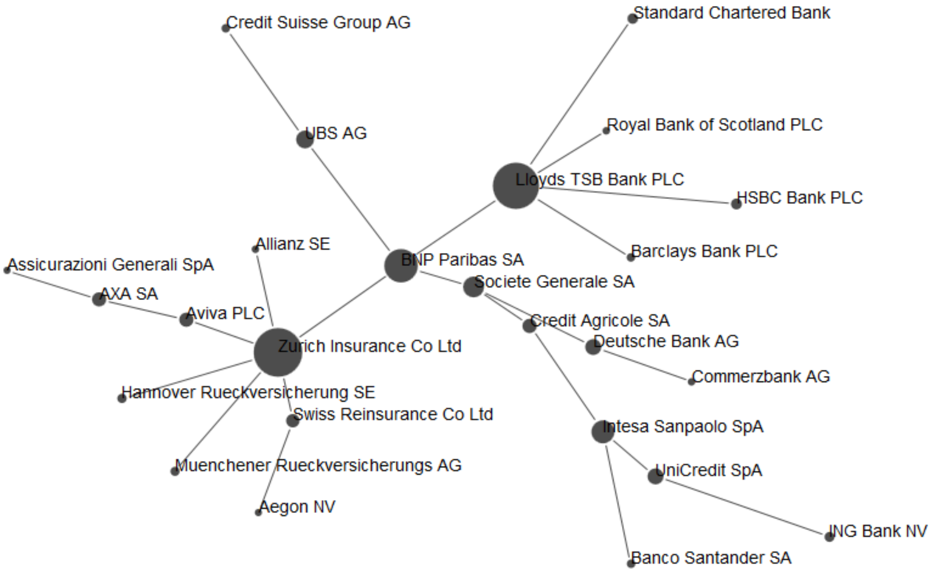
4.3. Debt Crisis Period

A network in the debt crisis period represents a period of 1277 calendar days. Two sub-trees were still evident in the MST. Lloyds TSB Bank PLC and BNP Paribas SA had the most important roles in the network within the bank cluster. Zurich Insurance Co Ltd gained important position within the insurance cluster. As it was previously established, CDS spreads are homogeneous with respect to their economic sector, rather than country’s origin. All observed CDS spreads of the UK banks are correlated with Lloyds TSB Bank PLC. Correlations among CDS spreads inside the network have lowered, while the distances became higher compared to the distances in the network represented in Figure 3.

5. Conclusion

Analysis of market topology is a powerful tool to filter meaningful information from correlation coefficient matrix and to capture market dynamics if it is implemented over time. Networks built as a MSTs allow us to explore and monitor large-scale dependence structures and dynamics of financial markets in a more interactive way.

Figure 4: Minimum spanning tree in the debt crisis period



Source: Authors' processing

The aim of our paper was to examine network structures of the European financial institutions CDS market with respect to changing characteristics of correlation-based network in the period before, during and after the financial crisis. Network modeling of CDS spread was employed in order to provide interesting insight and understanding of mutual dependence of CDS spreads behavior. We conclude that network structures changed over investigated period. First, the final networks demonstrate that in all cases, the vertices in the particular industries formed sub-trees, which means that CDS spread were homogeneous with respect to their economic sector, rather than country's origin. Second, the increasing correlations among CDS spreads were observed in the second phase of the financial crisis, which could have created more suitable conditions for dispersion of systemic risk. Results can be beneficial for both investors and regulators as an indication of channels of financial contagion, particularly, if networks are observed continuously over time.

Cross correlation as the most common method of dependability was chosen to illustrate the application of network theory for the analysis of the part of financial markets. Nonetheless, we believe that future research including more institutions, sectors or CDS exposures can give us much deeper insight into network structures and their importance from the perspective of systemic risk.

Acknowledgement

Support of Masaryk University within the project MUNI/A/0753/2012 "European financial systems 2013" (Student Project Grant at MU) is gratefully acknowledged.

References

BARIGOZZI, M., BROWNLEES, C. T. (2013). *NETS: Network Estimation for Time Series.* Available at SSRN: http://ssrn.com/abstract=2249909 or http://dx.doi.org/10.2139/ssrn.2249909.

BLANCO, R., BRENNAN, S. and MARSH, I. W. (2005). An Empirical Analysis of the Dynamic Relationship between Investment Grade Bonds and Credit Default Swaps. *Journal of Finance*, vol. 60, no. 5, pp. 2255-2281.

BONNANO, G., CALDARELLI, G., LILLO, F., MICCICHE, S., VANDEWALLE, N., MANTGENA, R. N. (2004) Networks of equities in financial markets. *The European Physical Journal B – Condensed Matter and Complex Systems*, vol. 38, no. 2 pp. 363-371.

BORŮVKA, O. (1926). O jistém problému minimálním. *Acta Societatis Scientiarum Naturaliste Moravicae*, vol. 3, pp. 37–58.
BROUTIN, N., DEVROYE, L., AND MCLEISH, E. (2010). Note on the Structure of Kruskal's Algorithm. *Journal: Algorithmica*, vol. 56, no. 2, pp. 141-159.
CUPAL, M., DEEV, O., LINNERTOVÁ, D. (2012). Network Structures of the European Stock Markets. In *Proceedings of 30th International Conference Mathematical Methods in Economics.* Karviná: Silesian University in Opava, School of Business Administration in Karviná, pp. 79-84.
EUROPEAN CENTRAL BANK (2010). *Recent Advances in Modelling Systemic Risk Using Network Analysis.* Frankfurt am Main: European Central Bank. ISBN 978-92-899-0611-1 (online).
HEISE, S. KÜHN, R. (2012) Derivatives and Credit Contagion in Interconnected Networks. *The European Physical Journal B*, vol. 85, no. 115, pp. 1-19.
KRUSKAL, J. B. (1956). On the Shortest Spanning Subtree of a Graph and the Travelling Salesman Problem. *Proceedings of the American Mathematical Society*, vol. 7, no. 1, pp. 48-50.
LIU, X. F., TSE, C. K. (2012). Dynamics of Network of Global Stock Markets. *Accounting and Finance Research*, vol. 1, no. 2, pp. 1-12.
LYÓCSA, S, VÝROST, T., BAUMÖHL, E. (2012). Stock Market Networks: The Dynamic Conditional Correlation Approach. *Physica A: Statistical Mechanics and Its Applications*, vol. 391, no. 16, pp. 4147-4158.
MARKOSE, S. M. (2012). *Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-Spreader Tax*. IMF Working Paper No. WP/12/282. Washington: International Monetary Fund.
MARKOSE, S., GIANSANTE, S., SHAGHAGHI, A. R. (2012). 'Too Interconnected to Fail' Financial Network of US CDS Market: Topological Fragility and Systemic Risk. *Journal of Economic Behavior & Organization*, vol. 83, no. 3, pp. 627-646.
MAYORDOMO, S., PEÑA, J. I., SCHWARTZ, E. S. (2013). Are All Credit Default Swap Databases Equal? *European Financial Management*, vol. 9999, no. 9999, pp. 1-37, doi: 10.1111/j.1468-036X.2013.12023.x.
ONNELA, J. P., CHAKRABORTI, A., KASKI, K., KERTÉSZ, J. (2003). Dynamics Asset Trees and Black Monday. *Physica A: Statistical Mechanics and Its Aplications*, vol. 324, no. 1-2, pp. 247-252.
PRIM, R. C. (1957). Shortest Connection Networks and Some Generalizations. *Bell System Technical Journal*, vol. 36, no. 6, pp. 1389–1401.
ROY, R. B., SARKAR, U. K. (2011). Identifying Influential Stock Indices from Global Stock Markets: A Social Network Analysis Approach. *In Procidia Computer Science – The 2nd International Conference on Ambient Systems, Networks and Technologies (ANT)*, vol. 5, pp. 442-449.
TERZI, N., ULUÇAY, K. (2011). The Role of Credit Default Swaps on Financial Market Stability. In *Procedia Social and Behavioral Sciences – 7th International Strategic Management Conference*, vol. 24, pp. 983-990. Available at: http://dx.doi.org/10.1016/j.sbspro.2011.09.066.
TRAPP, M., WEWEL, C. (2013). Transatlantic Systemic Risk. *Journal of Banking & Finance*, vol. 37, no. 11, pp. 4241-4255.
TSE, C. K., LIU, J., LAU, F. C. M. (2010). A Network Perspective of the Stock Market. *Journal of Empirical Finance*, vol. 17, no. 4, pp. 569-667.