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Financial resilience of insurance network during Covid-19 pandemic

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Abstract
We provide a novel approach for analysing the financial resilience of the insurance sector during coronavirus pandemic. To this end, we build temporal directed and weighted networks where the weights on the arcs take into account the tail dependence between couple of firms. To assess the resilience of the network, we provide a new global indicator, aimed at capturing the impact on the clustering coefficient of a shock affecting in turn each firm and diffusing in the network via shortest paths. A local measure of resilience is also provided by quantifying the contribution of each firm to the global indicator. In this way, we are able to detect most critical firms in the system. A numerical application has been developed in order to test the proposed approach. The results show that the proposed resilience measure appears able to detect main periods of financial crises. The first wave of COVID-19 pandemic results as a extreme phenomenon in the market and the lowest resilience is associated to the period in which COVID-19 has been declared pandemic.

Keywords COVID-19 · Insurance market · Resilience · Complex networks · Clustering Coefficient

JEL classification G01 · D85 · G32 · G28

1 Introduction

Over last years, an increasing attention to the concept of financial resilience by both regulators and academics has been paid. The New Economics Foundation defined it as a tool for dealing with long-term change and short-term shocks (Berry et al. 2015). In general, it is based on assessing the ability of a system to absorb shocks and it could be a very relevant task. Indeed, large fluctuations of a complex system could be generated by a very small impulse occurring in one of its components and the consequences of such instability might be devastating. In financial sector, particular attention has been devoted to strengthening the resilience by absorbing and adapting to shocks and disruptions.

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A recent example of a purely exogenous shock is represented by the pandemic event. As well-known, on December 2019, the outbreak of coronavirus (COVID-19) started in China and spread to countries and territories around the globe. On March 11, 2020, the World Health Organization (WHO) declared it a global pandemic. This pandemic has been not only the most serious global health crisis since the Spanish Flu, but according to the Bank of International Settlements it was likely to be one of the most economically costly pandemics in recent history due to the unprecedented and synchronised global sudden stop in economic activity induced by containment measures.

Many analysts and researchers have also linked the drop in global financial markets with the ongoing COVID-19 pandemic that leads to volatile and negative aggregate market reactions (see, e.g., Nikiforos 2020 and Ullah 2022). In this context, the analysis of the reactions and the resilience of the financial sector including stock markets, banking and insurance appears as a promising area of research (see, e.g., Ceron 2020 Goodell 2020 and So 2021).

While very few attempts have been made in this area (see Ashraf 2020; Zhang et al. 2020), resilience has been widely studied in complex network. Indeed, starting from (Albert et al. 2000), resilience has been theoretically analysed (Gao et al. 2000) and then extended by considering the effects of different vertex or link removal strategies on the network structure (see Clemente and Cornaro 2020; Ferraro and Iovanella 2017 and Iyer et al. 2013) or as a function of vertices' mixing preferences (D'Agostino et al. 2011). Particular relevance in the assessment of the resilience of a financial network is related to the measurement of the effects of a shock propagation over a system as a transition from different firms through their connecting links. Many analyses of financial resilience have been made considering dynamic evolution (Peron et al. 2012), incomplete information (Cinelli et al. 2021), risk management (Nagurney and Ke 2006), the diffusion of contagion and its relationship with the network structure (Elliott et al. 2013; Glasserman and Young 2016) and the proposal of resilience measure based on shocks' propagation (Cerqueti et al. 2022). In this framework we aim at evaluating the financial resilience of the insurance market by proposing a new measure of resilience applied to temporal directed and weighted networks. In particular, the proposed measure is based on the assessment of the effects on the clustering coefficient, a topological indicator widely used in the context of systemic risk (see, e.g., Bongini et al. 2018; Cerqueti et al. 2020; Minoiu and Reyes 2013; Tabak et al. 2014), of the shocks occurring in one of the vertices and on its propagation over the links of the network. As in Cerqueti et al. (2019), we assume that the propagation of a shock from a vertex to another one occurs over the shortest paths and that the propagation of the shock is opportunely rescaled as the distance from the shocked nodes increases. In this way, in each time period, we obtain both a global resilience measure for the whole network and a local one for each insurance company. To this end, we can both provide an indication of the resilience of the whole system and a ranking of the more risky firms in the market. This second aspect could be also important for the identification of global systemically important insurers (G-SIIs) (see IAIS 2013a and b for details).

Hence, the contribution of this paper to the existent literature is twofold. Firstly, few attention has been paid in the literature to the measurement of the resilience of the insurance sector and to the identification of most relevant insurers. Indeed, a model for evaluating systemic risk of different financial firms has been provided in Acharya et al. (2016). Systemic risk for the U.S and the European insurance sectors has been instead explored in Bertin and Sottocornola (2015) and (Cummins and Weiss (2014). The importance related to the identification of G-SIIs has been stressed in Clemente and Cornaro (2020, 2022); Denkowska and Wanat (2020) and Guiné 2014), focused on the assessment of relevant insurance companies. To the best of our knowledge, this work considers for the first time the financial resilience of the insurance market during COVID-19 pandemic by means of a network approach. Indeed, some preliminary analyses of the impact of COVID-19 on the insurance sector have been developed in Ramanasany (2020) and (Puławska 2021) using different approaches.

Secondly, the proposed resilience measure shows some advantages with respect to the existing ones. In the context of complex network, the most popular resilience measures evaluate the reaction of the overall system to an extreme shock based on vertex or edge removals (see Albert et al. 2000). Here, as in Cerqueti et al. (2022) and (Cerqueti et al. 2019) we analyse the direct reaction of the single firms to the shocks propagating from other firms. With respect to (Cerqueti et al. 2022) and (Cerqueti et al. 2019), we calibrate the weights in the network using market-based risk measures (as in Clemente et al. (2020)) and we assess the impact of the shock on the clustering coefficient, an indicator proved to be effective in measuring systemic risk in financial sector. The advantage is to be able to provide both a local and global measure of resilience.

An empirical analyses based on a very large set of insurance companies have been developed. The results show that networks' weights appear to be strictly related to the financial condition of the market. We observe indeed larger weights in periods of stressed conditions due to a higher tail dependence between firms' returns. Additionally, the proposed resilience measure appears able to detect main periods of financial crises.

The first wave of COVID-19 pandemic results as a extreme phenomenon in the market, characterized by a very dense graph, higher weights and lower values of resilience. In particular, the methodology associates the lowest value of global resilience to the period in which COVID-19 has been declared pandemic (i.e. March 2020). These results are in line with other works in the literature that explored the same topic on different perspective. For instance, Fontana (2021) shows in March the fastest fall in global stock markets due to the impact of Covid-19 announcements on the financial market. Furthermore, the local measure of resilience shows that insurers, classified as G-SIIs, appear as key risk spreaders.

The paper is organized as follows. Preliminaries and notations are introduced in Sect. 2. In Sect. 3 we describe the methodology for building the network and we introduce the proposed measure of resilience. In particular, in Sect. 3.1 we model the insurance market in different time periods using temporal directed weighted networks. In Sect. 3.2 we provide the methodology used for evaluating the resilience of the system and a local measure for identifying riskier firms. In Sect. 4 we describe how the sample of insurance companies has been selected over the period from 2000 to June 2022 and we present how we construct the network in each time period. Then, results are presented and discussed. Section 5 concludes.

2 Preliminary definitions and notations

We briefly introduce the mathematical definitions used in the paper (for further details we refer to Bang-Jensen and Gutin 2008 and Harary 1969). A graph $G = (V, E)$ is identified by a set V of n vertices and a set E of m unordered edges. Vertices i and j are adjacent (or neighbours) if $e_{i,j} \in E$.

A path between two vertices i and j is a sequence of distinct vertices and edges between i and j. In this case, i and j are connected. The graph G is connected if every pair of vertices is connected. A shortest path between two vertices is a path with the minimum number of edges.

The distance $d_{i,j}$ is the length of any shortest path between i and j. If i and j are not connected, then $d_{i,j} = \infty$. The diameter $diam(G)$ of a connected graph is the length of any longest shortest path.

A graph G is weighted when a positive real number $w_{i,j} > 0$ is associated with the edge $e_{i,j}$. We set $w_{i,j} = 0$ if nodes i and j are not adjacent. For weighted graphs, a shortest path is a path with the minimum sum of edge weights. A weighted distance $d^W_{i,j}$ can be also defined as the sum of weights of the shortest path. As for the unweighted case, if i and j are not connected, then $d^W_{i,j} = \infty$.

The adjacency relationships between vertices of G and the weights on the edges are described by a nonnegative, real n-square matrix $\mathbf{W}$ (the *weighted adjacency matrix*), with entries $w_{i,j}$.

A directed graph $D = (V, E)$ is obtained from G by adding to its edges a direction and G is the underlying graph of D. In this case, the links connecting pairs of vertices are called arcs (or directed edges). Also in this case, a weight $w_{i,j} > 0$ is associated with the arc $e_{i,j}$ and, in general, the matrix $\mathbf{W}$ is not symmetric. In fact, since two distinct arcs between a pair of vertices can exist, both $w_{i,j}$ and w_{ji} can be positive with $w_{i,j} \neq w_{ji}$.

A directed path from i to j is a sequence of distinct vertices and arcs from i to j such that every arc has the same direction; in this case, we say that j is reachable from i and we define this directed path as the out-path of the node i. The distance $\overrightarrow{d}_{i,j}$ from i to j is the length of the shortest out-path if any, otherwise $\overrightarrow{d}_{i,j} = \infty$.

Since directed paths from j to i can also exist, we denote with $\overleftarrow{d}_{i,j}$ the length of the shortest *in-path* of the node i based on the directed path from j to i. If i is not reachable from j, then $\overleftarrow{d}_{i,j} = \infty$.

D is strongly connected if every two vertices are mutually reachable. D is instead weakly connected if the underlying graph G is connected. Weighted directed distances $\overleftarrow{d}^W_{i,j}$ and $\overrightarrow{d}^W_{i,j}$ can be also defined as the sum of the weights of the weighted directed shortest paths.

In addition, we define the following sets in the directed graph:

- $\overrightarrow{N}_i(l) = \{j \in V | \overrightarrow{d}(i,j) = l\}$, for each $l = 1, \ldots, diam(G)$;
- $\overleftarrow{N}_i(l) = \{j \in V | \overleftarrow{d}(i,j) = l\}$, for each $l = 1, \ldots, diam(G)$.

The set $\overrightarrow{N}_i(l)$ collects the vertices j that can be reached from i with a directed path of length l. Vice versa the set $\overleftarrow{N}_i(l)$ considers the vertices j from which i can be reached with a directed path of length l.

3 Insurance network and financial resilience

We provide in this section the approach for describing the insurance market as a complex network. In particular, we construct temporal directed and weighted networks where, in each time period, insurance companies are vertices while the weights of the arcs measure the impact on the tail of the distributions of returns between insurers in the same time period.

In particular, in Sect. 3.1, we describe how the network is built and how the weights of the arcs are calibrated using market-based risk measures. In Sect. 3.2, we provide the proposed methodology used for assessing both the resilience of the network and the most critical firms.

3.1 Risk network of the insurance market

We are interested in representing the insurance market as a network in each time period. In particular, we consider a set of n insurance companies and we split the whole time period in different non-overlapping windows $t = 1, .., T$ of the same length.

In each window t, we denote the random variable (r.v.) equity returns of the insurance company i as X_i^t and the observed returns as x_i^t. Therefore, for each window, we collect the realizations of this random variable (i.e. the empirical returns of each listed insurance company) and we compute a set of measures in order to build a directed and weighted network.

Formally, we consider a set of directed and weighted networks $D_t = (V_t, E_t)$ where V_t is the set of n_t vertices ($n_t \leq n$), represented by the insurance companies for which returns are available in the window t. $E_t \subseteq V_t \times V_t$ is the set of m_t arcs in period t. We associate to each arc $e_{i,j}^t \in E_t$ with $i \neq j$, that connects adjacent nodes, a positive weight $w_{i,j}^t \in (0, 1]$. For each network D_t, we represent the adjacency relations between pairs of nodes by a n_t -square symmetric matrix $\mathbf{A}_t$ (the adjacency matrix) with entries $a_{i,j}^t = 1$ if $e_{i,j}^t \in E_t$, 0 otherwise. Similarly, the real n_t-square matrix $\mathbf{W}_t$ with entries $w_{i,j}^t$ is the weighted adjacency matrix of the network D_t in the window t.

A key aspect is represented by the procedure for calibrating the weights. To this end, we adapt to our context the approaches provided in Clemente and Cornaro (2022) and Clemente et al. (2020) that allow to consider the "tail effect "between institutions by means of standard market-based measures of systemic risk. These approaches, based on equity returns, also have common points with correlation networks that are applied to the financial sector and their evolution (e.g. Billio et al. 2012; Kenett et al. 2012 and Onnela et al. 2003).

Therefore, we set the weights in each period t as follows:

$$w_{i,j}^t = \begin{cases} 1 - r_{j|i}^t & \text{if } i \neq j \text{ and } E(X_j^t) \geq -MES_{j|i}^t \\ 0 & \text{otherwise} \end{cases}. \tag{1}$$

with $r_{j|i}^t = \frac{ES_j^t - MES_{j|i}^t}{ES_j^t + E(X_j^t)}$.

In formula (1), the term $r_{j|i}^t$ considers the impact of the distress of an insurer i on the insurer j in the same window t. In particular, the numerator is the difference between the expected shortfall of the firm (ES_j^t) and the marginal expected shortfall ($MES_{j|i}^t$), given by $ES_j^t - MES_{j|i}^t = -E(X_j^t | X_j^t \leq VaR_j^t) + E(X_j^t | X_i^t \leq VaR_i^t)$, where VaR_i^t is the Value at Risk[1] of the company i at time t. Notice that this difference is always non-negative and values close to zero indicate a stronger tail impact of i on j. Indeed, it could be interpreted as a proxy of

[1] The VaR of a generic firm j at a confidence level $1 - \alpha$ is here defined as (see, e.g., Artzner et al. 1999):

$$VaR_j^t(1 - \alpha) = inf\{x_j^t : F_{X_j^t}(x_j^t) > \alpha\} \tag{2}$$

where $F_{X_j^t}(x_j^t)$ is the cumulative distribution function of X_j^t. For a general definition of MES see Acharya et al. (2017). Please notice that we will neglect the reference to the confidence level $(1 - \alpha)$ in the text.

the risk of the insurer j that is not driven by the insurer i. Additionally, to assure comparability among institutions, we scale this quantity by a measure of the whole individual risk of the insurer j, given by the difference between the unconditional expected return $E(X_j^t)$ and the tail expected return ES_j^t.

Hence the term $r_{j|i}^t$ is always non-negative since both the numerator and the denominator are non-negative. Additionally, when the inequality $E(X_j^t) < -MES_{j|i}^t$ is satisfied, we have a positive reaction of j to the distress of the company i. Since we focus on risk propagation, we neglect these positive impacts assuring that the ratio is bounded between 0 and 1.

Therefore, since $r_{j|i}^t$ measures the portion of this risk of j that is not due to i, we define the weights $w_{i,j}^t$ as $1 - r_{j|i}^t$ to reflect the impact of the insurer i on insurer j (see formula (1)).

A higher value of $w_{i,j}^t$ means a higher impact between institutions or, in other words, it corresponds to a lower portion of the risk of j not being driven by the company i. In other words, when $w_{i,j}^t$ is close to one, a high level of dependence between i and j is observed. We have indeed that the average returns on the left tail of the distribution of j are approximatively the same when either the returns of i or the returns of j are lower than the correspondent Value at Risks.

3.2 Assessing the relevance of insurance firms

In this section we introduce the measure of resilience that is used in order to analyse the network in different time periods.

We start considering a topological indicator, the clustering coefficient, that has been widely applied to study systemic risk and to identify periods of financial turbulence (see, e.g., Cerqueti et al. 2020; Minoiu and Reyes 2013 and Tabak et al. 2014). Since we deal with a directed graph, different patterns have to be considered in the computation of the coefficient (see Clemente and Grassi 2018 and Fagiolo 2007). However, in Tabak et al. (2014), the authors argue that higher clustering of the "in "and "out"types may reflect higher systemic risk because the failure of the focal vertex in a triangle can propagate the risk to its neighbours, and these, in turn, can be unable to honour their own obligations. The implications of the other types of clustering (cycle and middleman) are more unclear in this context. Also the authors in Cerqueti et al. (2021) focus on the in and out coefficients to provide two novel measures of systemic risk.

Since we are interested in measuring the effect on the network of a shock propagation, we consider here the out-clustering coefficient provided in Fagiolo (2007). For a generic node i and considering the weighted and directed network D_t, we recall here the definition:

$$C_i^{out,t} = \frac{\left(\hat{\mathbf{W}}_t^2 \hat{\mathbf{W}}_t^T\right)_{ii}}{d_i^{out,t}\left(d_i^{out,t} - 1\right)}, \tag{3}$$

where $\hat{\mathbf{W}}_t = \left[\mathbf{W}_t\right]^{\frac{1}{3}}$ is the matrix whose entries are the 3^{rd} roots of $w_{i,j}^t$, $\hat{\mathbf{W}}_t^T$ is the transpose of $\hat{\mathbf{W}}_t$ and $d_i^{out,t} = \sum_{j \neq i} a_{i,j}^t$ is the out-degree of the vertex i in the network D_t. In what follows, we use the convention $C_i^{out,t} = 0$ when $d_i^{out,t} = 0$ or $d_i^{out,t} = 1$.

The overall out-clustering coefficient for the whole network $C^{out,t}$ is obtained as the average of the out-coefficients $C_i^{out,t}$ for all the vertices.

We now define the shocks, which are here modelled as local events occurring to a firm and that can propagate to other firms in the network. The entity of the shock plays a key role in the assessment of the resilience of the network and it is here defined by a positive parameter $\lambda \in (0, \infty)$. At a specific time period t, the shock starts from a given vertex $i \in V_t$ and propagates over the shortest paths with initial vertex i. It means that the firm becomes infected and the risk is propagated to the other firms that are connected to i through a directed shortest path. It is noteworthy that we assume that the vertex i does not react to subsequent solicitations given by the same shock. This assumption is in line with the approach provided in Cerqueti et al. (2022).

To model the propagation, we assume that in a period t the effect of the shock on a vertex i affects the network producing a new weighted matrix $\tilde{\mathbf{W}}_t(i)$, whose generic entries $\tilde{w}^t_{h,k}(i)$ are defined as follows:

$$\tilde{w}^t_{h,k}(i) = \begin{cases} \min\left(w^t_{h,k} \cdot \left(1 + \frac{\lambda}{\vec{d}_{i,k}}\right), 1\right) & \text{if } h, i \neq k \text{ and } k \in \overrightarrow{N}_i(l) \text{ for at least one } l \\ \min\left(w^t_{h,i} \cdot \left(1 + \frac{\lambda}{\vec{l}_{i,h,i}}\right), 1\right) & \text{if } h \neq k, k = i \text{ and } \vec{l}_{i,h,i} \text{ is finite} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where $\vec{l}_{i,h,i}$ is the length of the shortest directed cycle starting from i and ending in i and where the last arc is $e^t_{h,i}$. In case this cycle is not present, we set $\vec{l}_{i,h,i} = \infty$. The length of the shortest directed cycle can be obtained as follows:

$$\vec{l}_{i,h,i} = \begin{cases} \vec{d}_{i,h} + 1 & \text{if and } h \in \overrightarrow{N}_i(l) \text{ for at least one } l \text{ and } e^t_{h,i} \in E_t \\ \infty & \text{otherwise} \end{cases}. \tag{5}$$

It is noteworthy that the proposed approach based on formula (4) assumes that the shock affecting the firm i propagates in the network via shortest paths. Therefore, the effect on the other nodes depends both on the entity of the shock λ and on the distance with the infected firm. We have indeed that out-neighbours of the vertex i (i.e. vertices $j \in \overrightarrow{N}_i(1)$) are fully affected by the shock receiving an increase of the weight of the arc $e^t_{i,j}$ equal to $(1 + \lambda)$. Farthest firms (i.e. vertices $j \in \overrightarrow{N}_i(l)$ with $l > 1$) have instead a lower effect due to the presence of the reduction factor $\frac{1}{\vec{d}_{i,j}}$.

Given the new matrix $\tilde{\mathbf{W}}_t(i)$, the out-clustering coefficient is computed for each node $j \in V_t$ via formula (3). We denote the average value with respect to all the vertices as $\tilde{C}^{out,t}(i)$. This coefficient represents the average out-clustering of all the vertices computed on the network obtained by applying a shock to a vertex i and modelling the related propagation through formula (4).

Therefore, we introduce the following measure of resilience:

$$S^t_i = \tilde{C}^{out,t}(i) - C^{out,t}. \tag{6}$$

It is worth pointing out that $S^t_i \in [0, 1]$. We have indeed that formula (4) could lead to higher weights in the network but does not introduce new arcs. The out-clustering coefficient defined in formula (3) considers at numerator the geometric mean of the weights involved in a out-triangle. The number of potential triangle at the denominator of the formula remains instead unchanged. Therefore, a higher value of weights could lead to a higher coefficient, when these weights are involved in a triangle.

Additionally, it is noteworthy that S_i^t measures the systemic effect on the network due to a shock affecting a vertex i and its possible propagation in the network to other vertices. Given a specific choice of λ, lower is S_i^t and more resilient is the network. Therefore, for a time period t the procedure is repeated assuming that the shock will affect in turn each vertex $i \in V_t$ obtaining a set $\mathbf{S}^t = [S_i^t]_{i=1,\dots,n_t}$.

Each element of the vector can be interpreted as a local measure of resilience, assessing the effect on the system of shocks affecting in turn each vertex at time t. Indeed, the analysis of the heterogeneity between vertices can give information about the most critical firms in the network. The vertex with the higher value of S_i^t can be interpreted as the riskiest one for the network in case a shock occurs. At the same time, a global measure of resilience is provided by synthesizing the whole distribution. In particular, we introduce $R^t = \frac{n_t - \sum_{i=1}^{n_t} S_i^t}{n_t}$ as a global resilience measure. Notice that $R^t \in [0,1]$ and a higher value means a higher resilience of the network at time t. In the extreme case in which $S_i^t = 0\ \forall i$, we have $R^t = 1$. Indeed, in this case, each vertex, when subject to a shock, has no effect on the clustering coefficient (i.e. $\tilde{C}^{out,t}(i) = C^{out,t}\ \forall i$) and therefore, the network is assumed to be fully resilient.

4 Numerical application

4.1 Network description and preliminary results

The proposed approach has been applied to a very large set of insurance companies in the world. In particular, 348 listed insurance companies have been considered. The companies that belong to the sample are listed in Table 1 in Appendix. For each firm, equity returns have been collected[2] on daily basis from the beginning of January 2000 to the end of June 2022.

Returns have been split in non-overlapping windows of 2 months and have been used to construct a directed time-varying weighted network in each period as described in Sect. 3.1. To compute weights as defined in formula (1), VaR, ES and MES at the 95% confidence level have been estimated for each firm. Alternative methods can be used to estimate these risk measures, we applied historical simulations in this application[3].

For each window, we initially built a sequence of directed and weighted networks $D_t = (V_t, E_t)$ (with $t = 1, \dots, 135$), where insurance companies are vertices and the weights of the arcs measure the directed MES-based impact between insurers. It is worth pointing out that the number of assets can vary over time, since some of the firms have no information available for specific time periods. Therefore, in each window, to ensure a robust estimation of weights, we considered only insurers with a number of observations higher than 90% of trading days.

Hence, we consider 135 different networks, that, on average, have more than 230 vertices and more than 36,000 arcs. But in several windows, the networks are composed by all the firms with more than 75,000 edges. We plot in Fig. 1 the density of the networks over

[2] The equity returns and the companies have been collected from Yahoo finance only for firms for which that information was available in that period. We take into account all firms that are classified in the insurance sector.

[3] Risk measures are here computed under the real-world probability measure.

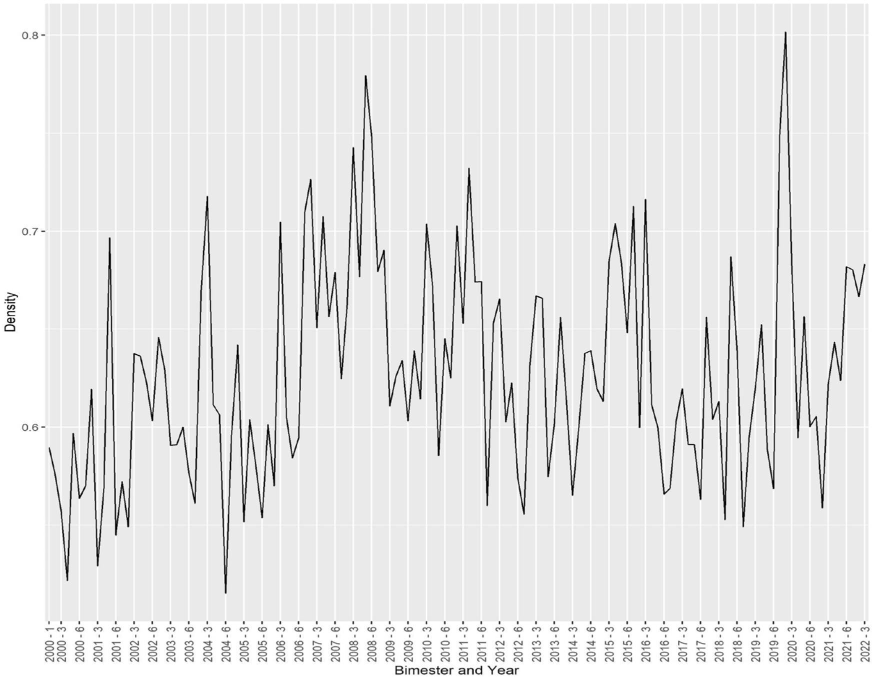

Fig. 1 Density of the networks over time. On the x-axis, we use the notation "Year-Bimester". For instance "2000 - 6" means the six bimester of 2000 (i.e. November–December 2000)

time. In particular, for each graph D_t we computed the ratio between the observed arcs and the maximum number of arcs that the graph can contain. We have on average networks very dense (the average density is indeed equal to 0.62) that confirms a significant dependence between firms. It is also interesting that the density increases in periods of financial turbulence due to a higher tail dependence in the returns' distributions. A relevant peak is indeed observed in 2008. This is mainly due to a very dense subgraph characterized by a subset of insurers (mainly U.S. firms) highly correlated and with higher values of ES. It is also noticeable the effect of the first wave of COVID-19 pandemic. We have indeed that the density has a relevant increase in the first bimester of 2020 moving from 0.57 at the end of 2019 to 0.75. The highest peak is reached in March-April 2020 with a density of 0.80 also higher than the values observed during the financial crises.

To better focus on this behaviour we start studying the patterns of the returns and of the weights. Main elements that are involved in the assessment of $r_{j|i}$ are displayed in Figures 2 and 3, where the distributions of average returns and Expected Shortfall are plotted over time.

In Fig. 2 the fluctuations of average returns of the companies in the sample can be noticed. As expected, the average returns are negative in the second semester 2007 and in 2008 because of the financial crisis. Also a higher volatility among firms is observed in the same periods. A slightly negative expected return is also observed in 2011 due to the sovereign debt crisis, that mainly affected the European firms in the sample. Furthermore, it is evident the impact of coronavirus on the financial market in the first semester of 2020 with

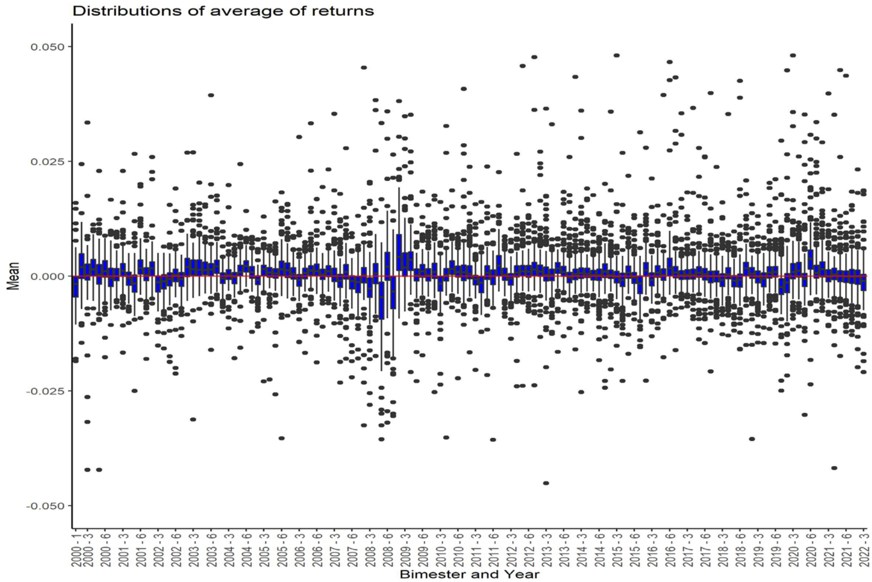

Fig. 2 Distributions of average returns at various time periods. On the x axis, we use the notation "Year-Bimester". For instance "2000 - 6" means the six bimester of 2000 (i.e. November–December 2000)

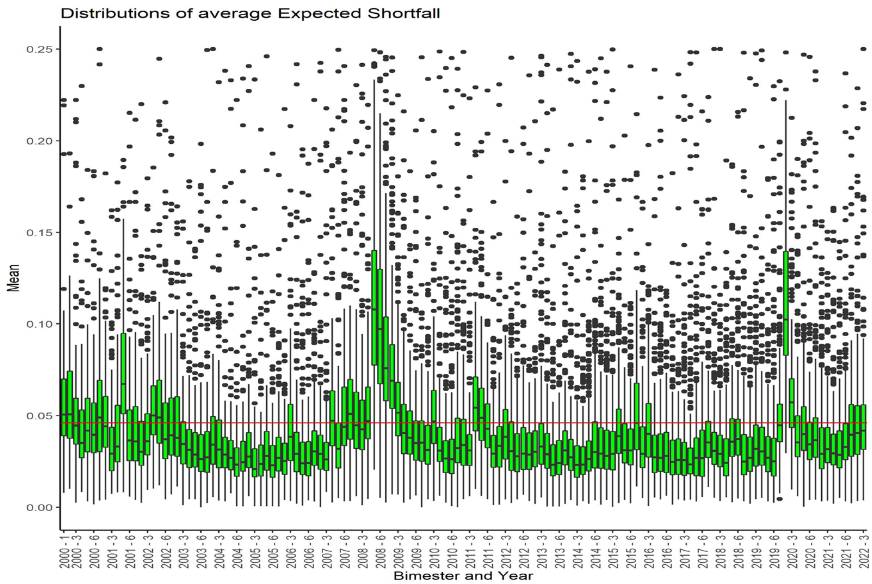

Fig. 3 Distributions of Expected Shortfall at various time periods. On the x axis, we use the notation "Year-Bimester". For instance "2000 - 6" means the six bimester of 2000 (i.e. November–December 2000)

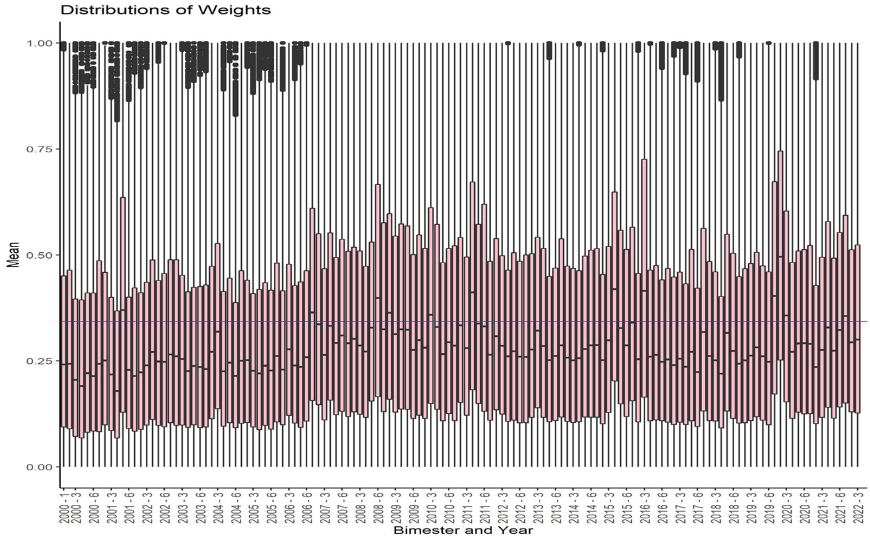

Fig. 4 Distributions of arc weights at different time periods, i.e. for the networks D_t previously introduced

an average return close to the values observed in 2008 and with a lower variability between firms due to a common behaviour in the period.

According to the ES distribution (Fig. 3), the 2007-2008 crisis is outstanding in terms of size and frequency of the extreme daily market losses. In the last months of 2007 and in the first semester of 2008, the median of this distribution reaches values close to 6%, higher than the average median in the whole period equal to 4.5%.

It is noticeable again the effect of the first wave of COVID-19 on the market with a higher turmoil in the first semester of 2020, when international investors start getting worried about the coronavirus spread outside of China and its impact on the global economy. For instance, between February and April 2020, it has been observed the fastest fall in global stock markets since 1929, identified by multiple daily drops (see, e.g., Fontana 2021 and Wagner 2020). This effect is fully reflected by the ES distributions. We have indeed that the median value at the end of 2019 is equal to 3.9%, while in the first and second bimesters of 2020 it increases to 5.7 and 11.6% respectively. The median goes down to 6% in May-June 2020 and then returns to quiet values in the second semester of the same year.

As described in previous Section, average returns and risk measures represent the elements used for calibrating the weights of the arcs in the network. To this end, we display in Fig. 4 the distributions of arcs' weights over time. Since weights $w^t_{i,j}$ measure the impact of the institution i on the insurers j at time t, distributions in Fig. 4 fully capture the increased distress that already affected the market in 2007 and reached a peak in 2008. Another important effect can be detected in 2011 during the sovereign crisis. We have indeed an average increase in the weights because MES is growing faster than ES.

A specific focus on the weights distributions during the first and second wave of COVID-19 pandemic has been reported in Fig. 5. In particular, it is noticeable the significant increase in the average value in the first and second bimester of 2020. In the period March-April 2020, the average weights are very close to 0.5, with the highest value in the whole period. Also in this case, we have a similar pattern between firms with a lower volatility of the distribution with respect to periods of financial crisis (e.g., 2007 and 2008).

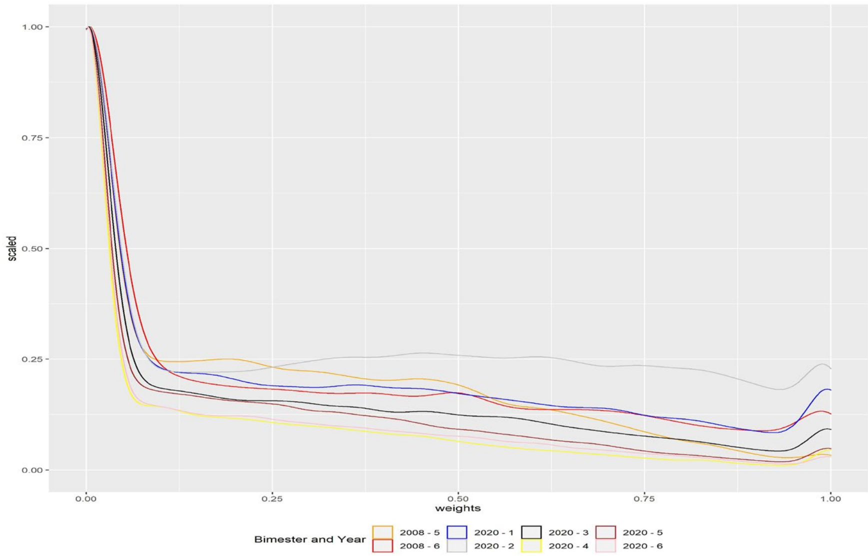

Fig. 5 Comparison of distributions of arcs weights in 2008 and 2020

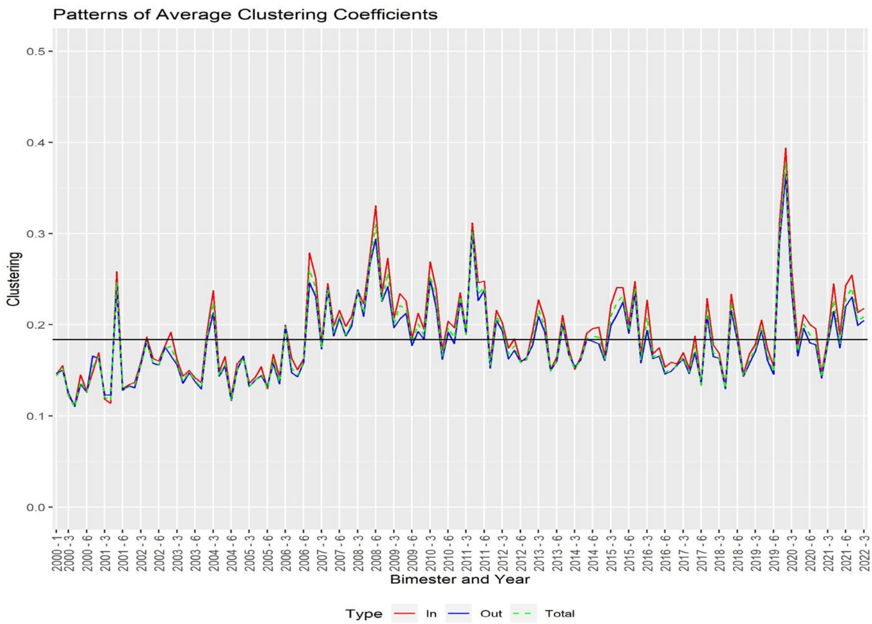

Fig. 6 Average clustering coefficients of the out, in and total type (see Fagiolo 2007 for details) over time

These results are mainly due to negative performances and significant tail dependences between firms. They are consistent with the findings in Zhang et al. (2020) that showed a significant increase in returns correlation in March 2020 when a pandemic has been announced by the World Health Organization.

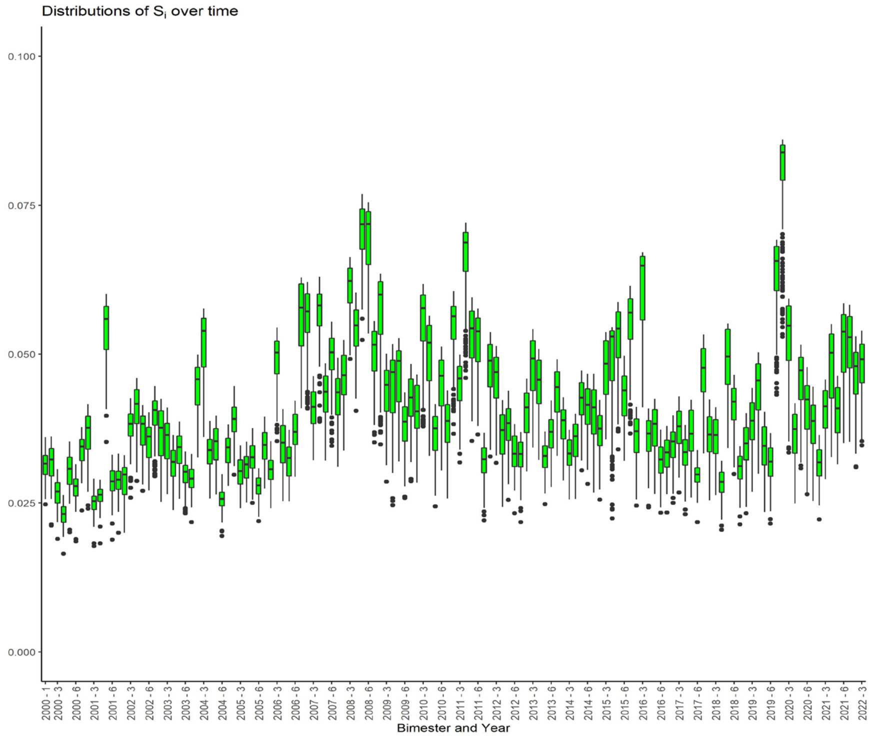

Fig. 7 Distributions of S_i^t over time computed assuming $\lambda = 0.3$

4.2 Financial resilience of insurance network

As described in Sect. 3.2, we now focus on the financial resilience of the insurance network during different periods. In particular, we start reporting in Fig. 6, the pattern of the clustering coefficients over time. As said before, this indicator has been widely used in the context of systemic risk. To this end, as in Holló et al. (2012) and Minoiu and Reyes (2013), we check if peaks can be plausibly associated with well-known crisis events. We observe that the coefficients' pattern evolves consistently with the underlying financial events. They tend to be lower in calm periods and rise before crises. Sharper spikes occur around highly popular events that caused severe stress in the global financial system. In particular, the 2008 financial crisis and the 2011 sovereign debt crisis stand out as unusually large perturbations to the network. Although based on a different dataset, these findings are in line with (Clemente et al. 2020). Finally, it is really noticeable the highest peak in the second bimester of 2020 during the fist wave of COVID-19 pandemic. As noticed before in Figs. 1 and 5, both the weights and the density of the network reach the highest values in that window providing a very high level of interconnectedness.

We also notice that to the same periods is associated, on average, a lower level of resilience of the firms. As shown in Fig. 7, the median value of S_i^t is higher than 6% between May and December 2008, in July-August 2011 and during the first semester of 2020. In particular, when the COVID-19 has been declared pandemic, the highest median value, equal to 8%, has been reached. Although, in general, the insurance market has proved to

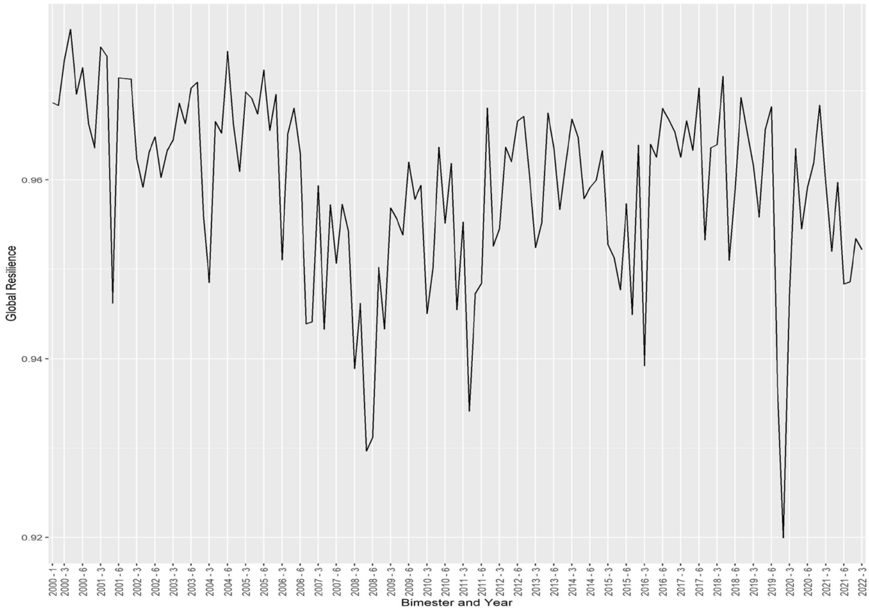

Fig. 8 Distributions of R^t over time computed assuming $\lambda = 0.3$

be resilient during the first wave of COVID-19 pandemic, this result shows that the effect of a shock propagation could undermine the stability of the system. It is also interesting to note that in this period a lower volatility between firms is observed with respect to financial crises, but, at the same time, the lowest skewness (equal to -1.72) has been obtained. This patten can be motivated with a general common behaviour between firms and the presence of very few insurers that reacted in a different way with respect to the market.

In terms of global resilience, Fig. 8 shows the pattern of R^t over time[4]. The resilience measure proves to be effective in capturing periods of financial crises showing significant reductions both in 2008 and 2011. Again, the most considerable effect is observed in March-April 2020 during the first phase of COVID-19 when the panic reaction of the global financial markets was primarily expected due to the high uncertainty surrounding the economic shock.

We also focus on the behaviour of each firm in terms of local resilience. In particular, in each period we rank firms on the basis of the value of S_i^t. We display in Fig. 9 the ranking of the insurance companies that have been classified as G-SIIs. Since Aegon has replaced Generali Assicurazioni on the list in November 2015, we consider as G-SIIs all firms that belong to the list at any time during the period.

Since we are considering measures computed on a network whose weights depend on the tail dependence between equity' returns, we can interpret firms in the top ranking as

[4] For the sake of simplicity, we report the results only for $\lambda = 0.3$ but the proposed approach has been tested also for alternative values of λ. Most important patterns detected holds also for different values.

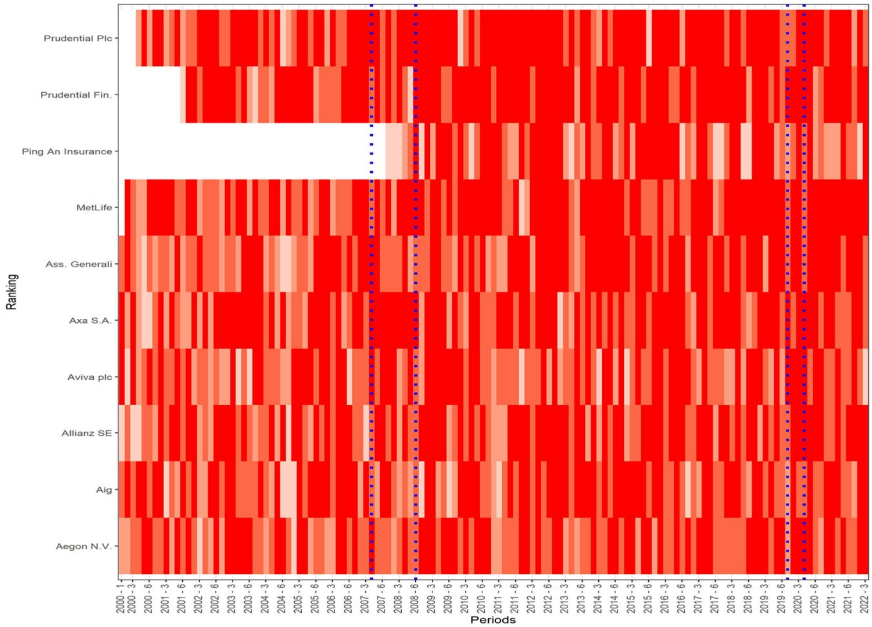

Fig. 9 Ranking based on S_i^t for G-SIIs. Rankings have been divided in four quartiles. Darker red means that the firm belongs to the top quartile. The blue lines highlight two key periods (June 2007–June 2008 and January 2020–August 2020)

the most relevant in spreading risk in the system. The methodology used by International Association of Insurance Supervisors (IAIS) for identifying systemic important insurers depends on several aspects, but the sizes of the firms and their interconnectedness with the system are two relevant issues. However, other elements, as global activity, asset liquidation and substitutability, have been considered (see, e.g., [25] and [36]). In our analysis, we assess the relevance of the firm mainly on its interconnections in the system measured through the tail of the returns distributions. Hence, the proposed approach cannot be interpreted as a replacement of the methodology provided by IAIS, but more as a complement that focuses on a specific issue.

It is worth pointing out that insurance companies, that are classified as G-SIIs, are present in Fig. 9 in the top ranking. The main exception is represented by Ping An Insurance, that, although is classified as a G-SII, belongs to very low quartiles of the distributions. However, the presence of Ping An Insurance in the G-SIIs list is mainly justified by its size[5] that is not considered in our approach.

These results are in line with (Clemente and Cornaro 2022) and (Denkowska and Wanat 2020). Although a smaller sample of firms has been considered in Denkowska and Wanat (2020) and different approaches have been used in Clemente and Cornaro (2022) and (Denkowska and Wanat 2020), a common point is represented by the use of market-based indicators computed on equity returns and by the application of methodologies to catch the

[5] The company has been classified as the third insurer in the world in terms of net premiums and in the top ten in terms of non-banking assets by AM Best in 2018.

dependence in the tails. As in our case, the authors confirmed the relevance of several firms that belong to the list.

It is also interesting to note that both during the financial crises and the first wave of COVID-19, G-IIs behave as key firms in spreading risks.

5 Conclusions

In this paper we study the financial resilience of the insurance market with particular focus on the COVID-19 pandemic period. To this end, we provide a methodology based on a combination of market-based measures and a network approach for assessing the resilience of the market.

In particular, we provide a novel resilience measure for the whole network, calibrated considering the effect of a shock that, in turn, affects each vertex of the network and propagate over shortest paths. Indeed, the proposed measure considers which is the effect of a shock propagation on the clustering coefficient, a topological indicator widely used in the field of systemic risk.

We also evaluate the contribution of each firms to the resilience providing a suitable tool for assessing the riskier insurance companies in the market.

The empirical analysis shows that the global resilience indicator evolves consistently with the main crisis events observed in the market. In particular the first wave of COVID-19 emerges as a unusual perturbation in the network and it has been detected by the proposed resilience measure.

Additionally, we find that the insurers, present in the G-SIIs list by the IAIS, are classified as relevant firms with very few exceptions. Further researches will regard the use of community detection approaches to investigate how insurance company tend to cluster togheter in different periods. This analysis should allow to identify the presence of common patterns in period of financial crises or in stressed conditions as during the COVID-19 pandemic period.

A List of Insurance Companies in the sample

See Table 1.

Table 1 List of insurance companies in the sample

Admiral Group plc	Markel Corporation
Advance Create Co., Ltd.	Marsh & McLennan Companies, Inc.
Aegon N.V. (AEG)	Max Financial Services Limited
Aflac Incorporated	MBIA Inc.
ageas SA/NV	Medibank Private Limited
Agesa Hayat ve Emeklilik A.S.	Mediolanum S.p.A.
AIA Group Limited	Menora Mivtachim Holdings Ltd
AIG	Mercuries Life Insurance Co., Ltd.
Aksigorta A.S.	Mercury General Corporation
Al Alamiya for Cooperative Insurance Company	Meritz Fire & Marine Insurance Co., Ltd.
Al Khaleej Takaful Insurance Company Q.P.S.C.	MetLife
Al Rajhi Company for Cooperative Insurance	Metromile, Inc.
AlAhli Takaful Company	MGIC Investment Corporation
Al-Etihad Cooperative Insurance Company	Midwest Holding Inc.
Alinma Tokio Marine Company	Migdal Insurance and Financial Holdings Ltd.
Aljazira Takaful Taawuni Company	Min Xin Holdings Limited
Alleghany Corporation	Mirae Asset Life Insurance Co., Ltd.
Allianz Ayudhya Capital Public Company Limited	Momentum Metropolitan Holdings Limited
Allianz SE	MS &AD Insurance Group Holdings, Inc.
Alm. Brand A/S	Muang Thai Insurance Public Company Limited
Amana Cooperative Insurance Company	Munich.Re
Ambac Financial Group, Inc.	Nam Seng Insurance Public Company Limited
American Equity Investment Life Holding Company	National Western Life Group, Inc.
American Financial Group, Inc.	Net Insurance S.p.A.
American National Group, Inc.	New China Life Insurance Company Ltd.
AMERISAFE, Inc.	NFC Holdings, Inc.
AmTrust Financial Services, Inc.	nib holdings limited
Anadolu Anonim Türk Sigorta Sirketi	NMI Holdings, Inc.
Anadolu Hayat Emeklilik Anonim Sirketi	NN Group N.V.
Anicom Holdings, Inc.	NobleOak Life Limited
Aplus Asset Advisor Co. Ltd	Novus Acquisition & Development Corp.
Arabia Insurance Cooperative Company	Oicintra, Inc.
Arabian Shield Cooperative Insurance Company	Old Mutual Limited
Arch Capital Group Ltd.	Old Republic International Corporation
Argo Group International Holdings, Ltd.	Oxbridge Re Holdings Limited
Asia Financial Holdings Limited	Palomar Holdings, Inc.
Aspen Insurance Holdings Limited	Personal Group Holdings Plc
ASR Nederland N.V.	Phoenix Group Holdings plc
Assicurazioni Generali S.p.A. (G.MI)	PICC Property and Casualty Company Limited
Assurant, Inc.	Ping An Insurance (Group) Company of China, Ltd.
Assured Guaranty Ltd.	Power Corporation of Canada
Athene Holding Ltd.	Power Financial Corporation
Atlantic American Corporation	Powszechny Zaklad Ubezpieczen SA
Atlas Financial Holdings, Inc.	Primerica, Inc.
Aviva	Principal Financial Group, Inc.
AXA	ProAssurance Corporation

Table 1 (continued)

AXIS Capital Holdings Limited	Protector Forsikring ASA
Ayalon Holdings Ltd	Prudential Financial plc
Bajaj Finserv Limited	Prudential.plc
Bâloise Holding AG	PT Asuransi Bina Dana Arta Tbk
Bangkok Life Assurance Public Company Limited	PT Asuransi Bintang Tbk
BB Seguridade Participações S.A.	PT Asuransi Jasa Tania Tbk
Beazley plc	PT Asuransi Jiwa Sinarmas MSIG Tbk
Berkshire Hathaway Inc. (BRK-B)	PT Asuransi Kresna Mitra Tbk
Brighthouse Financial, Inc.	PT Asuransi Multi Artha Guna Tbk
Broad-minded Co.,Ltd.	PT Asuransi Ramayana Tbk
Brookfield Asset Management Reinsurance Partners Ltd.	PT Asuransi Tugu Pratama Indonesia Tbk
Bupa Arabia for Cooperative Insurance Company	PT Equity Development Investment Tbk
Buruj Cooperative Insurance Company	PT Lippo General Insurance Tbk
CASH.LIFE AG	PT Malacca Trust Wuwungan Insurance Tbk
Cathay Financial Holding Co., Ltd.	PT Maskapai Reasuransi Indonesia Tbk
Central Reinsurance Corporation	PT Panin Financial Tbk
Challenger Limited	PT Paninvest Tbk
Charan Insurance Public Company Limited	PT Victoria Insurance Tbk
Chesnara plc	Public joint-stock company Asko-Strakhovanie
China Development Financial Holding Corporation	Qatar General Insurance & Reinsurance Company Q.P.S.C.
China Life Insurance Company Limited (LFC)	Qatar Insurance Company Q.S.P.C.
China Pacific Insurance (Group) Co., Ltd.	Qatar Islamic Insurance Group Q.P.S.C.
China Taiping Insurance Holdings Company Limited	QBE Insurance Group Limited
Chubb Limited	QLM Life & Medical Insurance Company Q.P.S.C.
Chuou International Group Co., Ltd.	Quad M Solutions, Inc.
CIG Pannónia Életbiztosító Nyrt	Quálitas Controladora, S.A.B. de C.V.
Cincinnati Financial Corporation	Radian Group Inc.
Citizens Financial Group, Inc.	Rand Merchant Investment Holdings Limited
Clal Insurance Enterprises Holdings Ltd.	Randall & Quilter Investment Holdings Ltd.
Clientèle Limited	Ray Sigorta Anonim Sirketi
CNA Financial Corporation	Reinsurance Group of America
CNO Financial Group, Inc.	RenaissanceRe Holdings Ltd.
CNP Assurances SA (CNP.PA)	RheinLand Holding AG
COFACE SA	RLI Corp
Companhia de Seguros Alianca da Bahia	Root, Inc.
Conifer Holdings, Inc.	Rosgosstrakh Insurance Company
CTBC Financial Holding Co., Ltd.	RSA Insurance Group plc
Dai-ichi Life Holdings, Inc. (DLICY)	Ryan Specialty Group Holdings, Inc.
DB Insurance Co., Ltd.	SABB Takaful Company
DFV Deutsche Familienversicherung AG	Safety Insurance Group, Inc.
Dhipaya Group Holdings Public Company Limited	Saga plc
Direct Line Insurance Group plc	Sagicor Financial Company Ltd.
Discovery Limited	Sampo Oyj
Doha Insurance Group Q.P.S.C.	Samsung Fire & Marine Insurance Co., Ltd.

Table 1 (continued)

Donegal Group Inc.	Samsung Life Insurance Co., Ltd.
Ecclesiastical Insurance Office plc	Sanlam Limited
E-L Financial Corporation Limited	Santam Ltd
Employers Holdings, Inc.	Saudi Indian Company for Cooperative Insurance (Wafa Insurance)
Enact Holdings, Inc.	Saudi Re for Cooperative Reinsurance Company
Enstar Group Limited	SBI Life Insurance Company Limited
Equitable Holdings, Inc.	SCOR SE
Everest Re Group, Ltd.	Selective Insurance Group, Inc.
Fairfax Financial Holdings Limited	Shin Kong Financial Holding Co., Ltd.
Farglory Life Insurance Co., Ltd.	Shinkong Insurance Co., Ltd.
FBD Holdings plc	SHL Holdings Ltd.
Federal Life Group, Inc.	SiriusPoint Ltd.
FedNat Holding Company	SJVN Limited
FG Financial Group, Inc.	Società Cattolica di Assicurazione
Fidelity National Financial, Inc.	Sompo Holdings, Inc.
First Acceptance Corporation	Standard Life Aberdeen PLC Reg
First American Financial Corporation	State Auto Financial Corporation
Fubon Financial Holding Co., Ltd.	Stewart Information Services Corporation
General Insurance Corporation of India	Storebrand ASA
Genworth Financial, Inc.	Sul América S.A.
Gjensidige Forsikring ASA	Sumitomo Mitsui Financial Group, Inc.
Global Indemnity Group, LLC	Sun Life Financial Inc.
Globe Life Inc.	Suncorp Group Limited
Goosehead Insurance, Inc	Sundance Strategies, Inc.
Great Eastern Holdings Limited	Swiss Life Holding AG
GREAT WEST LIFECO PREF SERIES M	Swiss Re AG
Great-West Lifeco Inc.	Syn Mun Kong Insurance Public Company Limited
Greenlight Capital Re, Ltd.	T &D Holdings, Inc.
Grupo Catalana Occidente, S.A.	Talanx AG
Grupo Nacional Provincial, S.A.B.	Target Insurance (Holdings) Limited
GWG Holdings, Inc.	Thai Reinsurance Public Company Limited
Hallmark Financial Services, Inc.	Thaire Life Assurance Public Company Limited
Hannover Rück SE	The Allstate Corporation
Hansard Global plc	The Company for Cooperative Insurance
Hanwha Life Insurance Co., Ltd.	The Hanover Insurance Group, Inc.
Harel Insurance Investments & Financial Services Ltd	The Hartford Financial Services Group, Inc.
HCI Group, Inc.	The Mediterranean and Gulf Cooperative Ins. and Reins. Company
HDFC Life Insurance Company Limited	The National Security Group, Inc.
Health Assurance Acquisition Corp.	The Navakij Insurance Public Company Limited
Health Revenue Assurance Holdings, Inc.	The New India Assurance Company Limited
Helios Underwriting Plc	The People's Insurance Company (Group) of China Limited
Helvetia Holding AG	The Phoenix Holdings Ltd.
Heritage Insurance Holdings, Inc.	The Progressive Corporation

Table 1 (continued)

Heungkuk Fire & Marine Insurance Co., Ltd.	The Thai Setakij Insurance Public Company Limited
Hippo Holdings Inc.	The Travelers Companies, Inc.
Hiscox Ltd	Till Capital Corporation
Horace Mann Educators Corporation	Tiptree Inc.
HORAI Co., Ltd.	Tokio Marine Holdings, Inc.
Hyundai Marine & Fire Insurance Co., Ltd.	Tong Yang Life Insurance Co., Ltd.
iA Financial Corporation Inc.	Topdanmark A/S
ICC Holdings, Inc.	Tower Limited
ICICI Lombard General Insurance Company Limited	TQR Public Company Limited
ICICI Prudential Life Insurance Company Limited	Trean Insurance Group, Inc.
ICPEI Holdings Inc.	Triad Guaranty Inc.
Independence Holding Company	Trisura Group Ltd.
Industrial Investment Trust Limited	Trupanion, Inc.
Insr Insurance Group ASA	Trustco Group Holdings Limited
Insurance Australia Group Limited	Tryg A/S
Intact Financial Corporation	Türkiye Sigorta Anonim Sirketi
Inversiones La Construcción S.A.	Unico American Corporation
ipet Holdings,Inc.	Union Insurance Co., Ltd.
IRB-Brasil Resseguros S.A.	Unipol Gruppo S.p.A.
IRRC Corporation	UNIQA Insurance Group AG
James River Group Holdings, Ltd.	United Cooperative Assurance Company
Japan Post Insurance Co., Ltd. (7181.T)	United Fire Group, Inc.
Just Group plc	United Insurance Holdings Corp.
Kansas City Life Insurance Company	United Overseas Insurance Limited
Kemper Corporation	Universal Insurance Holdings, Inc.
Kingstone Companies, Inc.	Unum Group
Kinsale Capital Group, Inc.	UTG, Inc.
Korean Reinsurance Company	Vaudoise Assurances Holding SA
Lancashire Holdings Limited	Vericity, Inc.
Legal & General Group Plc	Vienna Insurance Group AG
Lemonade, Inc.	Voya Financial, Inc.
Liberty Holdings Limited	W. R. Berkley Corporation
Lifenet Insurance Company	Walaa Cooperative Insurance Company
Lincoln National Corporation	Wataniya Insurance Company
Loews Corporation	Waterdrop Inc.
Lotte Non - Life Insurance Co., Ltd.	Wesure Global Tech Ltd
LPI Capital Bhd	White Mountains Insurance Group, Ltd.
Maiden Holdings, Ltd.	Wüstenrot & Württembergische AG
Malath Cooperative Insurance Company	ZhongAn Online P & C Insurance Co., Ltd.
Manulife Financial Corporation	Zur Shamir Holdings Ltd
Mapfre, S.A.	Zurich Insurance Group AG

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