Network analysis of the EU insurance sector: a tail dependence-based MST in modelling systemic risk

Anna Denkowska[1]

Abstract

In this article we analyse the dynamics of indirect linkages between insurance companies resulting from market price channels. For our purposes we assume that the stock quotations of insurance companies reflect market sentiments. The latter are a very important systemic risk factor. Interconnections between insurers and the dynamics thereof have a direct impact on systemic risk spread in the insurance sector. The approach we are proposing is novel in that it is hybrid: in order to analyse the interlinkages dynamics we combine the copula-DCC-GARCH model and Minimum Spanning Trees (MST). Using the copula-DCC-GARCH model we determine the correlation coefficients in the distribution tails. Then, for each analysed period we construct MST based on these coefficients. The dynamics is analysed by means of time series of selected topological indicators of the MSTs. Our empirical results show the usefulness of the proposed approach to the analysis of systemic risk in the insurance sector. Moreover, the phenomena occurring on the market are reflected by the times series obtained from the proposed hybrid approach. The MST topological indicators we analyse turn out to be systemic risk predictors.

Keywords: systemic risk, insurance sector, copula-DCC-GARCH model, tail dependence, minimum spanning tree, deltaCoVaR, network topology indicators.

JEL Classification: G22, C10

1. Introduction

In the last decade, research in the insurance sector has been intensified in the context of systemic risk (SR). Before the 2008 subprime crisis and the excessive sovereign debt crisis in the euro area, it was thought that the insurance sector, whose tasks on the financial market consist mainly in taking over, dispersing and redistributing the financial effects of risk, does not generate SR. However, as reality showed, on the example of AIG in 2008, insurers undertake non-insurance activities, have direct exposures to other insurers, banks and other financial institutions through debt, debt securities and other financial instruments. These exposures can cause direct infection and thus spread of systemic risk. Alves *et al.* (2015) analyzed direct links between the 29 largest insurers in the EU and banks. At the same time, they emphasize that their research does not

[1] Department of Mathematics, Cracow University of Economics, Kraków, Poland, anna.denkowska@uek.krakow.pl.

include the analysis of connections between insurers under reinsurance contracts, indirect connections via market price channels and information channels, and analysis of banks' exposure to insurers. In the present article, we focus on the problem of indirect connections which arise from market price channels for the group of insurers analyzed in Alves *et al.* (2015) together with nine additional insurance institutions from the list of the 50 largest companies in Europe for which stock quotes were available. Assuming that each insurance company is a node in a network, we can use the MST method to identify the strongest and most direct connection for each node in the network.

Linkages between insurers and their dynamics have a direct impact on propagation of systemic risk in the insurance sector. We propose here a new hybrid approach to analyzing the dynamics of interconnections. It consists in combining the copula-DCC-GARCH and Minimum Spanning Trees (MST). The copula-DCC-GARCH model is used to determine dependency coefficients in distribution tails. Then, based on these coefficients for each analyzed period, we determine the "distance" matrix between insurance companies using the Mantegna metric (Mantegna and Stanley, 1999) and construct minimum spanning trees. Then the dynamics is analysed using selected topological indicators for the MST obtained in this way.

The main purpose of the work is to check whether the time series of topological indicators of the network of connections between insurance companies obtained using the proposed hybrid approach reflect the situation on the financial market and whether they can be used as predictors of systemic risk in the insurance sector. Our results corroborate this hypothesis.

The article is organized as follows. The second section discusses shortly SR in the insurance sector, the way to determine systemically relevant insurance companies (G-SIIs) and gives an overview of the existing literature devoted to the interlinkages in the insurance sector from the point of view of network theory. The third section presents the methodology and the empirical strategy used in the paper, the fourth one contains the data and a discussion of the results obtained, while the fifth and last one presents the conclusions.

2. Systemic risk in the insurance sector, G-SII and MST

Financial systemic risk (SR), which was first addressed in the famous work "The General Theory of Employment, Interest, and Money" (Keynes, 1936), is currently one of the most important issues in globalized economics and financial systems analyzed, e.g. by Acharya *et al.* (2012), Acharya *et al.* (2017), Li (2018). A satisfying definition of the concept of SR is hard to find. Eling and Pankoke (2014) provide 43 definitions of SR, indicating that they share three common elements: SR are undesirable events whose causes are systemically significant and whose effects have an impact on the real economy. In order to avoid economic crises such as the subprime crisis in 2008 or the crisis in the euro area related to excessive public debt in 2011 whose effects are still felt today, particular attention should be paid to the prediction of the phenomenon and, in parallel, to the possibility of the crisis spreading once it occurs.

After the subprime crisis, all the financial supervising authorities drew attention to the need for macro-prudential policy, which would take into account the dynamics of structure changes and linkages between financial institutions. Therefore, in 2013 IAIS, when developing a method of identifying insurance institutions of particular importance for financial stability, took into account the following five dimensions (IAIS, 2013): the size of the insurance institution (5%), the range of global activity (5%), the assessment of the degree of direct and indirect linkages of the institution within the financial system (40%), the non-traditional and non-insurance activity of the insurer (45%), the product substitutability (5%). In line with the IAIS recommendations, the Financial Stability Board (FSB) announced in 2016 a list of systemically important insurers (G-SIIs)[2]. From the point of view of the problem of measuring SR, in the last few decades several network models have been studied, e.g. Bilio (2012). Recently, the study of models using MST has also been intensified. MST are coherent, acyclic graphs realizing a minimum sum of weights assigned to edges. Various MST constructions are used in the literature, most often using the correlation coefficients of return rates. In our work we use a less standard MST construction method based on the tail-dependencies. The novelty of our contribution to literature consists in the use of a different MST construction than the ones known before, and the use of MST topological indicators for the multidimensional analysis of a group of 38 European insurance institutions in order to identify systemically significant ones. We empirically confirm the predictive capacities of the considered model.

3. Methodology

We carry out the analysis of the dynamics of interconnections between insurance companies using a new hybrid approach based on the combination of the copula-DCC-GARCH model and minimum spanning trees (MST). The construction of minimum spanning trees based on the dependencies in the tails plays a key role in it. To this end, using two-dimensional copula-DCC-

[2] Aegon N.V., Allianz SE, American International Group, Inc. (AIG), Aviva plc, Axa S.A., MetLife, Inc., Ping An Insurance (Group) Company of China, Ltd., Prudential Financial, Inc., Prudential plc.

GARCH models for each studied period t, $(t = 1, \ldots, T)$ and each pair of rates of return $r_{i,t}, r_{j,t}$, $(i, j = 1, \ldots, k, j > i)$ we estimate the bivariate joint distributions:

$$F_t(r_{i,t}, r_{j,t}) = C_{ij,t}\left(F_{i,t}(r_{j,t}), F_{j,t}(r_{i,t})\right), \tag{1}$$

where $C_{ij,t}$ denotes the copula, while F_t and $F_{i,t}$, $F_{j,t}$, respectively, are the joint cumulative distribution function and the cumulative distribution functions (*cdf*) of the marginal distributions at time t. In turn, making use of the copulas $C_{ij,t}$ we estimate the pairwise lower tail dependence of the returns $r_{i,t}, r_{j,t}$:

$$\lambda_t^L(i,j) = \lim_{q \to 0^+} \frac{C_{ij,t}(q,q)}{q} \tag{2}$$

Then, for each period t, we determine the "distance" matrix between insurance companies using the metric (Mantegna, Stanley, 1999):

$$d_t(i,j) = \sqrt{2(1 - \lambda_t^L(i,j))} \tag{3}$$

and using the Kruskal algorithm (Mantegna and Stanley, 1999), we construct minimum spanning trees MST_t with k vertices and $k - 1$ edges.

Based on the trees thus obtained MST_t $(t = 1 \ldots T)$ we determine the time series of the following selected topological network indicators, which describe the dynamics of the entire network: Average Path Length (APL), Maximum Degree (Max.Degree), the parameters α of the vertex degree distribution required to follow a power law, whose definitions can be found in the work Wang *et al.* (2014) and the indicators assessing the importance of network vertices: Betweenness Centrality (BC), Closeness Centrality, PageRank Centrality, whose definitions are given in the paper Sensoy and Tabak (2014).

4. Data and results of empirical analysis

The basis of the study are the stock quotes of 38 European insurance institutions. Most of them are on the list of the top 50 insurance companies in Europe based on total assets. AXA, a France-based company, is the largest insurance company in Europe and globally. It is also one of the world's largest asset managers with total assets under management of over 1.4 trillion euro. Allianz, headquartered in Munich, Germany, is the second largest European insurer in terms of assets. We include insurers analyzed in the work *Network analysis of the EU insurance sector* and nine additional ones[3]. We estimate the deltaCoVaR measure assuming that the European

[3] These are: Achmea (Eureko Group), Aegon Group/Unirobe Meeùs Group, AGEAS, Allianz, Aviva, AXA, BNP Paribas, Grupo Catalana Occidente, CNP Assurances, Royal Bank of Scotland Group, Generali, Groupe Crédit

insurance sector is represented by the STOXX 600 Europe Insurance index. We analyze weekly logarithmic rates of return for the period from January 7th, 2005 to December 20th, 2019.

In order to estimate $\lambda_t^L(i,j)$ we consider various specifications for two-dimensional copula-DCC-GARCH models. Finally, following the information criteria and model adequacy tests, we adopt for all the instruments the ARMA (1,1) -SGARCH (1,1) model with the skew Student distribution. When analyzing the dynamics of the dependencies between return rates, we consider Student copulas and various DCC model specifications. As before, based on information criteria, we select the Student copula with conditional correlations obtained from the DCC(1, 1) model and a constant shape parameter. We choose the same specifications for two-dimensional copula-DCC-GARCH models, which we use to estimate the deltaCoVaR measures. For each week-period we determine the MST_t and then the time series of three topological network indicators concerning the whole MST structure: APL, Max.Degree and the Parameter α.

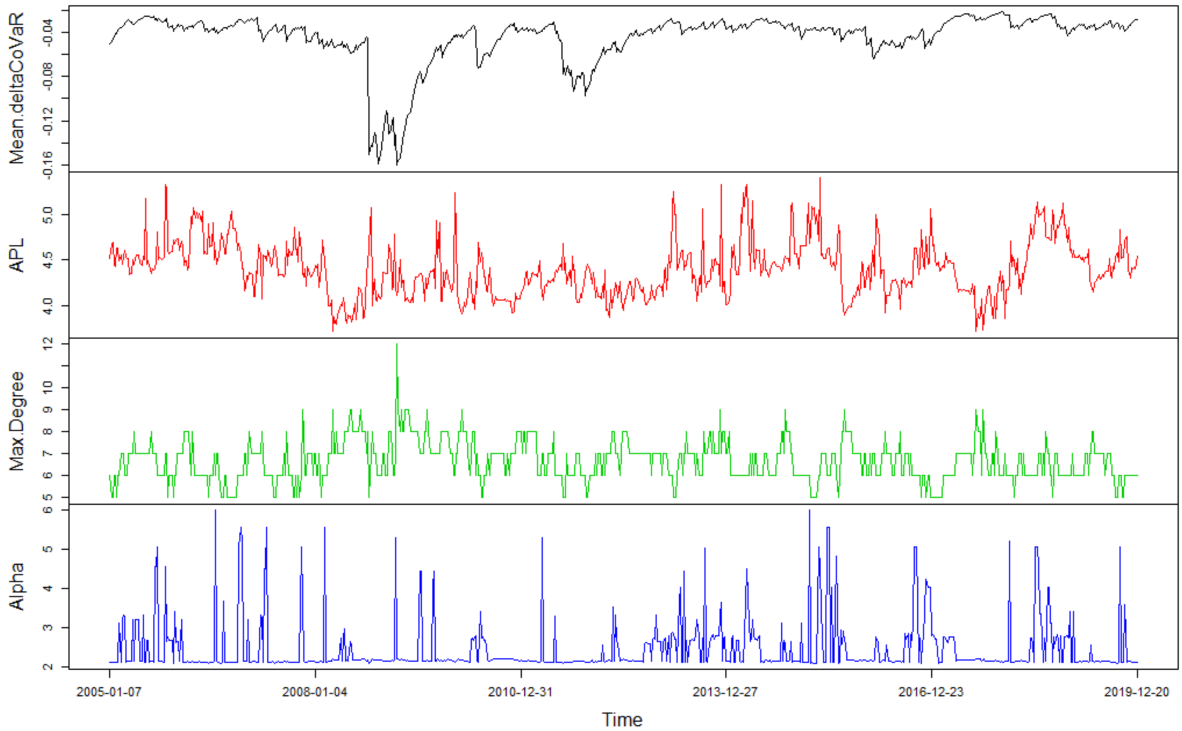

Figure 1. Mean deltaCoVaR, Average Path Length (APL), Maximum Degree (Max.Degree), The parameters α of the vertex degree distribution required to follow a power law

Agricole Assurances, HDI/Talanx, If P&C Insurance, ING Group, KBC, Legal & General Group plc, Mapfre, Munich Re, Old Mutual plc, Prudential, RSA Insurance Group, SCOR, Lloyds Banking Group, Unipol, UNIQA Insurance Group, Vienna Insurance Group, Zurich Insurance, Swiss Life, Chubb Ltd, Hannover Re, Storebrand, XL.Group, Helvetia Holding, Mediolanum, Sampo Oyj, Societa Cattolica di Assicurazione, Topdanmark A/S.

APL as the average number of steps along the shortest paths is responsible for the efficiency of information flow. The smaller the APL, the easier the network is to pass and thus the propagation of shock effects is faster. Max.Degree is the maximum number of all connections meeting in a single vertex of a given MST. The bigger Max.Degree the faster, because the possibility of negative events spreading is direct. The α parameter indicates the scale-free behavior of MST, i.e. if α takes values between 2 and 3, then MST has several vertices with numerous connections and many vertices with a low number of connections. We compare the obtained results with the results of the mean delta CoVaR analysis. Our study confirms that the insurance sector contributes to SR during and beyond the crisis (see Fig. 2). It follows that MST is scale-free, APL and Max.Degree indicators are mutually symmetrical, i.e. when APL decreases, Max.Degree increases. We see this in periods of subprime crises in 2008 and during excessive debt in the euro area. Another such behaviour of the ranks can be seen in 2017. what can be combined with the crisis of immigrants, which began already around 2014. These distinct periods coincide with the deltaCoVaR chart fluctuations. The smaller its value, the greater the sector's contribution to SR. Below Fig. 2 shows distribution of MST topological indicators APL, Max.Degree and Parametr α during 2005-2019.

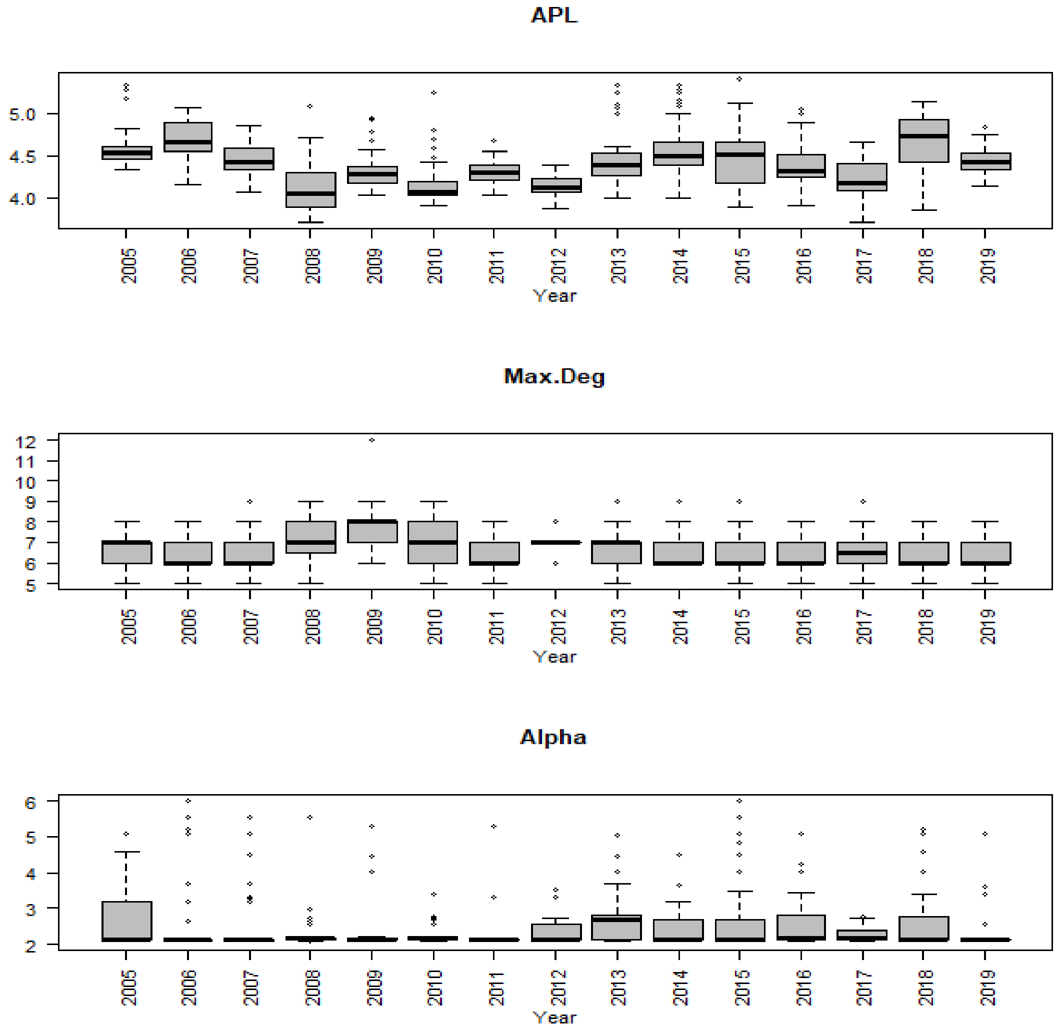

Figure 2. Distribution of MST topological indicators during 2005-2019

Next, we analyse the centrality indicators of the network, which reflect the importance of insurance institutions in the period from January 7th, 2005 to December 20th, 2019 and determine how much impact they have on the entire network. We confirm the systemic importance of the companies from the GSII list. Betweenness Centrality as a measure of "being in between" determines the "most important" vertices of a given MST, i.e. the most influential insurer. This measure indicates to what extent an institution serves as an intermediary for other network nodes. The higher the BC, the more "information" flows through it, in our case: the effects of financial turmoil. Closeness Centrality is a measure of the closeness between a node and all nodes in the network. If the vertices are relatively close together, it may foster contagion. If the nodes show similar results, it indicates a very connected network, and therefore an important mutual influence among the institutions. PageRank is a measure assigned to nodes based on their connections and then the connections of the latter. This measure reveals nodes whose influence goes beyond their direct connections.

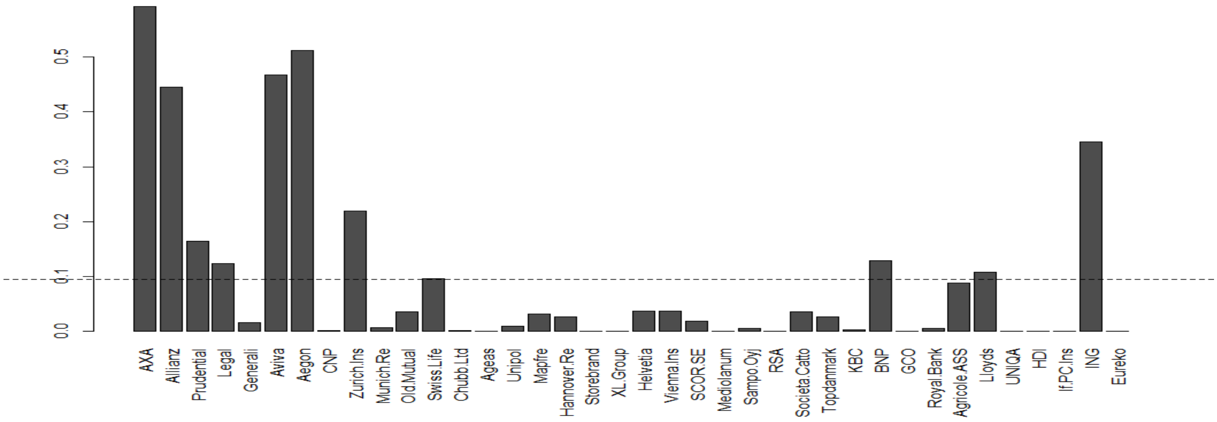

Figure 3. Average Betweenness

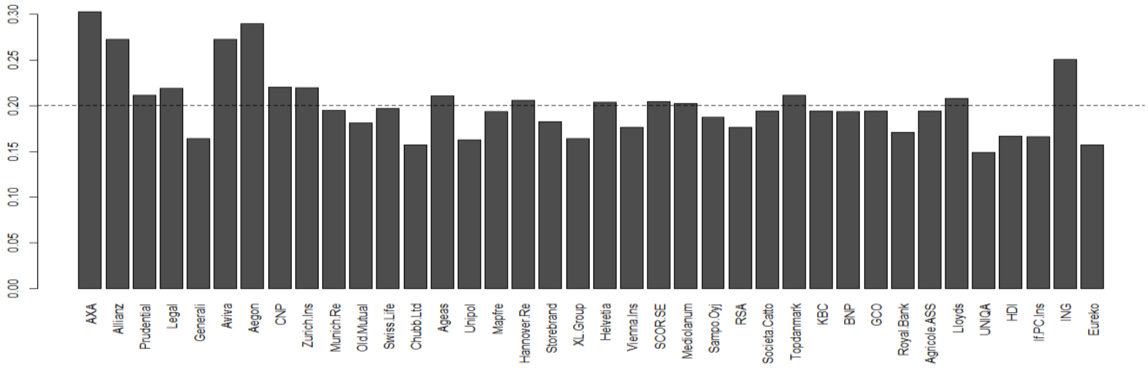

Figure 4. Average Closeness Centrality

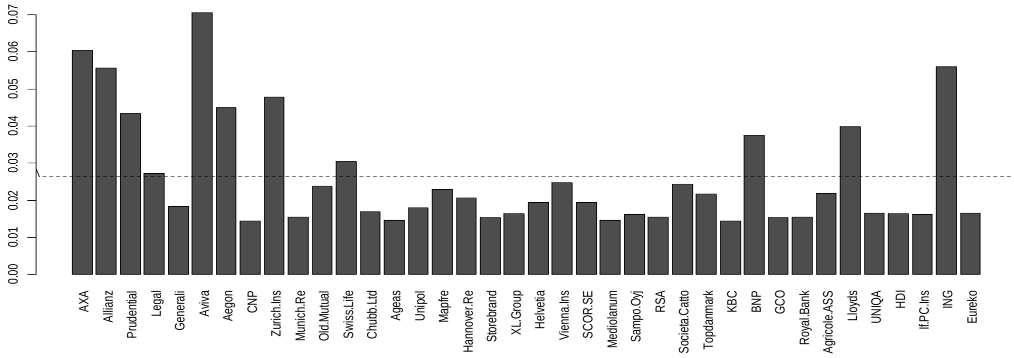

Figure 5. Average PageRang

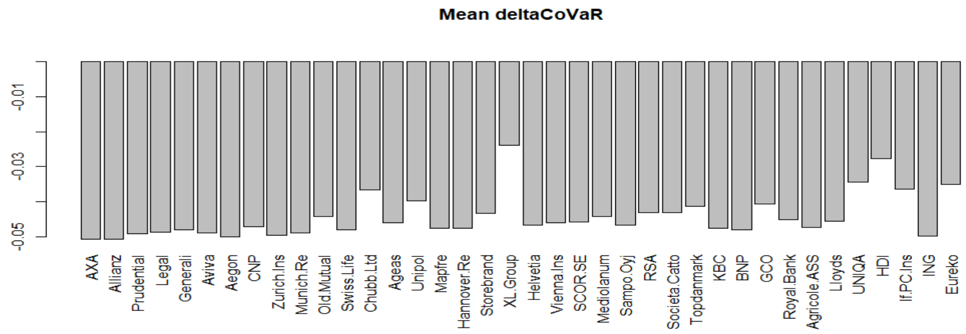

Figure 6. Average deltaCoVaR

The companies we cited previously have also the lowest deltaCoVaR as seen in Fig. 7. Below we show the *Vertex Strength* defined by Lautier and Raynaud (2013). It is another measure of closeness of a vertex to the others which has its significance in periods of crisis. The higher its value, the bigger area touched by economic turmoil and the large the impact of the latter on the whole sector.

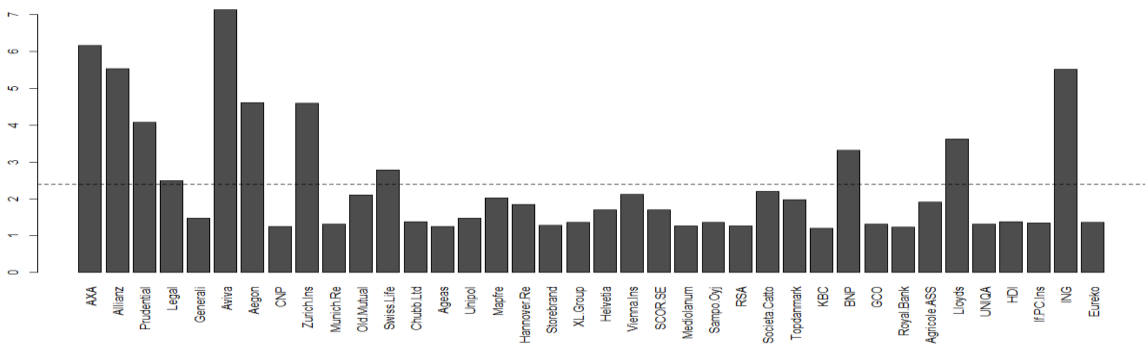

Figure 7. Average Vertex Strength

Sample MST's (Fig. 8) show different structures. During the subprime crisis, MST more concentrated. Their structure is more star-like, which favors the propagation of the negative effects of financial shocks and contributes to SR. However, during the period outside the crisis, MST have a more stretched structure, resembling a chain rather than a star.

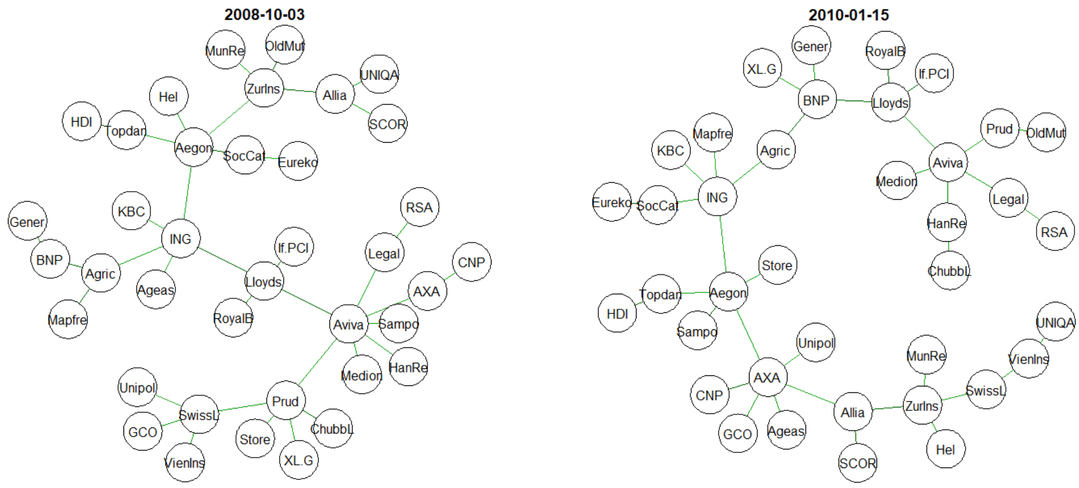

Figure 8. MST during and after the subprime crisis

5. Conclusions

Network analysis is an innovative method that improves data analysis. Discovering information contained in financial data, using a complex theory of indicators of the structure of the insurance market network, allows assessing the importance of institutions in the context of SR. Multidimensional MST analysis is a tool making it possible to observe the dynamics of connections in the insurance sector and thus the path of potential shock transmission. The centrality indicators from Fig. 3, 4, 5, 6 and 7 clearly show the importance in the context of SR of the following insurance institutions: Axa, Allianz, Aviva, Aegon, which all appear on the G-SIIs list, but the figures also expose the relevance of ING and Zurich Ins. The empirical analysis of the considered model indicates that the MST structure changes dynamically with the market situation. The crisis is preceded by a shrinking of the MST, the companies-hubs get a larger number of connections (Fig. 8), DeltaCoVaR decreases which means that the contribution to SR increases (Fig. 1). On Fig. 2 we observe the variation of the topological indicators. All this show the high predictive potential of the hybrid approach.

Acknowledgements

Publication was financed from the funds granted to the Department of Mathematics at Cracow University of Economics, within the framework of the subsidy for the maintenance of research potential. The author acknowledges her indebtedness to professor Stanisław Wanat for fruitful collaboration.

References

Acharya, V., Pedersen L.H., Philippon, T., Richardson, M. (2017). Measuring systemic risk. *Rev. Financ. Stud.* 30(1), 2–47.

Acharya, V., Engle, R., Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Econ. Rev.* 102 (3), 59–64.

Alves, I., Brinkhoff, J., Georgiev, S., Héam, J-C., Moldovan, I., di Carlo, M.S. (2015). Network analysis of the EU insurance sector, *ESRB Occasional Paper Series 07*, *European Systemic Risk Board.*

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, Vol. 104, nr 3, doi:10.1016/j.jfineco.2011.12.010.

Bisias, D., Flood, M., Lo, A.W., Valavanis, S. (2012). A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics*, Vol. 4, nr 1, doi:10.1146/annurev-financial-110311-10175.

Eling, M., Pankoke, D.A. (2016). Systemic Risk in the Insurance Sector: A Reviewand Directions for Future Research. *Risk Management and Insurance Review*, 19(2):249-284.

IAIS (2013). Global Systemically Important Insurers: Final Initial Assessment Methodology. *International Association of Insurance Supervisors*, July 18, Bank for International Settlements, Basel.

Keynes, J.M. (1936). The General theory of employment, interest, and money. *Macmillan and Co. Limited St. Martin's street, London.*

Lautier, D., Raynaud, F. (2013). Systemic risk and complex systems: a graph-theory analysis. *Econophysics of Systemic Risk and Network Dynamics*. Springer, pp. 19–37.

Li, W., Hommel, U., Paterlini, S. (2018). Network topology and systemic risk: Evidence from the Euro Stoxx market, *Finance Research Letters*, 27 105–112.

Mantegna, R.N., Stanley, H.E. (1999). Introduction to econophysics: correlations and complexity in finance, *Cambridge University Press*.

Sensoy, A., Tabak, B.M. (2014). Dynamic spanning trees in stock market networks: The case of Asia-Pacific. *Physica A: Statistical Mechanics and its Applications*, Vol. 414, pp. 387–402.

Wang, G.J., Xie, Ch., Zhang, P., Han, F., Chen, S. (2014). Dynamics of Foreign Exchange Networks: A Time-Varying Copula Approach, *Hindawi Publishing Corporation Discrete Dynamics in Nature and Society*, Vol. 2014, Article ID 170921, 11 pages.