

Systemic risk and financial interconnectedness: network measures and the impact of the indirect effect*

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Abstract

This paper considers several network measures of connectedness applied to the network extracted using pairwise quantile regressions, i.e. it proposes the use of quantile based network measures to estimate the importance of Globally Systemically Important Financial Institutions. The purpose is to assert the different informative content between quantile based network measures and quantile based loss measures such as ΔCoVaR . We consider Globally Systemically Important Banks and Insurers and several Hedge Fund indices. We investigate whether systemic risk indicators based on network measures are similar to those based on ΔCoVaR and show that they are capturing different features. In particular, quantile regression based on network measures capture the indirect effect of risk spillovers that is instead ignored by quantile based loss measures. Finally, we compare quantile based network measures and quantile based losses measures highlighting the predicting power of the former during the global systemic crisis of 2007/2008.

1 Introduction

The global financial crisis of 2007/2008 and the European sovereign debt crisis have led academics and policy makers to focus on the stability of the financial system which plays a pivotal role in the transmission of shocks to the real economy [see Creel et al., 2015].

Since the financial system is increasingly complex and strongly interrelated, the interconnectedness among financial institutions in period of financial distress can lead to a rapid propagation of illiquidity, insolvency, and losses. In this regard, financial

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interconnectedness represents a key aspect of the financial stability. In fact, a highly interconnected financial network can absorb shocks through its linkages and be robust, but beyond a given magnitude, the same linkages may act as a propagator mechanism for those shocks leading to financial contagion and thus systemic risk. Haldane [2009] has characterized such a (financial) system aptly as *robust-yet-fragile*, that is robust, i.e. risk absorber in most of the cases, but suddenly risk-spreader where fragility prevails [for an analysis of the properties of a robust-yet-fragile system see Acemoglu et al., 2015, Bisias et al., 2012, Chinazzi and Fagiolo, 2015, for an update survey on systemic risk.]

As suggested by Schweitzer et al. [2009], the complexity of the economic system can be revised and extended with new paradigms using economic networks; and recently, the literature on systemic risk has started to use network theory to investigate the topology of financial networks in order to measure systemic risk [see Billio et al., 2012, Diebold and Yilmaz, 2014, Hautsch et al., 2014, Diebold and Yilmaz, 2015]. This paper is related to this stream of the literature. We apply several network measures on the networks extracted using pairwise quantile regressions. The purpose is to assert the different informative content between quantile based network measures and systemic risk indicators also based on quantile regression such as the quantile based loss measure ΔCoVaR proposed by Adrian and Brunnermeier [2016]. The key idea is that network measures based on the connectedness of the single institution to the others is a good proxy of his ability to spread or absorb risk in the system and therefore a good proxy for identify systemically important financial institution. These measures do not consider only the direct linkages but also the “indirect linkages”, i.e. two institutions could be connected not directly but simply because they are both connected to a third institution. The aim of this paper is to propose several measures that do not capture only direct shocks but also indirect shocks that dynamically propagate into the system. These measures are therefore different than the systemic risk measures that just look to the “contemporaneous” shock propagation during distress like ΔCoVaR .

We consider Banks and Insurers selected by the Financial Stability Board (FSB) as Global Systemically Important Financial Institutions (G-SIFIs) as well as Hedge Funds indices given that in many circumstances Hedge Funds has been indicated as the drivers of shocks spillover.

We compare the ranking of the financial institutions based on network measures and losses measures. The analysis shows that there is not so much similarities among the two ranking indicating that the two measures captures different features of systemic risk.

Moreover, our analysis shows that Hedge Funds are not the main central financial institutions and are largely absorbing risk rather than spreading risk in the system. We also investigate the predicting power of the network measure with respect to the loss measures and show that network measures have a larger predicting power than loss measures.

The paper is organized as follows. Section 2 presents the methodology we use to estimate loss measures and network measures. Section 3 presents the data and the descriptive statistics. Section 4 presents the results. Finally, Section 5 concludes.

2 Methodology

In this Section we present the quantile based measures we use to identify the importance of systemically important financial institutions. We consider two quantile based systemic risk measures: the quantile based loss measure ΔCoVaR proposed by Adrian and Brunnermeier [2016] and the quantile based network measures.

2.1 Quantile based loss measures: ΔCoVaR

ΔCoVaR represents the Value at Risk (VaR) of an institution (or a set of financial institutions, i.e. the financial system) conditional to an other institutions being under distress. The well-known VaR_q^i is defined by the quantile $q \in (0, 1)$,

$$\mathbb{P}(X^i \leq VaR_q^i) = q, \quad (1)$$

where X^i is the loss return of institution i . Consequently, the higher VaR_q^i , the higher the risk.

Adrian and Brunnermeier [2016] define $CoVaR_q^{j|i}$ as the VaR of institution j conditional on some event $\mathcal{C}(X^i)$ of institution i ,

$$\mathbb{P}(X^j | \mathcal{C}(X^i)) = q. \quad (2)$$

The authors define a contribution of a given institution i to j as ΔCoVaR that is the difference between the VaR of institution j conditional on the institution i being under distress, i.e. the $CoVaR_q^{j|X^i=VaR_q^i}$ and the VaR of institution j when returns of institution i are at 50th percentile. More formally, that is,

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{0.5}^i}, \quad (3)$$

In case both j and i in ΔCoVaR refer to individual institutions, the analysis involves the tail-dependency across the network of financial institutions: the Network- ΔCoVaR . Differently, if j represents the financial system (i.e., a set of financial institution or a market index), we refer to the System- ΔCoVaR ,

$$\Delta CoVaR_q^{\text{system}|i} = CoVaR_q^{\text{system}|X^i=VaR_q^i} - CoVaR_q^{\text{system}|X^i=VaR_{0.5}^i}. \quad (4)$$

and is suggested by the authors as a measure of systemic risk, i.e. the contribution of institution i to the risk of the system. Adrian and Brunnermeier [2016] suggest to estimate ΔCoVaR using quantile regression, that is,

$$\begin{aligned} X_t^i &= \alpha_q^i + \gamma_q^i \mathbf{M}_{t-l} + \varepsilon_{q,t}^i, \\ X_t^{j|i} &= \alpha_q^{j|i} + \beta_q^{j|i} X_t^i + \gamma_q^{j|i} \mathbf{M}_{t-l} + \varepsilon_{q,t}^{j|i}, \end{aligned} \quad (5)$$

where $i \neq j$, $\forall i, j = 1, \dots, n_t$ and $\varepsilon_{q,t}^{j|i}$ is a white noise process with $q \in (0, 1)$ and \mathbf{M}_{t-l} is a vector of lagged state variables. Then, the predicted values from equation 5 can be used to obtain $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$,

$$\begin{aligned} VaR_{q,t}^i &= \hat{\alpha}_q^i + \hat{\gamma}_q^i \mathbf{M}_{t-l}, \\ CoVaR_{q,t}^i &= \hat{\alpha}_q^{j|i} + \hat{\gamma}_q^{j|i} \mathbf{M}_{t-l} + \hat{\beta}_q^{j|i} VaR_{q,t}^i. \end{aligned} \quad (6)$$

Finally, the $\Delta CoVaR_{q,t}^i$ for the given institution i is equal to

$$\Delta CoVaR_{q,t}^i = \hat{\beta}_q^{j|i} (VaR_{q,t}^i - VaR_{0.5,t}^i). \quad (7)$$

2.2 Network systemic risk measures

A network at time t is defined as a set of nodes $V_t = \{1, 2, \dots, N_t\}$ and E_t edges among nodes. It can be represented through an N_t -dimensional adjacency matrix A_t , with the element $a_{ijt} = 1$, if there is an edge from i to j with $i, j \in V_t$ and 0, otherwise. The adjacency matrix A represents formally a network defining with a_{ij} the element in the row i and column j . In our framework self-loops are not allowed, in other words the elements of the diagonal are equal to zero. As an example, we define below an adjacency matrix with $n = 6$ and the associated graph in Figure 1.

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (8)$$

Each graph is defined by N nodes and E edges, the E edges link the nodes of the graph. In our example the matrix A is symmetric, i.e. $a_{ij} = a_{ji}$ and consequently

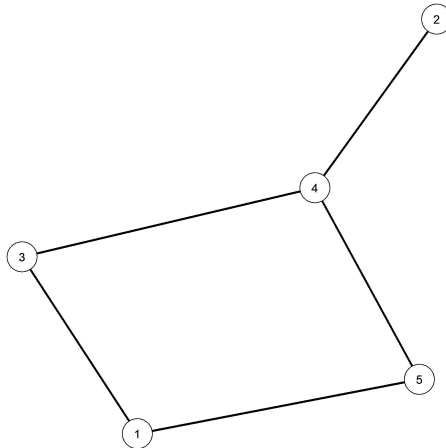


Figure 1: This Figure shows the resulting graph by using the adjacency matrix presented in the equation 8. Since the adjacency matrix is symmetric the graph is undirected. In this example, we show that each graph can be formally described by the adjacency matrix.

the associated graph is an undirected one, that is the effect of the node i on the node j is equal to the one of the node j on the node i . This type of graph is useful to model social interaction, web, molecular system and many more.

Differently, when the direction of the link matters, namely the link $i - j$ is different from $j - i$ then the graph is direct or called digraph. The matrix associated to this graph is not symmetric, and the edges have a direction represented by an arrow. In our analysis the networks are directed, in particular the convention we use for construct the adjacency matrix is the following: the element in the row i and column j is equal to 1 if the node j point out to the node i , i.e. $j \rightarrow i$ [for further information see Newman, 2010].

In this work, we represent the financial system with a network or a graph where nodes are the financial institutions and the links among nodes are estimated by

the the statistically significant relationship of tail dependence among institutions. Then we use network measures provided by the network theory to investigate the role of the different financial institution in the network in terms of risk spillovers and risk absorbers and therefore to identify whether one institution is more systemically important than another given its role in the network, i.e. in the financial system. In the next two Sections, we present in details first the methodology we use to construct the network using quantile regression. Second, we present the network measures that we then calculate from the network based on quantile regressions to investigate the role of each financial institution in propagating risk to the system that is the quantile based network measures we investigate later on in the empirical analysis reported in Section 4.

2.2.1 Network based on quantile regressions

The matrix A_t is estimated by using a pairwise quantile regression approach to detect the contemporaneous relationship in the (left) tail among the different financial institutions.

In order to test the quantile relationship the following model is estimated,

$$\begin{aligned} X_t^i &= \alpha_q^i + \sum_{l=1}^p \gamma_q^i X_{t-l}^j + \varepsilon_{q,t}^i, \\ X_t^{j|i} &= \alpha_q^{j|i} + \beta_q^{j|i} X_t^i + \sum_{l=1}^p \gamma_q^{j|i} X_{t-l}^j + \varepsilon_{q,t}^{j|i}, \end{aligned} \tag{9}$$

and

$$\begin{aligned} X_t^j &= \alpha_q^j + \sum_{l=1}^p \gamma_q^j X_{t-l}^i + \varepsilon_{q,t}^j, \\ X_t^{i|j} &= \alpha_q^{i|j} + \beta_q^{i|j} X_t^j + \sum_{l=1}^p \gamma_q^{i|j} X_{t-l}^i + \varepsilon_{q,t}^{i|j}, \end{aligned} \tag{10}$$

where $i \neq j$, $\forall i, j = 1, \dots, n_t$ and $\varepsilon_{q,t}^{j|i}$ and $\varepsilon_{q,t}^{i|j}$ are uncorrelated white noise processes with $q \in (0, 1)$. X_{t-l}^i and X_{t-l}^j are the autoregressive components. The relationship implies, $t = 1, \dots, T$,

- if $\beta_q^{j|i} X_t^i \neq 0$ and $\beta_q^{i|j} X_t^j = 0$, X_t^j is tail dependent from X_t^i and $a_t^{ij} = 1$ but not vice versa, $a_t^{ji} = 0$;
- if $\beta_q^{j|i} X_t^i = 0$ and $\beta_q^{i|j} X_t^j \neq 0$, X_t^i is tail dependent from X_t^j and $a_t^{ji} = 1$ but not vice versa, $a_t^{ij} = 0$;
- if $\beta_q^{j|i} X_t^i \neq 0$ and $\beta_q^{i|j} X_t^j \neq 0$, there is a tail mutual dependence among X_t^i and X_t^j , and $a_t^{ij} = a_t^{ji} = 1$.

The relationship between the financial institutions using the quantile regression is asymmetric which in turn implies an asymmetric adjacency matrix. Our approach is in spirit similar to the Network- Δ CoVaR proposed by Adrian and Brunnermeier [2016]. In fact, equation 5 is very similar to equations 9 and 10, the only difference are the covariates. However, in their case they look to the magnitude of the coefficient $\beta_q^{i|j}$ to estimate the loss as shown in equation 7 instead in our case we are

looking at the significance of the coefficient β_q^{ij} to generate the network of financial institution so that to apply the network measures that we describe in the next Section. Finally, we are similar in spirit to Billio et al. [2012] who also use network measure to investigate the systemically importance of financial institutions. The main difference between our approach and theirs is that the network in our case is based on quantile conditional dependence instead in Billio et al. [2012] it is based on Granger causality.

2.2.2 Quantile based Network measures

In this Section, we use the adjacency matrix A estimated using the quantile regressions in the previous Section to describe the network measures adopted for our analysis.

We distinguish the measures we consider between global measures if they aim to describe some particular feature of the network, and therefore measure the stability or fragility of the whole system, and local measures if they concentrate on the node or vertex level and measure the systemically importance of financial institutions.

Global Measures The measures we describe in this paragraph are labelled as “global” because, in contrast to the local measures, they give information on the whole network. These measures highlight the sparsity of the network or whether the links among the nodes are randomly distributed.

- **Density** is defined as the proportion between the number of edges actually present E and the number of edges theoretically possible N_t (the number of order 2 combination C_2^N among N nodes if the network is undirected; the number of order 2 permutation P_2^N among N nodes in the directed case),

$$D = \frac{E}{N_t} = \frac{E}{P_2^N} = \frac{E}{N(N-1)}. \quad (11)$$

The Density is equal to 0 if there are no edges E while it is equal to 1 if all linkages among nodes are present (full dense). According to Wasserman and Faust [1994], the density is a good indicator for capturing the whole network interconnectedness level.

- **Assortativity**

Assortativity by scalar properties

It is the difference between the number of edges among vertexes having the same characteristic and the expected number of edges among these vertexes if the attachment were purely random [Newman, 2002, 2003]. We define m_i the class of the vertex i , with n_m as the total number of classes in the network.

In the case of directed network, the number of edges among the vertexes of the same type results,

$$\sum_{ij} a_{ij} \delta(m_i, m_j), \quad (12)$$

where $\delta(m_i, m_j)$ is the delta Kronecker.

Assuming a random attachment, the expected number of edges among vertex of the same type is equal to

$$\sum_{ij} \frac{k_i^{out} k_j^{in}}{E} \delta(m_i, m_j), \quad (13)$$

where k_i^{out} is the OutDegree of the node i and k_j^{in} is the InDegree of node j . The assortativity Q divided by the number of edges E for the directed graphs results,

$$Q = \frac{1}{E} \left(\sum_{ij} a_{ij} - \frac{k_i^{out} k_j^{in}}{E} \delta(m_i, m_j) \right). \quad (14)$$

Since we want $-1 \leq Q \leq 1$ then we normalize Q with the maximum Q that can be obtained starting from N nodes and E edges; it happens when all E edges connecting all the vertexes which belong to the same category, so we can write the Q_{max} is equal to

$$Q_{max} = \frac{1}{E} \left(E - \sum_{ij} \frac{k_i^{out} k_j^{in}}{E} \delta(m_i, m_j) \right). \quad (15)$$

Therefore, the assortativity measures normalized is equal to,

$$r = Q/Q_{max}. \quad (16)$$

Since r can assume the values which belong in the range $-1 \leq r \leq 1$, they are interpreted in the following way

- if $0 < r \leq 1$, indicates the nodes have an homophily behaviour;
- r close to zero shows the network is a random graph, in other word the nodes don't have any preferential attachment;
- $-1 \leq r < 0$ indicates, the nodes offer disassortative pattern, in sense that nodes prefer to be linked to nodes belonging to different classes.

The assortativity is a measure related to the homophily of the network. The homophily is the behavior for which nodes with the same characteristics tend to connect each other. Sociologist evidenced assortative mix in the friendship, especially for these variables race and language [Moody, 2001]. The assortativity measure is very important for measuring systemic risk because it is useful to detect clusters in the network that can be useful to block the shocks propagation in some circumstances as a firewall.

Assortativity by degree

The assortativity can be also applied to the vertex degree. In other words, this measure is useful to capture the tendency of each node to connect with vertex having similar or different degree. This measure is interesting because it is able to detect a core-periphery structure of the graph when the assortativity coefficient is high. In Newman [2003], the assortativity by degree for undirected graph is defined as,

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2} \quad (17)$$

where,

- e_{jk} is the edges fraction connecting vertexes of j -th degree to vertexes of k -th degree;
- q_j is the probability to have an excess degree equal to j ;
- q_k is the probability to have an excess degree equal to k ;

– σ_q^2 standard deviation of the distribution of q_k .

For directed graph the assortativity measure is defined in the following way.

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j^{in}q_k^{out})}{\sigma_{in}\sigma_{out}} \quad (18)$$

where q_j^{in} and q_k^{out} are respectively the probability to have a excess InDegree equal to j and OutDegree equal to k .

Local Measures

In this Section, we explore some of the numerous local measures used to characterize the node centrality, i.e. the network measures used to identify which are the more central vertex, i.e. financial institutions that are more important, differentiating the directed case from the indirect one.

- **Degree**

In the undirected network, the degree indicates the number of links for which each vertex is linked to. If A is the adjacency matrix, then the degree is equal to

$$k_i = \sum_j A_{ij} \quad (19)$$

In the directed graphs, it is not possible to define the concept of a degree, because the edges are oriented, therefore is useful to distinguish the measures InDegree and OutDegree. Given the convention the same in Newman [2010], we use for representing the directed graph, the k_i^{in} InDegree and k_i^{out} OutDegree as defined according to these equations,

$$k_i^{out} = \sum_j A_{ij}, \quad (20)$$

$$k_i^{in} = \sum_j A_{ji}. \quad (21)$$

In particular, k_i^{in} (the InDegree of the node i) counts the number of edges pointing at the node i and k_i^{out} (the out degree of the node i) collects the number of outgoing edges from the node i . These measures are also known as InDegree centrality and OutDegree centrality which assess the centrality of a node and having explanatory power for the max percentage of financial losses [see Billio et al., 2012]. In particular, they indicate which are the nodes in the network spreading risk and which absorb it.

- **Eigenvector Centrality**

This measure proposed by Bonacich [1987], states that the centrality of one node is determined by the centrality of its neighbourhood. This could be formally defined as,

$$x_i = \sum_j A_{ij}x_j, \quad (22)$$

where the score x_i is related by the score of its neighbourhood and A is the usual adjacency matrix for undirected graph. Since this equation is self-referential,¹ in order to solve this equation it is necessary to apply an iterative

¹See Jackson et al. [2008].

process of t steps [Newman, 2010] that converges to this equation,

$$A\mathbf{x} = \lambda_1\mathbf{x} \quad (23)$$

where \mathbf{x} is the score vector collecting each vertex centrality x_i , and λ_1 is the maximum eigenvalue of the matrix A .² Therefore, for each vertex the centrality x_i is equal to the scored of its neighbours scaled by the maximum eigenvalue of the adjacency matrix A , that is,

$$x_i = \frac{1}{\lambda_1} \sum_j A_{ij}x_j \quad (24)$$

The concept of the eigenvector centrality could be applied to the directed network, but since the adjacency matrix is not symmetric the right and the left eigenvector are different. The question on which eigenvector to use is relevant. In general, this depends on the concept of centrality we give. If we consider a social network where each person can be represented by a node, then it is reasonable to think that, the node is more central as much as its neighbours have outgoing edges on it.³ In this case, the right eigenvector should be used. At the contrary, if we use the left eigenvector, then the node more central is the node having more outgoing edges pointing at nodes with high score.⁴ We chose this centrality measure because it explains the propagation of economic shocks better than other measure as closeness and between centrality [see Ahern, 2013]. The explanatory power of eigenvector centrality for the max financial loss percentage is also reported in Billio et al. [2012]. In addition, this measure from another perspective is the first principal component able to explain the greatest variation among the edges. Therefore, nodes having higher values are more central and they contribute more respectively to spread the risk (if we want to capture the OutDegree effect), or absorbing it (if we want to detect the InDegree effect).

Finally, this measures fit well to the systemic risk phenomenon because the shocks are characterized by the feedback effect [see Ahern, 2013] or called also indirect effect [see LeSage and Pace, 2009, Abreu et al., 2005]. With this formula, we are able to capture not just the contemporaneous shocks from one institutions to the others but also the following effects that this shock has on the institutions that are not directly connected to the one originating the shock, i.e. it captures the dynamic propagations of the shocks.

- **Katz Centrality**

The Katz centrality is slightly different with respect to the standard eigenvector centrality proposed by Bonacich [1987]. The measure proposed by Katz [1953], considers a node centrality as a function of the directed and undirected walks of its neighbours, weighted by an attenuation parameter alpha $0 < \alpha < 1$.⁵

²Perron-Frobenius theorem guarantees there exists only max real eigenvalue λ_1 if A is non-negative.

³The more central nodes have high InDegree, and they are pointed by nodes with high InDegree.

⁴The more central nodes have high OutDegree, and they are pointed by nodes with high OutDegree.

⁵A walk is a sequence of vertex and edges through which two vertex are linked. Some authors distinguish the concept of *path* from the concept of *walk*. For them a path is a walk where the intermediate vertex and edges are all different. The number of walk of length k from node i to node j is equal to A_{ij}^k .

The Katz centrality relative to the node i is defined as,

$$x_i = \alpha \sum_j A_{ij} x_j + \beta \quad (25)$$

where α is the attenuation parameter and β is an arbitrary term that avoids to consider in the centrality score all vertex having degree equal to zero. This term assumes the value of 1. For $\alpha = 1/\lambda_1$ and $\beta = 0$, the Katz centrality reduces to the centrality measure introduced by Bonacich [1987].⁶ If we write equation 25 in matrix form, we obtain,

$$\mathbf{x} = \alpha A \mathbf{x} + \beta \mathbf{1}. \quad (26)$$

If we write the expression function of \mathbf{x} , we obtain,

$$\mathbf{x} = (I - \alpha A)^{-1} \beta \mathbf{1}. \quad (27)$$

Since the $0 < \alpha < 1$, $(I - \alpha A)^{-1}$ is a convergence of a geometric series with

$$\mathbf{x} = (I + \alpha A + \alpha^2 A^2 + \dots + \alpha^k A^k) \beta \mathbf{1}. \quad (28)$$

Equation 28 is useful to understand the indirect impacts of connections, i.e. in which way the neighbours, and the neighbours of neighbours, affect the nodes centrality. The word “indirect effect” is used in spatial econometric in order to capture the spatial or the spillover impacts that arise in these models in response to neighbours changes in the explanatory variables [see LeSage and Pace, 2009, Abreu et al., 2005]. In this case, we use the term ”indirect effect”, because we aim to detect the effect coming from the neighbours using the Katz centrality equation that distinguishes the propagation of the shocks as a function of the number of walks. Short length walks are weighted more than higher order walks because of the attenuation parameter α . All the effects due to the neighbourhood are collected in this centrality measure.

In the empirical analysis, we compute the Katz centrality, both by making the matrix symmetric and by studying the behaviour of each single financial institution disentangling the ingoing effect and the outgoing effect separately. In this way, we can distinguish the nodes spreading the risk from those that absorb it with the Bonacich measure. The gain we obtain using the Katz centrality is the freedom to weight the feedback effects by choosing an appropriate attenuation parameter α . We are not the first to use this measure in finance: Branger et al. [2014] uses the Katz centrality to analyse shocks propagation in an equilibrium asset pricing framework.

3 The data

We use monthly returns data for Banks, Insurers and Hedge Funds downloaded from Datastream and Hedge Fund Research (HFR). We consider for the Banks and the Insurers the list of the global systemically important Banks (G-SIBs) and the

⁶The Bonacich centrality is a particular case of the Katz Centrality. We use both in our empirical analysis because they are able to capture the indirect effect coming from the neighbours. The first one is very common in the standard literature $\alpha = 1/\lambda_1$ and $\beta = 0$, the second one allows more freedom, because we can choose the α and β parameters.

list of the global systemically important Insurers (G-SIIs) as indicated by FSB.⁷ In particular, we include for the Banks the components of the fourth, third and second buckets⁸ while, for the Insurers, we include all the components. Therefore, the considered G-SIBs comprises HSBC, JP Morgan Chase (JP), Barclays, BNP Paribas (BARC), Citigroup (CITI), Deutsche Bank (DB), Bank of America (BoA), Credit Suisse Group (CSR), Goldman Sachs (GS), Mitsubishi UFJ FG (MUFG) and Morgan Stanley (MS). The considered G-SIIs are: Aegon N.V. (AGN), Allianz SE (ALC), American International Group Inc. (AIG), Aviva plc (AVA), Axa S.A. (AXA), MetLife, Inc. (MET), Ping An Insurance Group Company of China, Ltd. (PAI), Prudential Financial (PRU FIN), Inc. and Prudential plc (PRU).

The hedge-fund data consists of aggregated indices from the HFR provider where we consider two macro-categories: geographic (HFRX) and strategy (HFRI).⁹ For the geographic category, the following indices are included: Asia excluding Japan (ASI-AexJP), Japan (JP), North America (NA), Brasil (BR), China (CN), India (IND), Latin America (LA), Northern Europe (NE), Russia (RUS) and Western/Pan Europe Index (WPE). For the strategy category, the following indices are included: Equity hedge (EH), Emerging markets (EM), Event driven (ED), Fond of Funds (FOF), Macro and Relative value (RV).

As proxy for the market, we consider the MSCI World index which represents a broad global equity benchmark. Table 1 reports the full sample and biannual aggregated statistics including the annualized mean, annualized standard deviation, minimum, maximum, annualized median, skewness, kurtosis and the first-order autocorrelation coefficient ρ_1 for Banks, Insurers and Hedge Funds from January 2005 to January 2016. We consider equally weighted aggregated indices for Hedge Funds (Geographic and investment strategy), Insurers, and Banks. Insurers have the highest annual mean of 13% and the highest standard deviation of 31%. Banks have the lowest mean, 3%, and second highest standard deviation, 28%. Hedge Funds Geographic strategy indices have the highest first-order autocorrelation of 0.34, Hedge Funds Investment Strategy 0.21, Banks 0.25, and Insurers 0.25. This finding is consistent with the hedge-fund industry's higher exposure to illiquid assets and return-smoothing [see Getmansky et al., 2004] but it is striking for the Banks sector. We calculate the same statistics for different time periods: January 2005 - December 2007, 2008-2010, 2011-2013 and 2014-2016. These subsamples reflects tranquil, boom, and crisis periods. It is worth noting that the period 2014-2016 shows negative mean returns for both Hedge Funds categories and Banks. The period 2008-2010 is characterized by very large standard deviations, skewness, and kurtosis. In particular, the Insurers have the highest kurtosis in the full sample 8.23 and in almost all the subperiods.

⁷Lists updated in November 2015 available at <http://www.fsb.org/wp-content/uploads/2015-update-of-list-of-global-systemically-important-banks-G-SIBs.pdf> and <http://www.fsb.org/wp-content/uploads/FSB-communication-G-SIIs-Final-version.pdf>, for Banks and Insurers, respectively.

⁸Buckets identify the higher loss absorbency requirements that Banks will be required to hold.

⁹The minimum Asset Size for fund inclusion in the HFRX dataset is \$50 Mil. with at least 24-Month trackrecord while for the HFRI dataset is \$50 Mil. or at least 12-Month track record. For further details please see <https://www.hedgefundresearch.com/compare-hfr-index-types>.

Table 1: Summary statistics for monthly returns of Geographic and Investment strategy Hedge Funds, Banks, and Insurers for the full sample: January 2005 to January 2016, and five time periods: 2005-2007, 2008-2010, 2011-2013, and 2014-(January)2016. The annualized mean, annualized standard deviation, minimum, maximum, annualized median, skewness, kurtosis, and first-order autocorrelation are reported. We consider equally weighted aggregated indices for Hedge Funds (Geographic and investment strategy), Insurers, and Banks.

Full Sample									
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.	
HF Geographic	4	6	-7	5	7	-1.00	5.66	0.34	
HF Strategy	6	9	-8	7	8	-0.57	3.51	0.21	
Insurers	13	31	-39	35	15	-0.20	8.23	0.16	
Banks	3	28	-26	31	6	0.26	5.26	0.25	
January 2005 - December 2007									
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.	
HF Geographic	11	5	-2	3	12	-0.51	2.46	0.01	
HF Strategy	18	8	-4	5	21	-0.69	2.98	-0.03	
Insurers	20	14	-10	9	24	-0.56	3.58	0.02	
Banks	9	12	-9	7	13	-0.73	2.98	0.24	
January 2008 - December 2010									
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.	
HF Geographic	2	9	-7	5	6	-0.94	4.24	0.50	
HF Strategy	3	12	-8	7	7	-0.56	3.05	0.31	
Insurers	6	51	-39	35	14	-0.03	3.91	0.20	
Banks	-4	42	-26	31	-35	0.57	3.48	0.32	
January 2011 - December 2013									
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.	
HF Geographic	3	5	-4	3	6	-0.84	3.53	0.13	
HF Strategy	2	8	-5	4	4	-0.62	2.87	0.11	
Insurers	17	24	-16	18	21	-0.26	3.42	0.03	
Banks	11	28	-17	15	25	-0.39	2.47	0.12	
January 2014 - January 2016									
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.	
HF Geographic	-1	4	-3	2	-1	-0.32	2.53	0.17	
HF Strategy	-1	7	-4	4	-3	0.21	2.48	0.15	
Insurers	4	15	-10	10	11	-0.42	3.88	0.05	
Banks	-7	19	-16	11	3	-0.83	4.30	-0.02	

4 Empirical Analysis

In this Section, we estimate the systemic risk measures defined in Section 2 using data described in Section 3. To estimate systemic risk measures, we use a rolling window approach [e.g., see Zivot and Wang, 2003, Billio et al., 2012] with a window size of 36 monthly observations. Section 4.1 contains the results of the quantile based loss measure ΔCoVaR , and Sections 4.2 reports the quantile based network measures including a simple visualizations via network diagrams.

4.1 Quantile based loss measures: ΔCoVaR

We perform the rolling window quantile regression and estimate the ΔCoVaR for the 11 Banks, the 10 Insurers, 10 Hedge Funds geographical indices and 5 Hedge Funds strategy indices. Figure 2 shows the estimation results in terms of inter-quantile range at the 95% (gray area) and the mean (solid line) of the cross-sectional distribution of ΔCoVaR for Hedge Funds investment strategy, Hedge Funds geographic, Banks and Insurers over time. Figure 2 shows that Hedge Funds investment strategy and Banks have a ΔCoVaR dispersion higher (gray area) than the Insurers and Hedge Funds geographic, this also points out the systemic contribution heterogeneity of the institutions.

The Figure shows also a level shift for the mean and the median from 2008 to 2011 for all the considered financial institutions. The dispersion is also larger during the global financial crisis of 2007/2008 indicating the different roles of the financial institutions in contributing to systemic risk during the crisis.

For all the four categories we observe a reduction in the contribution to systemic risk in the last part of the sample indicating that either the economic and financial environment has been stabilized or the huge intervention of regulators on one side, that imposes a strong recapitalization of both Banks and Insurers, and the large injections of liquidity by central Banks has reduced indeed systemic risk.

Several other papers have investigated the performance of ΔCoVaR in identifying systemic risk [see in particular Giglio et al., 2016], we prefer to concentrate more on quantile based network measures and the comparison between quantile based loss measures ΔCoVaR and quantile based network measures.

Although the ΔCoVaR method can be easily implemented, one of its drawbacks is the systemic risk underestimation, because of its inadequacy in capturing the non-linear tail effect [Jiang, 2013]. This is the main purpose of the comparison that we perform in the following Sections.

4.2 Quantile based network measures

This Section reports the results of the centrality measures for the network estimated with the pairwise quantile regression. Figure 3 shows the network diagrams for June 2014 and July 2015. The total number of connections between financial institutions was 864 and 507, respectively, over a total of potential connections of 1260.

Figure 4 reports the global network measure we describe in Section 2.2. Figure 4 Panel a) shows the first of these global measure: the density of the network (equation 11), i.e. the percentage of significant connection through time. The figure shows a positive trend of the network density, from December 2007 until June 2014 and successively a sharply drop in July 2015 from 0.7 to 0.25. This pattern is in line with the reduction of systemic risk contribution of the different financial institutions

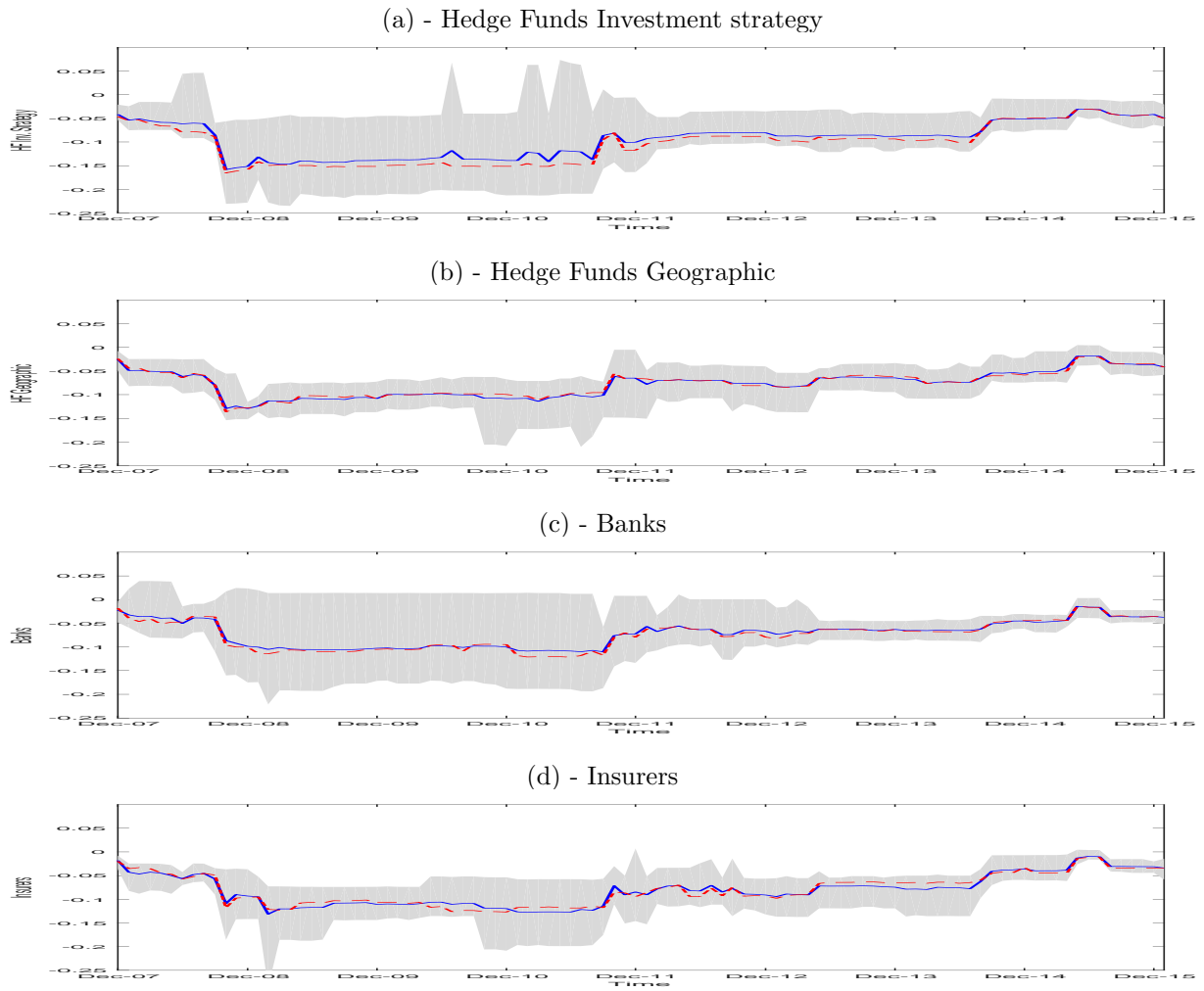


Figure 2: 95% high density region (gray area) and the cross-section mean (solid blue line) and median (dashed red line) of ΔCoVaR for Hedge Funds investment strategy (first Panel), Hedge Funds geographic (second Panel), Banks (third Panel) and Insurers (forth Panel) over time.

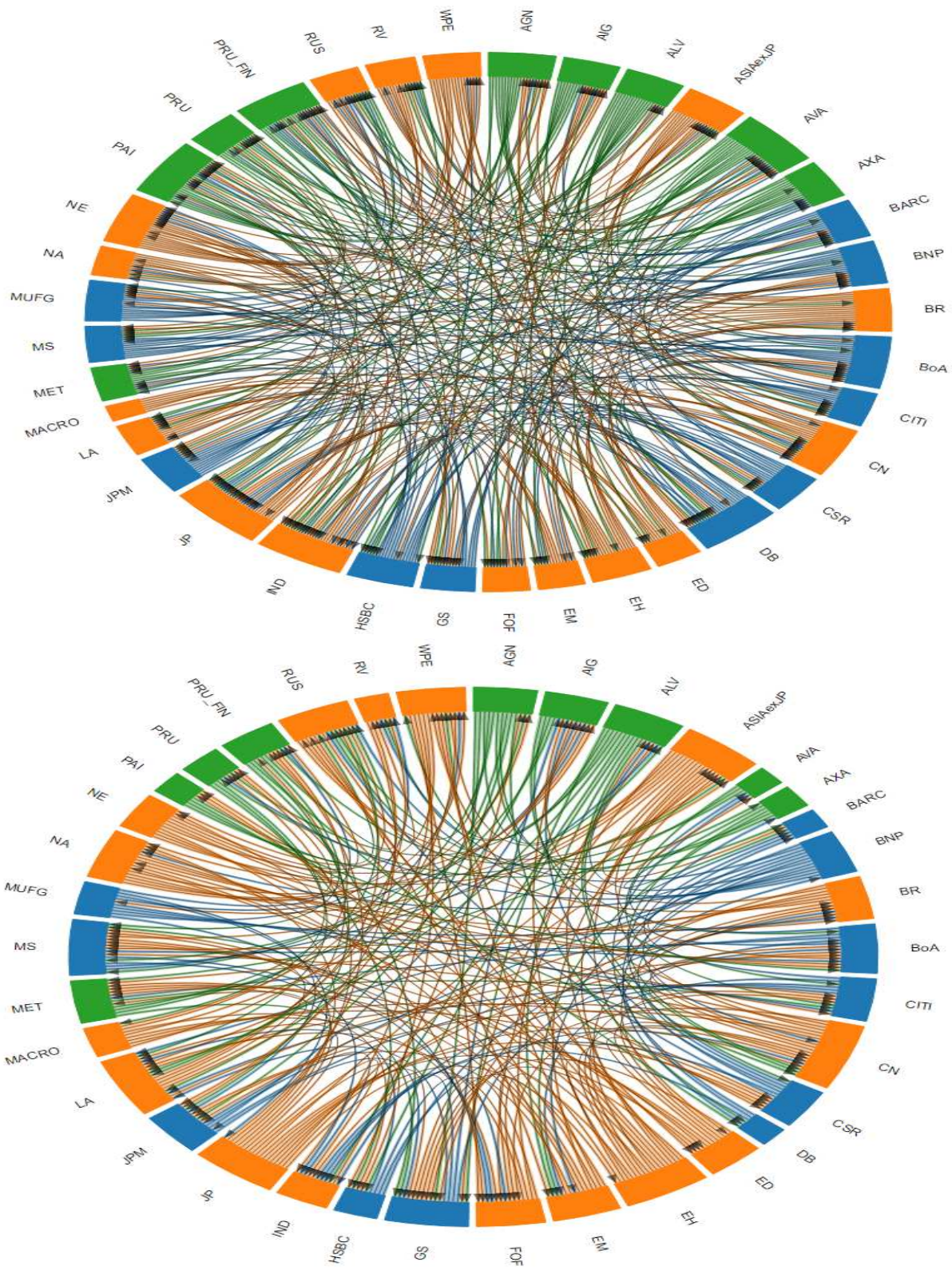


Figure 3: Network diagrams of pairwise quantile relationships that are statistically significant at the 1% level among the monthly returns in June 2014 (top) and July 2015 (bottom). Each node represents Hedge Funds indices (orange), Banks (blue), Insurers (green) and the edge describes the financial linkages. Labels are described in Section 3.

reported for the ΔCoVaR measure and indicates that the level of connections in the system are very low compared to the past.

Figure 4 Panel b) shows the behaviour of the Assortativity by degree (equation 18). This measure oscillates from a value close to zero in May 2008 to a negative values, or properly from a random graph to a graph with a slight disassortative tendency. A disassortative network has the property that high degree node tends to connect low degree nodes. A possible explanation of this behaviour can be imputed to the high density we observe in the period, the average is 0.5. The assortativity by degree reaches its minimum value in October 2008 with a value of -0.21. Acemoglu et al. [2012] highlight that the relationship between this measure and the systemic risk is relevant since in highly assortative or disassortative networks (as in this case), the moderate rate for which the aggregate idiosyncratic shock cancels out the diversification benefit. Thus, in a network with assortative or dissociative patterns, the shock propagation could be difficult to absorb. This is exactly what happens just after Lehman default in September 2008 as this measure indicates.

Figure 4 Panel c) reports the behaviour of the Assortativity by scalar properties (equation 16). The Figure shows that the network has an higher assortativity values respectively in the period from 2008-2011 and after June 2015. A deeper analysis of the measure (available upon request) indicates that during these periods Banks, Insurers and Hedge Funds tend to form groups separately. From June 2012 to December 2014, instead, the network could be associated to a random graph because the assortativity is close to zero. We then move to the local measures reported in Figure 5.

Figure 5 Panel a) and Figure 5 Panel b) exhibit respectively for each node the monthly rolling window InDegree and OutDegree (equation 21) and (equation 20), with the median (blue dotted line) and the mean (red line with circle 'o' marker). In addition, we computed the median for the three financial institutions groups: Hedge Funds (green line), Insurers (magenta line with asterisk '*' marker) and Banks (black dashed line).¹⁰ The Figure shows that the dispersion of the degree (the grey shadow area) is higher for InDegree than the OutDegree. Focusing on institutions categories by looking to the medians of the Figure 5 Panel a), we observe that before July 2011 there is a clear difference between Insurers (with the highest degree) and Hedge Funds and Banks (with the lowest InDegree). This indicates that Insurers during the global financial crisis where largely risk absorbers.

In the last part of the sample, there is a convergence among the median of the three groups. Figure 5 Panel b) shows that Hedge Funds (green line) have the highest OutDegree before October 2011, successively, the difference with the other institutions classes is unclear. Thus, after the 2011, the system becomes more interconnected and the categories start to be more connected in line with the drop of the assortativity for that period as reported in Figure 4 Panel c).

Finally, we report centrality measures. Figure 7 reports the Katz centrality measure (see equation 27). We distinguish two kinds of centrality, the first type considers the node prestige (centrality) directly related to the number of neighbours pointing at this node; the second type, instead, defines the centrality as function of outgoing links starting from that node and pointing at its neighbours. This differentiation allows us to understand how the orientation can influence the aggregation of the contribution to systemic risk of each financial institution. Panel a) of Figure 7 shows

¹⁰We also computed the average for each institutions class that can be compared with the median values.

a large dispersion in the last part of the period, instead, Figure 7 Panel b) has the highest peak in December 2011. For both Figures, we computed the median (blue dotted line) and the mean (red line with circle 'o' marker) for all the nodes, and also the median by institutions. Panel a) of Figure 7 shows that the Insurers Katz centrality dominates the other institutions classes until October 2011. In Figure 7 Panel b), the Hedge Funds Katz centrality dominates the other institutions until December 2011. In the last part of the sample, we observe again the convergence of the medians.

Figure 7 provides to us an overview of the heterogeneous centrality of the different institutions through time. However, it is important to investigate which institutions contribute more to the risk of the system or absorbed more risk. The median per group of institution already provides an idea. However, in order to analyse the centrality evolution among the institution classes, once computed all the Katz Centrality measures with $\alpha = 0.5$ and $\beta = 1$, we rank all the institutions, and choose the first 10% best centrality score, and successively we group them by class for each period, as in Figure 6. Panel A shows that after the July 2011, the Hedge Funds (blue area) are the more central institutions if we take into account the InDegree effect. Before July 2011, they were more central by looking at the OutDegree effect. This is also confirmed by Figure 5. Looking at the dynamic of the centrality, we observe a structural break in the last part of 2011 where there is a change in the topology property of the network.

In particular, the Hedge Funds role appears mutated although always central. If we consider the graph orientation, they behave as an “Hub” spreading the risk from December 2007 till December 2011, and as an “authority” absorbing the risk in the last part on the sample.¹¹

4.3 Rank correlation among the Δ CoVaR and network measures

To highlight the different information content of the quantile based loss measure and the quantile based network measure, we perform a rank correlation over time. We rank the financial institutions from 1 to 36 using both the quantile based loss measure Δ CoVaR and the quantile based network measures such as the Katz centrality InDegree and OutDegree with $\alpha = 0.75$. We then perform a rank correlation of the rankings. Results are reported in Figure 8.

Figure 8 shows that the correlation assumes negative and positive values with the rank correlation ranging from -0.40 to 0.40 both for the In and Out Katz centrality measures. Moreover, Katz centrality measure based on InDegree and OutDegree have a different rank correlation through time with Δ CoVaR indicating that they provide a different information content. Thus, a deeper investigation on the “directed” centrality measures is useful to understand in which way the directionality matters. Overall, our findings confirm that loss and connectedness measures exploit different dimensions of systemic risk.

¹¹In this context, the concept of hub and authority is purely network related [Newman, 2010]. A hub is a central node pointing other central nodes while authorities are central nodes that are pointed by hubs or other nodes.

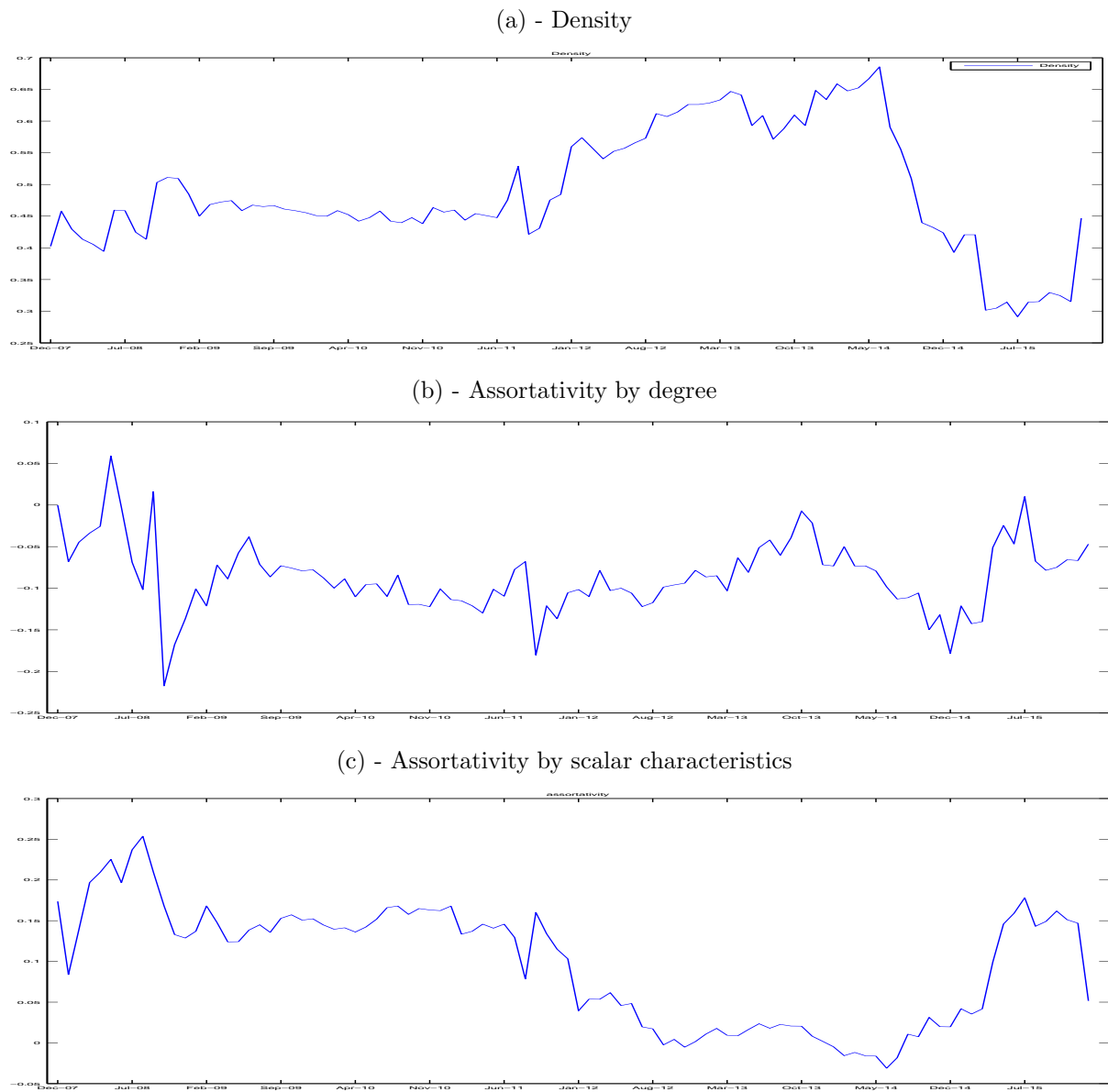


Figure 4: This Figure shows the global network measures from December 2007 till January 2016. Panel a) reports the density measures. Panel b) reports the assortativity measures by degree. Panel c) reports the assortativity by scalar characteristics.

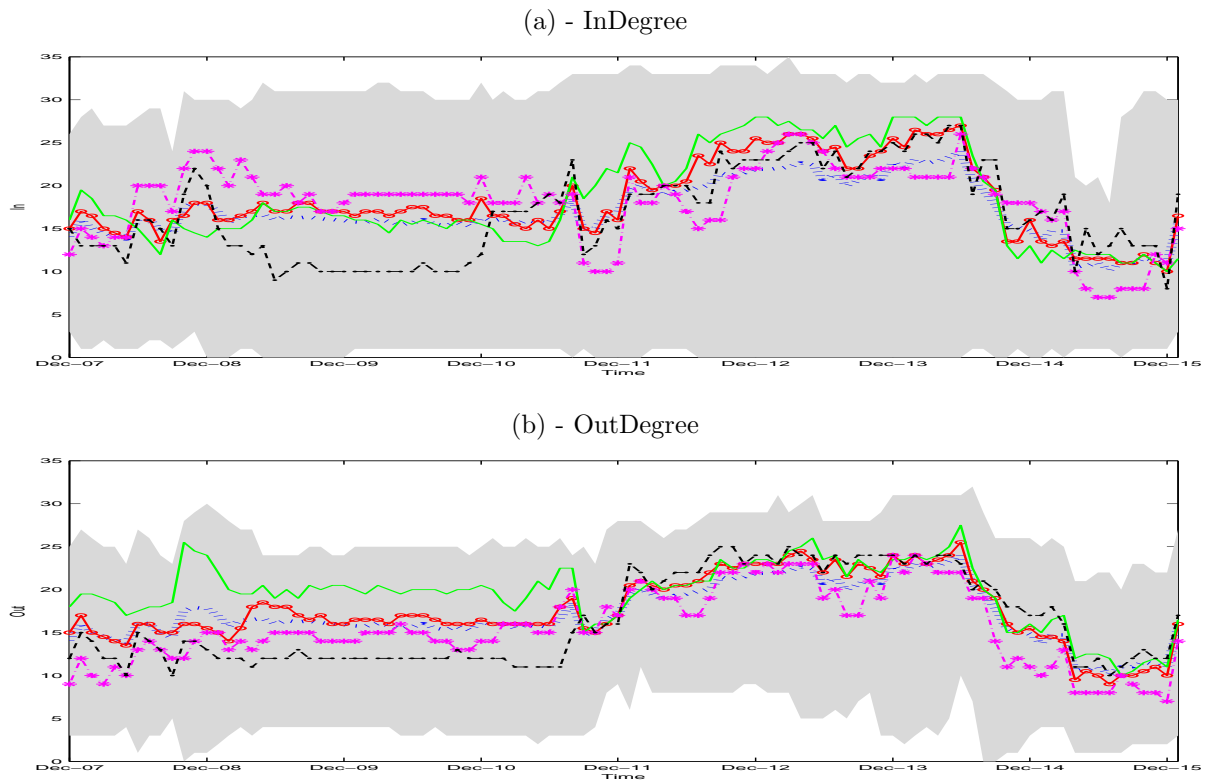


Figure 5: The Figure reports the local measure based on degrees for the period December 2007 to January 2016. Panel a) shows the dispersion of the InDegree, the red line (with 'o' marker) represents the InDegree average, the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks InDegrees. Panel b) shows the dispersion of the OutDegree. The red line (with 'o' marker) represents the InDegree average, the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks OutDegrees.

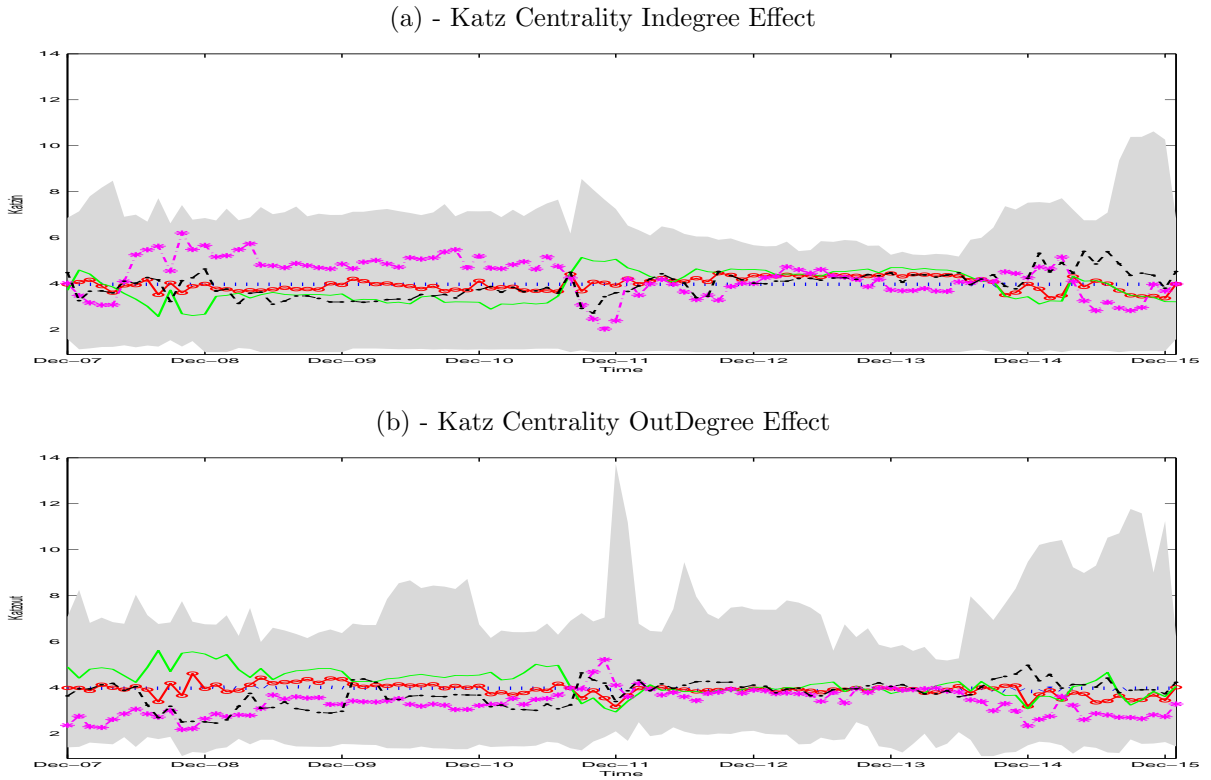
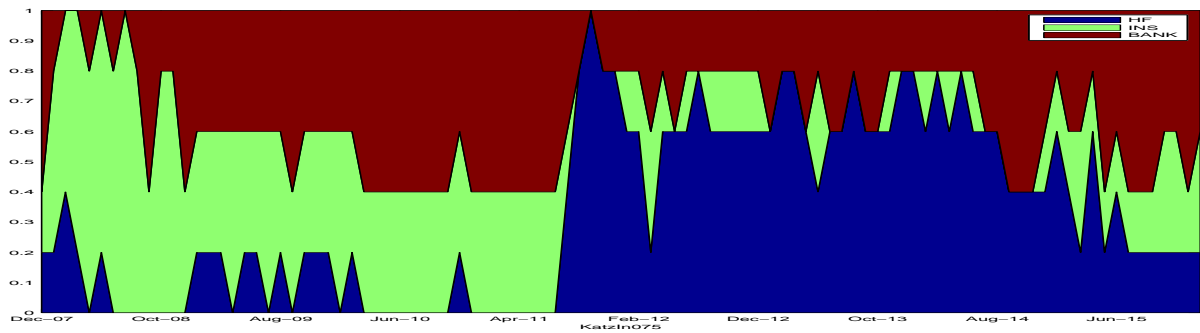


Figure 6: The Figure reports the Katz centrality measure for the sample period December 2007 to January 2016. Panel a) shows Katz centrality dispersion with $\alpha = 0.75$ and $\beta = 1$ based on InDegree. The red line (with 'o' marker) represents the average and the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks. Panel b) shows Katz centrality with $\alpha = 0.75$ and $\beta = 1$ based on OutDegree. The red line (with 'o' marker) represents the average and the blue line indicates the median. The green line, magenta (with '*' marker) line and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks.

(a) - Top Katz Central Institutions InDegree Effect



(b) - Top Katz Central Institutions OutDegree Effect

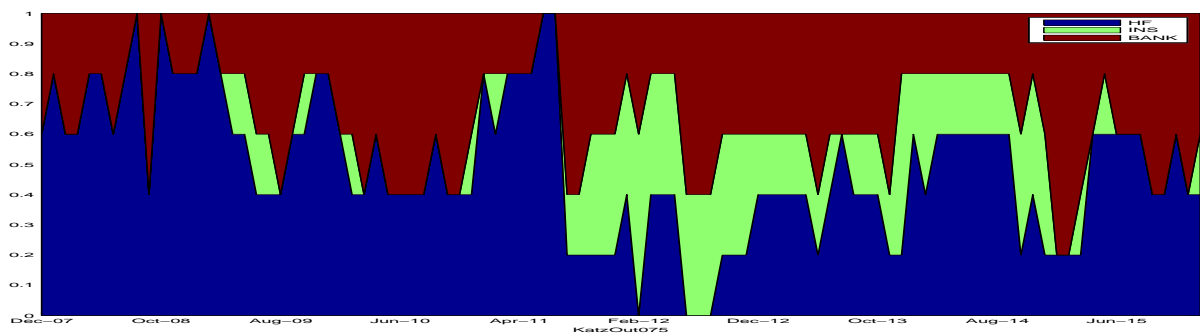


Figure 7: The Figure reports the top 10% central institutions by using the Katz centrality with $\alpha = 0.75$ and $\beta = 1$ from December 2007 to January 2016. Panel a) reports the Top Central institutions based on on the Katz centrality InDegree. Panel b) reports the Top Central institutions based on the Katz centrality OutDegree. The blue area indicates the fraction of top central Hedge Funds, the green area the fraction of the top central Insurers, the red area the fraction of the top central Banks.

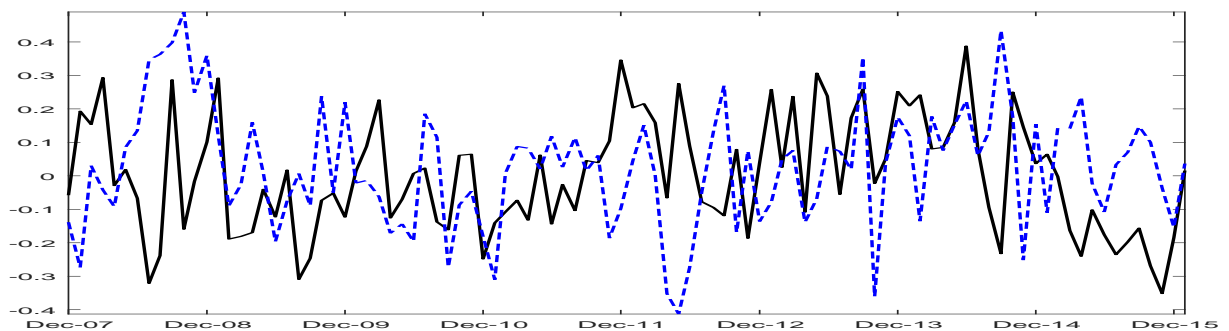


Figure 8: Figure reports the rank correlation patterns computed respectively between ΔCoVaR and Katz-In (black line) and ΔCoVaR and Katz-Out (dashed blue line) with $\alpha = 0.75$.

4.4 Predictive power of the measures

To evaluate the predictive power of the quantile based loss measure $\Delta CoVaR$ and quantile based network measures, we follow an out-of-sample analysis as in Billio et al. [2012]. We first compute the maximum percentage financial loss (Max%Loss) suffered by each of the financial institutions during the crisis period from January 2008 to June 2009. We then perform a cross-sectional analysis among institutions by considering the Max%Loss as dependent and systemic risk measures. The results are reported in Table 2 for the sample January 2005 to December 2007. The Table shows that quantile based network measures such as Katz centrality and degrees measures are significant determinants of the Max%Loss variable. In particular, orientation matters for explaining the maximum percentage financial loss. The Katz centrality measure based on the outgoing links is significant and has an R^2 of 0.29. Instead, the Katz centrality measure based on the ingoing links is not significant. Similarly, the InDegree is significant but the R^2 is 0.13 and the OutDegree is also significant but have an R^2 of 0.25. Based on the R^2 criterion, the Katz centrality measure based on outgoing links provides a superior information content and a better prediction ability than the other network measures. Surprisingly, the $\Delta CoVaR$ it is also significant but is shows a negative dependence with the maximum percentage financial loss, revealing, in this case, a meaningless measure, i.e. financial institutions of which the $\Delta CoVaR$ predicts the largest losses are the one that loose less during the crisis. Also the network measures have negative signs. This result is coherent with Allen and Gale [2000] and Freixas et al. [2000] who suggested that a more interconnected architecture enhances the resilience of the system and consequently, the chances to tackle the insolvency of any individual Bank. In summary, the results confirm the goodness of the quantile based network measures as valid tools for policy makers to investigate systemic risk and G-SIFIs.

5 Conclusion

In designating G-SIFIs a variety of factors have been considered by regulators with interconnectedness being one of the criteria. The key reason is that the complexity of the financial system highlights the importance of the interconnectedness among financial institutions in generating systemic risk. In this paper, we apply several econometric measures of connectedness on the network extracted using pairwise quantile regressions. We highlight the different informative content between quantile based network measures and quantile based loss measures such as $\Delta CoVaR$. We consider G-SIFI Banks and Insurers and Hedge Funds. We use the degree and the Katz Centrality measures for capturing the indirect network effect on risk spillover. The results show the following: Firstly, the network measures and the loss measures are not highly correlated, this means that they are capturing different features of systemic risk. Secondly, Hedge Funds that during the Global financial crisis were among the institutions that largely spread risk, in the recent period largely absorb risk. Instead, Insurers largely absorb risk during the global financial crisis and more recently are playing a lower role both as risk spreader and risk absorber. Banks are always having an important role both as risk absorber and risk spreader. Thirdly, the centrality measures substantially explain the Max financial loss percentage more than the loss measures based on $\Delta CoVaR$. Finally, centrality measures based on an oriented graph have a higher explanatory power than degree measures. These

Table 2: Out-of-sample analysis. Parameter estimates of a multivariate rank regression of Max% Loss for each financial institution during January 2008 to June 2009 on loss measures and network measures. The maximum percentage loss (Max% Loss) for a financial institution is the maximum decline in returns for each financial institution during January 2008 - June 2009. Loss measures and network measures are calculated over January 2005 - December 2007. The table reports the coefficients and the standard errors in round brackets. Parameter estimates that are significant at the 5% level are shown in bold. All the Katz centrality measures are computed with $\alpha = 0.75$.

<i>Variable</i>	<i>Max%Loss</i>				
	<i>January 2005 - December 2007</i>				
(intercept)	0.58 (0.11)	0.60 (0.18)	0.88 (0.15)	0.66 (0.13)	0.79 (0.11)
ΔCoVaR	-9.13 (3.89)				
Katz-In		-0.06 (0.04)			
Katz-Out			-0.13 (0.04)		
InDegree				-0.02 (0.21)	
OutDegree					-0.03 (0.18)
R^2	0.17	0.14	0.06	0.29	0.13
					0.25

results confirm the importance of investigating the role played in the financial system of the different financial institutions using network measures since they better capture the “indirect” effects of risk spillovers.

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