Systemic risk spillovers and interconnectedness between systemically important banks

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Abstract

In this paper we gauge the degree of interconnectedness and we quantify the linkages between systemically important institutions and the entire system. We document an increase in interconnectedness during the crisis, especially between global systemically important banks and the system. As we expected, global systemically important banks are the main contributors to system wide distress being at the same time the most exposed to systemic risk. However, on average, the other systemically important institutions have a greater idiosyncratic risk, reiterating again the drawbacks of a micro-prudential supervision. Global systemically important banks and the system appear to be the transmitters of return spillovers, whereas other systemically important institutions are the receivers of return spillovers.

Key words: systemic risk, interconnectedness, bank networks

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1. Introduction

Understanding contagion among financial institutions is a top priority for regulators and policy makers who aim to foster financial stability and to prevent financial crises. Policymakers and supervisory bodies (see for instance BCBS, 2010; EC, 2013; and OCC, 2013) have agreed that new regulatory measures are required in order to assure a more resilient banking system that is capable to absorb losses and not to make use of public money, to reduce systemic risk and, ultimately, to foster financial stability, including capital surcharges, liquidity requirements and resolution regimes. Given these considerations, on November 4, 2011 at the G20 Summit in Cannes, the Financial Stability Board (FSB) in consultation with Basel Committee on Banking Supervision (BCBS) published a list of 29 global systemically important banks (G-SIBs), which is a particular category of systemically important institutions (SIFIs)[1]. All these banks were required to increase their capital in a range that varies from 1% to 3.5% of their risk-weighted assets in order to improve the loss absorption capacity (FSB, 2011). Moreover, the G-SIBs will be subject to a tighter and a more effective supervision, given their systemically importance. The G-SIBs list is updated and published every year in November by the FSB. In addition, the BCBS (2012) developed a framework for assessing the domestic systemically important banks (D-SIBs).

The European Banking Authority (EBA), besides the G-SIBs adopted by the Basel Committee, established upon consultation with the European Systemic Risk Board (ESRB) its own guidelines for identifying other systemically important institutions (O-SIIs), that is, institutions "[...] that, due to their systemic importance, are more likely to create risks to financial stability[2]" for the European Union or a Member State. The identification process, followed the principles of Basel Committee to deal with D-SIBs and it includes both national and supranational authorities. Therefore, the O-SIIs are the financial institutions that are systemically important at the European Union or Member State level. The criteria on which these institutions are selected are size, interconnectedness, relevance to the economy and complexity. The identified institutions must maintain a Common Equity Tier 1 (CET1) capital buffer of up to 2%

[1] Besides financial intermediaries (banks), SIFIs include insurance companies (non-bank financial intermediaries), and other financial institutions. According to Zhou (2012), systemically important financial institutions may jeopardize financial stability through counterparty, liquidity and contagion risk.
[2] http://www.eba.europa.eu/risk-analysis-and-data/other-systemically-important-institutions-o-siis-/2015.

of the total risk exposure they hold. The first official list was disclosed by the EBA on 25 April 2016 and it is updated on a yearly basis.

In this paper we measure the spillover effects: a) from the G-SIBs to the O-SIIs and the system; b) from the O-SIIs to the G-SIBs and the system; and c) from the system to the G-SIBs and the O-SIIs. Our aim is to gauge the degree of interconnectedness and to quantify the linkages between the two groups of systemically important institutions and the system. As some G-SIBs are also O-SIIs, we exclude them from the O-SIIs list. Our study covers a period that starts in 2004, long before the release of the first list of G-SIBs (November 4, 2011) or the first list of O-SIIs (April 25, 2016). Thus, we are able to carry-out an ex-post analysis concerning the systemic risk contribution of these institutions and we are able to capture the spillover effects focusing especially on the GFC period.

We document an increase in interconnectedness during the GFC crisis, especially between G-SIBs and the system. As expected, G-SIBs are the main contributors to the system wide distress, being at the same time highly exposed to systemic risk. However, on average, the O-SIIs displayed a greater individual market risk as measured by value-at-risk (VaR), reiterating again the drawbacks of a micro-prudential supervision. Our analysis suggests that G-SIBs play the role of transmitters of return spillovers, whereas O-SIIs are the receivers of return spillovers.

Given the systemically importance of the banks, a strand of literature has emerged, especially in the last decade, trying to quantify the systemic risk and to identify the institutions with a great contribution or exposure to systemic risk (for some surveys and comparisons of the measures of systemic risk, see for instance Bisias et al., 2012; Zhang et al., 2015; Benoit et al., 2017; Silva et al., 2017). However, as systemic risk varies with time, institutions may prove not to be systemically important in some periods while remaining critical in others (Elliott and Litan, 2011) such that the systemic risk rankings may move in opposite directions (van de Leur et al., 2017). Moreover, the majority of the systemic risk measures proposed in the literature are market- and/or accounting-based and Löffler and Raupach (2018) pointed out that market-based measures' ability to identify systemically important banks is limited. Furthermore, many senior economists have agreed that imposing capital and/or liquidity surcharges based on institution's contribution to systemic risk in order to absorb future losses may be a good tool to reduce negative externalities (e.g. Adrian and Brunnermeier, 2016; Acharya et al., 2017; Ötker-Robe et al., 2011; Elliott and Litan, 2011). Elliott and Litan (2011) argue that charging additional capital for SIFIs may not result in less risk-taking. In addition, Benoit et al. (2014) document that different measures of systemic risk may lead to conflicting results in identification of systemically important financial institutions.

In order to overcome these deficiencies and to augment the systemic risk metrics, several methodologies have been developed or have been borrowed from other fields, emphasizing on the degree of interconnectedness and contagion between financial institutions. Indeed, Betz et al. (2016) point out that the GFC highlighted that a lesson that the idiosyncratic risk of a company tends to spill over to another company and thus a common framework is needed to analyze the riskiness of firms.

The remainder of this paper is structured as follows: In Section 2 we discuss the connection between contagion and systemic risk as it is reflected in the literature so far. In Section 3 we describe the data and in Section 4 we describe the systemic risk methodology we employ, in Section 5 we discuss the empirical findings, and in Section 6 we conclude.

2. Connecting Contagion and Systemic Risk

Systemic risk and contagion are often seen as a "hard-to-define-but-you-know-it-when-you-see-it" concept (Benoit et al., 2017). Even though the literature on contagion was quite rich before 2008, this was not enough to prevent the crisis as the metrics to quantify the contagion did not have an early warning component. They were ex-post rather than ex-ante. Thus, new methodologies were needed in order to address these concepts and to understand the deep vulnerabilities of financial system.

Contagion[3] is broadly defined as the spillovers triggered by extreme negative events (Masson, 1999; Dornbusch, and Park, 2001; Forbes and Rigobon, 2002; Pericoli and Sbracia, 2003; Forbes, 2012). Forbes (2012) contrasts contagion to interdependence - high correlations across markets during all states of the world, arguing that the former has deep roots in this globalized framework, being therefore "extremely difficult to stop". Forbes and Rigobon (2002), analyzing the 1994 Mexican and the 1997 Asian crises, using a heteroskedasticity-adjusted correlation coefficient, report no contagion but find interdependence during both crises among 24

[3] For some excellent reviews, see Pericoli and Sbracia (2003) and Chinazzi and Fagiolo (2015).

developed and emerging markets. More recently, De Bruyckere et al. (2013) use excess correlations to measure bank / sovereign risk spillovers in the European debt crisis and they found significant empirical evidence of contagion between bank and sovereign credit risk.

Diebold and Yilmaz (2012,2009) develop a General VAR (GVAR) approach based on the seminal paper by Koop et al. (1996) to measure total and directional volatility spillovers from and to four assets classes: stocks, bonds, foreign exchange and commodities. They find an increase intensity of volatility spillovers from stock market to all other markets following the collapse of Lehman Brothers. Ballester et al. (2016) apply their methodology for the bank CDS market and discover supporting evidence of contagion in banking markets.

Other methods in detecting dependence and contagion are based on copula functions in which marginal distributions and dependence structures of time-series are modeled separately. Abbara and Zevallos (2014)'s work is built on Patton (2006)'s framework in which they analyze linkages and contagion among stock markets from Latin America, Europe, Asia and the US from a bivariate standpoint. Their SJC time-varying copula models indicate evidence of contagion between Latin American stock markets during the Asian and Russian crises and during the GFC. Silva Filho et al. (2012) and Fei et al. (2017) model dependence through dynamic copula with Markov-switching regimes in equity and CDS markets, respectively. Both studies document an increase in the dependence structure across equity and CDS markets following the GFC.

Recently, a new strand of literature has emerged, making use of network graphs in order to describe the interdependence between markets / institutions. Fagiolo et al. (2010) are among the first to model financial system as a network, applying it to international trade flows[4]. The relationship between the institutions acting within the financial system can be represented as a network[5] where these institutions are the nodes and edges represent the existence of credit/lending relationships between any two parties (Chinazzi and Fagiolo, 2015). Billio et al. (2012) develop measures of connectedness based on principal-component analysis and Granger-causality networks and apply the methodology to hedge funds, banks, broker / dealers, and insurance companies. Their findings indicate that banks are the main actors in transmitting

[4] Easley and Kleinberg (2010), Acemoglu et al. (2012), Babus (2016) and Adamic et al. (2017), describe financial applications of network graphs.
[5] Empirical investigation of network connectedness includes, inter alia, the work of Diebold and Yilmaz (2009), Billio et al. (2012), Allen et al. (2012), Barigozzi and Brownlees (2018), Minoiu and Reyes (2013), Diebold and Yilmaz (2014), Bianchi et al. (2018), Peltonen et al. (2015), Giglio et al. (2016), Constantin et al. (2018) and Demirer et al. (2017).

shocks within four categories of financial institutions. Diebold and Yilmaz (2014) propose connectedness measures based on variance decomposition and apply them to US financial institutions' stock return volatilities. Peltonen et al. (2015) employ macro-networks to measure the interconnectedness of the banking sector and document that a more central position of the banking sector in the network significantly increases the probability of a banking crisis. In the same context, Constantin et al. (2016) develop early-warning models based on network linkages for European banks and find that these models outperform the benchmark, without network. Finally, a novel approach is introduced by Linton and Whang (2007) through the so-called quantilogram that captures predictability in different parts of a univariate distribution. Han et al. (2016) extend it to cross-quantilogram that measures serial dependence between two series at different conditional quantile levels, with application to systemic risk measurement.

3. Data

A complete description of the data used in our analysis is given in the Table 1. For system risk indicators we use total assets, total shareholders' equity and total liabilities with daily frequency derived from linear interpolation from quarterly data, market capitalization, equity returns and market indices with daily frequency.

Table 1. Description of variables

Variable name	Definition	Units	Frequency	Source
Balance sheet data				
Market Equity	Market capitalization	million USD	D	Datastream
Total Liabilities	The book value of Total Liabilities	thousands USD	Q	Worldscope
Total Assets	The book value of Total Assets	thousands USD	Q	Worldscope
Book Equity	The book value of Common Equity	thousands USD	Q	Worldscope
Market indices				
MSCI World Index return	Log-return of MSCI World Index	%	D	Datatsream
VIX	Volatility index published by Chicago Board Options Exchange (CBOE) based on S&P 500 index options	-	D	Datastream
Real Estate market_Bank market	MSCI World Real Estate Index log-return in excess of MSCI World Banks Index log-return	%	D	Datastream
T-bill rate	Change in the three-month T-bill rate	%	D	Federal Bank Reserve of St. Louis (FRED)
Repo rate_T-bill rate	The spread between three-month repo rate and three-month T-bill rate	%	D	Federal Bank Reserve of St. Louis (FRED)
10-year bond_T-bill rate	The spread of change in 10-year bond yield and three-month T-bill rate	%	D	Federal Bank Reserve of St. Louis (FRED)
Indices				
System	Log-return of MSCI World Financials Index	%	D	Datatsream
G-SIBs	Market capitalization-weighted index of G-SIBs returns. The index is dynamic in the sense that we add or remove financial institutions in computing the index as the annual Financial Stability Board (FSB) list of G-SIBs changes	%	D	Datatsream
O-SIIs	Market capitalization-weighted index of O-SIIs returns. The index is dynamic in the sense that we add or remove financial institutions in computing the index as the annual European Banking Authority (EBA) list of O-SIIs changes	%	D	Datastream

4. Tools for Measuring Interconnectedness of Systemic Risk

In this section we describe how we assess and quantify the spillover effects from / to G-SIBs, O-SIIs and System. We focus on the following approaches: systemic risk indicators, network measures, cross-quantilogram and dynamic copula with Markov-switching regimes. For network measures we use equity returns whereas for the remaining methodologies, that is cross-quantilogram and dynamic copula with Markov-switching regimes, we construct market capitalization-weighted indices of O-SIIs and G-SIBs.

In Table 2 we report the descriptive statistics for market capitalization-weighted indices disaggregated for G-SIBs or O-SIIs, and the system overall.

Table 2. Descriptive statistics for market capitalization-weighted indices

	G-SIBs	**O-SIIs**	**System**
Mean	-0.0002	-0.0004	0.0000
Median	0.0002	0.0000	0.0005
Maximum	0.1564	0.1570	0.1147
Minimum	-0.1515	-0.1728	-0.1016
Std. Dev.	0.0162	0.0210	0.0135
Skewness	-0.1819	-0.1691	-0.2548
Kurtosis	16.9238	10.8291	15.1465
Jarque-Bera	28995.69	9178.00	22089.66
(p-value)	(0.0000)	(0.0000)	(0.0000)
LM test	60.2482	62.9040	94.3937
(p-value)	(0.0000)	(0.0000)	(0.0000)
Observations	3587	3587	3587

4.1 Systemic risk indicators

We employ three well-known metrics that are widely used in the literature together with their extensions and improvements.

The conditional Value at Risk (CoVaR) introduced by Adrian and Brunnermeier (2016) is based on Value at Risk (VaR) as a measure of idiosyncratic risk that is used in the context of micro-prudential regulation. It captures the contagion spillovers from a financial institution to the whole system when the institution's market value of assets decreases below a target level. The market value of assets ($Market\ Assets_t^i$) for institution *i* at time *t* is defined as the book value of assets ($Total\ Assets_t^i$) adjusted by the ratio of market value of equity or market capitalization ($Market\ Equity_t^i$) and book value of equity ($Book\ Equity_t^i$):

$$Market\ Assets_t^i = Total\ Assets_t^i\ x\ \frac{Market\ Equity_t^i}{Book\ Equity_t^i} \tag{1}$$

We focus on the daily change of the market assets of institution *i* from *t-1* to *t* and define the return of each institution:

$$R_t^i = \frac{Market\ Assets_t^i - Market\ Assets_{t-1}^i}{Market\ Assets_{t-1}^i} \tag{2}$$

As total assets and book equity have a quarterly frequency whilst market equity has a daily frequency, we transform the former two accounting measures into daily frequencies through linear interpolation between two consecutive quarters[6].

Following Adrian and Brunnermeier (2016), we estimate CoVaR as the *qth* quantile of the system's returns[7] (R_t^{system}) distribution over a given period of time conditioned on the event that each financial institution registers the maximum possible loss of its returns for the same significance level q[8]:

$$Pr(R_t^{system} \leq CoVaR_{q,t}^{system|R_{Market\ Assets,t}^i = VaR_{q,t}^i} | R_{Market\ Assets,t}^i = VaR_{q,t}^i) = q \quad (3)$$

In order to capture the time-variation of the financial institutions' individual and systemic risk, we estimate the tail risk measures VaR and CoVaR using a vector of market indices (MI_t') that contains information representative for the world financial markets. More specifically, we have employed the following market indices[9]: (i) the daily return of MSCI World index, (ii) the volatility index (VIX), (iii) the daily real estate sector return (MSCI World Real Estate) in excess of the banking sector return (MSCI World Banks), (iv) the change in the three-month T-bill rate, (v) the spread between three-month repo rate and three-month T-bill rate, (vi) the spread of change in 10-year bond yield and three-month T-bill rate and (vii) the change in the spread of Moody's Baa corporate bond yield and 10-year bond yield.

We use the quantile regression (QR) with robust standard errors[10] (Machado et al., 2011) to estimate the following regressions:

$$R_{Market\ Assets,t}^i = \alpha^i + MI_{t-1}' \, x \, \beta^i + \gamma^i \, x \, Crisis_t + \epsilon^i \quad (4)$$

$$R_t^{system} = \alpha^{system|i} + \delta^{system|i} \, x \, R_{Market\ Assets,t}^i + MI_{t-1}' \, x \, \beta^{system|i} + \gamma^{system|i} \, x \, Crisis_t + \varepsilon_t^{system|i} \quad (5)$$

MI_{t-1}' is a (1 x k) vector of lagged market indices at time t-1, $Crisis_t$ is a dummy variable taking the value of 1 after the fall of investment bank Lehman Brothers and 0 otherwise, α^i, $\alpha^{system|i}$, β^i, $\beta^{system|i}$, $\delta^{system|i}$, γ^i, $\gamma^{system|i}$ are the parameters to be estimated and ε^i and

[6] As a robustness check, we also perform the cubic spline interpolations and the findings remain robust.
[7] Here we define the system as MSCI World Financials Index. Alternatively, we re-estimate the quantile regressions using the assets market value.
[8] All our systemic risk indicators are estimated for a 5% quantile.
[9] Initially, all market variables have been tested for unit stationarity using the Augmented Dickey-Fuller test. When the series were not stationary, we used instead the change of variables or the spread.
[10] The standard errors are asymptotically valid under heteroskedasticity and misspecification assumptions, which is not the case for financial markets data (Pagan, 1996).

$\varepsilon^{system|i}$ are *iid* error terms. $\delta^{system|i}$ reflects the conditional dependence of the system's return on financial institution *i*'s return, a large coefficient being associated with an increased contribution of that institution to systemic risk and thus with large spillover effects.

Running regression from Eq. (3) and Eq. (4) for a quantile of 5% (distressed periods) and a quantile of 50% (median or tranquil state) we obtain the value of regressors to be used in VaR and CoVaR estimations:

$$\widehat{VaR^{\iota}_{q,t}} = \widehat{\alpha^{\iota}_{q,}} + MI'_{t-1}\, x\, \widehat{\beta^{\iota}_q} + \widehat{\gamma^{\iota}_q}\, x\, Crisis_t \quad (6)$$

$$\widehat{CoVaR^{\iota}_{q,t}} = \alpha_q^{\widehat{system|\iota}} + \delta_q^{\widehat{system|\iota}}\, x\, \widehat{VaR^{\iota}_{q,t}} + MI'_{t-1}\, x\, \beta_q^{\widehat{system|\iota}} + \gamma_q^{\widehat{system|\iota}}\, x\, Crisis_t \quad (7)$$

In the end, each financial institution's contribution to systemic risk (ΔCoVaR) is defined as

$$\Delta CoVaR^{system|i}_{q,t} = CoVaR_{q,t}^{system|R^i_{Market\ Assets}=VaR^i_{q,t}} - CoVaR_{q,t}^{system|R^i_{Market\ Assets=VaR^i_{50\%}}} \quad (8)$$

In addition, we estimate a modified version of ΔCoVaR proposed by López-Espinosa et al. (2012), i.e., *Asymmetric ΔCoVaR (ΔACoVaR)* that accounts for asymmetries in the initial model as systemic risk presents a strong degree of asymmetric response, since negative returns pose greater contagion effects to the system compared with the positive ones (see López-Espinosa et al., 2012 for details). Furthermore, in a Dynamic Conditional Correlation (DCC) framework of Engle (2002), we compute two alternative measures, namely *ΔCoVaR DCC* and *ΔCoVaR QR* using asymmetric GJR-GARCH models, but without market indices, considering only the dependence between system's returns and financial institutions' returns.

Another systemic risk measure that we apply is *Marginal Expected Shortfall (MES)* of Acharya et al. (2017). It works in the opposite direction as compared with CoVaR, denoting the exposure of financial institutions to systemic risk. MES is defined as the average return on financial institution's market capitalization on the days the total market capitalization of the sample experienced a loss greater than a specified threshold C indicative of market distress:

$$MES^i_{t-1} = E_{t-1}(R^i_t | R^{system}_t < C) \quad (9)$$

where R^i_t is the return of financial institution i at time t and R^{system}_t is the return of the system, defined as MSCI World Financials Index. We model the bivariate process of firm and market returns as follows:

$$R^{system}_t = \sigma^{system}_t \varepsilon^{system}_t \quad (10)$$

$$R_t^i = \sigma_t^i \varepsilon_t^i = \sigma_t^i \rho_t^i \varepsilon_t^{system} + \sigma_t^i \sqrt{1 - \rho_{i,t}^2 \xi_{i,t}} \tag{11}$$

σ_t^i and σ_t^{system} are the volatilities of financial institution i and system, respectively, ρ_t^i is the correlation coefficient between the return of institution *i* and the return of the system, and ε_t^{system}, ε_t^i and $\xi_{i,t}$are the error terms which are assumed to be *iid*. It follows that:

$$MES_{t-1}^i = E_{t-1}\left(R_t^i \middle| R_t^{system} < C\right) = \sigma_t^i E_{t-1}(\varepsilon_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) = \sigma_t^i \rho_{i,t} E_{t-1}(\varepsilon_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) + \sigma_t^i \sqrt{1 - \rho_{i,t}^2} E_{t-1}(\xi_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) \tag{12}$$

Conditional volatilities of the equity returns are modelled using asymmetric GJR-GARCH models with two steps QML, whilst time-varying conditional correlation is modelled using the DCC framework. As in Benoit et al. (2014), we consider the threshold C equal to the conditional VaR of the system return, i.e., VaR(5%), which is common for all institutions. The higher the MES, the higher is the exposure of the institution to the systemic risk.

Finally, our last indicator to consider in our analysis is the *Systemic Risk Index (SRISK)* introduced by Acharya et al. (2012) and extended by Brownlees and Engle (2017). As in the case of the MES, SRISK is a measure of exposure of a financial institution to the wide systemic risk, defined as the loss of a specific institution (capital shortfall), conditioned by the whole financial system being in distress. A major convenient of SRISK is that it is expressed in monetary units making it very reliable in monitoring systemic exposure. As in the case of the MES, SRISK is estimated using the GARCH-DCC framework. When the institution is in distress, the SRISK indicator will be positive, indicating insufficient working capital, whilst a negative value indicates a capital surplus.

4.2 Measures of connectedness

Systemic risk involves a number of financial institutions that are connected one to each other through different channels and the financial system can be seen as a network composed of individual institutions (nodes), whereas the credit / lending relationships between any two parties can be seen as edges Similar to Billio et al. (2012), we analyze the interdependencies between G-SIBs and O-SIIs through *Granger-causality networks.*

In a Granger causality framework one can determine the directional return spillovers in the financial system (composed, in our case, from G-SIBs and O-SIIs). A time series j can

Granger-cause another time series i if information contained in the past values of i and in the past values of j are better in predicting the value of i than the information based only on the past values of i. Defining the following relationships:

$$(j \rightarrow i) = \begin{cases} 1 \; if \; j \; Granger \; causes \; i, \\ \quad 0 \; otherwise \end{cases} \tag{16}$$

and $(j \rightarrow j) \equiv 0$. Thus, based on these pairwise Granger causalities, one can construct the Granger-causality network. The network is defined as a set of nodes (G-SIBs and O-SIIs) connected by edges. It will be represented as an N_t-dimensional adjacency matrix A_t with the elements a_{ijt} zeros and ones, $a_{ijt} = 1$ if the node j Granger causes node i and $a_{ijt} = 0$ otherwise. Following Billio et al. (2012), the returns will be modelled using a GARCH(1,1) process and the following measures of connectedness are calculated:

a. *The Dynamic Causality Index (DCI)*, with the following expression:

$$DCI_t = \binom{N_t}{2}^{-1} \sum_{i=1}^{N_t} \sum_{j=1}^{N_t} a_{ijt} \tag{17}$$

b. *The In-Out network degree (IO)* defined by:

$$IO_t^i = \sum_{j=1}^{N_t} a_{ijt} + \sum_{i=1}^{N_t} a_{jit} \tag{18}$$

The first part of the right-hand side of the relationship is called *IN network degree* measuring the number of financial institutions that significantly (at 5% level) Granger-cause institution j, whereas last part of the right-hand side of the relationship is called *OUT network degree* and measures the number of financial institutions that are significantly (at 5% level) Granger-caused by institution j.

c. *The closeness centrality (CC)* measure determines the mean distance from a financial institution to other financial institutions and captures how close a node is to other nodes in the graph. If we denote $C_{ji}$the length of the shortest C-connection between j to i, CS for institution j is expressed as follows:

$$CC^j = \frac{1}{N_t - 1} \sum_{j=1}^{N_t} C^{ji} \tag{19}$$

d. *The betweenness centrality (BC)* measures the extent to which a financial institution lies on paths between other financial institutions. Very important, BC can capture how susceptible a node (financial institution) is to shocks that propagate through network. Denoting $k^{ji}(u)$ the number of shortest paths from j to i that pass through node u and K^{ji} the total number of shortest paths from j to i, we have:

$$BC^{u} = \sum_{j=1}^{N_t} \frac{k^{ji}(u)}{K^{ji}} \tag{20}$$

The above network measures have a static character. A more informative analysis requires taking into account the temporal dynamics of systemic risk that evolves based on the ebbs and flows of financial markets.

4.3 The Cross-quantilogram

The cross-quantilogram is a relatively new tool introduced by Han et al. (2016), continuing the work of Linton and Whang (2007) who proposed the quantilogram as measure for predictability in different parts of the distribution of a stationary time series based on the correlogram of "quantile hits" (Han et al., 2016). The cross-quantilogram measures the predictability of different quantiles of the distribution of a stationary time series, but this time into a bivariate setting and can be used to study the return spillovers between two time series. The cross-quantilogram is suitable for financial series that exhibit stylized facts, such as non-normality, fat tails and asymmetry. Moreover, quantifying the quantile dependence between time series, the cross-quantilogram can also be employed for assessing systemic risk.

Considering two time series R_t^i and R_t^j as continuous returns for G-SIBs and O-SIIs[11] weighted by market-capitalization with the unconditional distribution functions F^i and F^j, the unconditional density function f^i and f^j and the corresponding unconditional quantile functions $q^i(\tau^i) = inf\{u: F^i(u) \geq \tau^i\}$ and $q^j(\tau^j) = inf\{u: F^j \geq \tau^j\}$ for τ^i and $\tau^j \in (0,1)$. With the pairs $\tau = (\tau^i, \tau^j)$ we will estimate the dependence between $\{R_t^i \leq q_t^i(\tau^i)\}$ and $\{R_t^j \leq q_t^j(\tau^j)\}$ for $k = \pm1, \pm2, ...$ .Having the function $\psi^a(u) = I[u < 0] - a,$ the cross-quantilogram has the following form:

$$\rho^{\tau}(k) = \frac{E[\psi^{\tau^i}\left(R_t^i - q_t^i(\tau^i)\right)\psi^{\tau^j}\left(R_t^j - q_{t-k}^j(\tau^j)\right)]}{\sqrt{E[\psi^{2^{\tau^i}}\left(R_t^i - q_t^i(\tau^i)\right)]}\sqrt{E[\psi^{\tau^j}\left(R_{t-k}^j - q_{t-k}^j(\tau^j)\right)]}} \tag{21}$$

The cross-quantilogram is able to capture cross-correlation of quantile-hit processes and in the case where $R_t^i = R_t^j$, the cross-quantilogram becomes the quantilogram of Linton and

[11] Through this approach, we measure spillover effects from G-SIBs to O-SIIS, from O-SIIs to G-SIBs, from G-SIBs to system, from system from G-SIBS, from O-SIIs to system and from system to O-SIIs, but we consider only G-SIBs and O-SIIs when presenting the methodological aspects.

Whang (2007). Given the unconditional estimate of quantiles $q^{*^i}(\tau^i)$ and $q^{*^j}(\tau^j)$, the cross-quantilogram becomes:

$$\rho^{*^\tau}(k) = \frac{\sum_{t=k+1}^{T} \psi^{\tau^i}\left(R_t^i - q_t^{*^i}(\tau^i)\right)\psi^{\tau^j}\left(R_t^j - q_{t-k}^{*^j}(\tau^j)\right)}{\sqrt{\sum_{t=k+1}^{T} \psi^{2^{\tau^i}}\left(R_t^i - q_t^{*^i}(\tau^i)\right)}\sqrt{\sum_{t=k+1}^{T} \psi^{2^{\tau^j}}\left(R_t^j - q_{t-k}^{*^j}(\tau^j)\right)}} \tag{22}$$

In general $\rho^{*^\tau}(k) \in [-1, 1]$but if $\rho^{*^\tau}(k) = 0$, there is no directional predictability (Han et al., 2016). If R_t^i and R_t^j are the market capitalization-weighted indices of G-SIBs and O-SIIs, respectively and $\rho^{*^\tau}(1) = 0$ this implies that implies that if the returns on O-SIIs are below (above) a given quantile $q^j(\tau^j)$ at time $t - 1$, there is no possibility of prediction whether the return on the G-SIBs is below (above) a given quantile $q^i(\tau^i)$ at time t.

As in Han et al. (2016) we construct the confidence interval (95% level) using the stationary bootstrap procedure of Politis and Romano (1994) where pseudo samples are constructed from blocks of data with random block lengths.

4.4 Bivariate copula with Markov-switching regimes

Using a heteroskedasticity-adjusted correlation coefficient, Forbes and Rigobon (2002) could not find evidence in favor of contagion during crisis periods but rather an increase in the interdependence across markets. Thus, a non-linear dependency measure could be more appropriate in assessing the linkages between markets. Hence, we try to capture the dynamics between G-SIBs and O-SIIs through a bivariate copula model with Markov-switching regimes. To capture the time-varying dependence, we employ an approach similar to Patton (2006), where the dependence parameter follows an ARMA(1, 10) restricted process, whereas the intercept term depends on a hidden two-state Markov chain (MC). The marginal distributions are modelled using an ARMA(1,1) - GARCH(1,1) process with skewed-T disturbances proposed by Hansen (1994). The parameters of the model are estimated by maximum likelihood.

In our case, we consider a bivariate model defined by $X = (X_1, X_2)$ where X_1 and X_2 are the series of G-SIBs and O-SIIs, respectively. We proceed by first modelling the univariate time series for $X_1$and X_2 and then we estimate the dependence between these series using a copula density $c(u_1, u_2)$ where u_1 and u_2 have a uniform distribution. For our analysis, we employ two copula models: the Gaussian (normal) and the Symmetrized Joe–Clayton (SJC) defined in Patton (2006), which is a modified form of the Joe–Clayton copula as follows:

$$C_{SJC}(u_1, u_2) = 0.5[C_{JC}(u_1, u_2) + C_{JC}(1 - u_1, 1 - u_2) + u_1 + u_2 - 1] \quad (24)$$

where

$$C_{JC}(u_1, u_2) = 1 - (1 - \{[1 - (1 - u_1)^k]^{-\gamma} + [1 - (1 - u_2)^k]^{-\gamma} - 1\}^{\frac{1}{\gamma}})^{\frac{1}{k}} \quad (25)$$

with $k = \frac{1}{log_2(2- \tau_u)}$ and $\gamma = - \frac{1}{log_2(\tau_l)}$, $\tau_u$and $\tau_l \in (0, 1)$ being lower tail index and upper tail index, respectively, of the JC copula. The tail indices indicate the dependence in extreme values of the variables, capturing the dependence in the joint tails of the bivariate distributions (Abbara and Zevallos, 2014). In addition, the tail index is similar to the probability that an extreme event occurs in a market, given that this event is occurring in another market (Silva Filho et al., 2012). In a nutshell, tail indices measure the tendency of institutions to crash or boom together. The normal copula is asymptotically independent in both, the lower (extreme losses) and upper (extreme gains) tails, the dependence structure being described by the correlation coefficient $\rho \in (-1, 1)$. On the contrary, the SJC copula presents asymmetry in tails when $\tau_u \neq \tau_l$ and symmetry when $\tau_u = \tau_l$. Given that negative shocks (news) affect more financial markets than positive shocks (news), the SJC copula could be more suitable in describing dependence, especially lower tail dependence.

The copulas functions described in Eq. (23), (24) and (25) are static. Allowing the dependence parameter to follow a restricted ARMA(1, 10) process as in Patton (2006) we can derive a time-varying copula. In addition, the intercept term is allowed to vary as a first-order Markov chain:

$$\theta_{ct}^{S_t} = \Lambda(\omega_c^{S_t} + \beta_c\theta_{ct-1} + \psi_t) \quad (26)$$

where S_t follows a first-order Markov chain parameterized by the transition probability matrix

$$p = \begin{pmatrix} p_{HH} & p_{HL} \\ p_{LH} & p_{LL} \end{pmatrix} \quad (27)$$

where p_{HH} is the probability of being in the high dependence regime at time *t* conditional on being in the same regime at time *t-1*, p_{HL} is the probability of being in the low dependence regime at time *t* conditional on being in the high regime at time *t-1*, p_{LH} is the probability of being in the high dependence regime at time *t* conditional on being in the low regime at time *t-1* and p_{LL} is the probability of being in the low dependence regime at time *t* conditional on being in the same regime at time *t-1*. Therefore, we assume two states: low dependence or a tranquil period (state S_1) and high dependence or a crisis period (state S_0). $\Lambda(\cdot)$ is a logistic transformation to constrain the dependence parameter in a fixed interval and $\psi_t$is a "forcing variable" defined as the mean absolute difference between u_1 and u_2 for the SJC copula:

$$\psi_t^{SJC} = \alpha_c \cdot \frac{1}{10}\sum_{j=1}^{10}\left|u_{1,t-j} - u_{2,t-j}\right| \tag{28}$$

For the normal copula, the "forcing variable" is defined as the mean of the products between

$$\psi_t^{N} = \alpha_c \cdot \frac{1}{10}\sum_{j=1}^{10} \Phi^{-1}(u_{1,t-j}) \cdot \Phi^{-1}(u_2, t-j) \tag{29}$$

across ten previous periods (Patton, 2006). Estimations[12] are based on Kim's filter (Kim, 1994).

5. Empirical results

In this section we analyze the empirical results resulted from applying the techniques described in the previous section.

5.1 Systemic risk rankings

Table 1 reports the main statistics of systemic and individual risk measures over the analyzed period. In terms of contribution to systemic risk as defined by ΔCoVaR and ΔACoVaR one can observe that on average, G-SIBs contribute more to systemic-wide distress than O-SIIs with 0.33 p.p. (ΔCoVaR) and with 0.21 p.p. (ΔACoVaR). This is also true if we use equity returns instead of asset market values, as showed by ΔCoVaR QR and ΔCoVaR DCC. In terms of exposure to systemic risk, again G-SIBs are more exposed to systemic risk than O-SIIs, as indicated by MES and SRISK. The major difference is with respect to SRISK, where on average G-SIBs have a capital shortfall greater with approximately 50 billion than O-SIIs.

[12] We follow Silva Filho et al. (2012) to compute log-likelihood functions and robust standard errors.

Table 3. Descriptive statistics of systemic and individual risk measures for G-SIBs and O-SIIs over the period January 1, 2004 – September 29, 2017

Variables	Mean	St. dev.	Min	p25	p50	p75	Max
G-SIBs							
VaR	3.4700	2.4700	0.9200	2.1500	2.7400	3.8800	74.8000
CoVaR	3.3100	2.1100	-3.0600	2.0000	2.7700	3.9500	27.0400
ΔCoVaR	0.9000	0.6600	0.0200	0.4700	0.7800	1.1400	6.7500
ΔACoVaR	1.6200	1.1700	0.0100	0.8700	1.3900	2.0100	15.5600
ΔCoVaR QR	1.1300	0.8900	0.1600	0.6500	0.9100	1.3200	20.8100
ΔCoVaR DCC	1.0700	0.9400	0.0900	0.5400	0.7800	1.2900	7.8100
MES	2.5700	2.2800	0.2300	1.3400	1.9500	3.0500	46.4800
SRISK	54.8955	58.8898	-153.3780	12.9871	47.3924	91.9418	309.7803
O-SIIs							
VaR	3.9600	2.5900	1.2000	2.5400	3.2900	4.4200	57.9900
CoVaR	3.8400	2.2600	-1.3100	2.4100	3.2800	4.5300	34.5800
ΔCoVaR	0.5700	0.4900	-0.0300	0.2300	0.5300	0.7700	5.5100
ΔACoVaR	1.4100	0.7900	-0.0500	0.8700	1.2600	1.7100	10.4200
ΔCoVaR QR	0.9600	0.6200	0.1600	0.5700	0.8500	1.1800	9.3600
ΔCoVaR DCC	0.7800	0.8100	-0.5300	0.3100	0.5400	0.9600	7.1600
MES	2.1800	1.7800	-2.2300	1.1400	1.7500	2.6800	28.5200
SRISK	4.1838	9.9733	-115.3400	-0.6823	0.4310	7.3803	67.0718

Note: With the exception of SRISK that is expressed in billion USD, all other individual and systemic risk indicators are expressed in percentage.

However, O-SIIs are more risky based on their VaR and CoVaR, which are measures of individual risk. Thus, we reiterate again the necessity of a macro-prudential supervision for financial institutions because metrics based on their idiosyncratic risk may be misleading. The evolution over time of the main systemic risk measures is depicted in Figure 1, comparatively for the two main groups of companies.

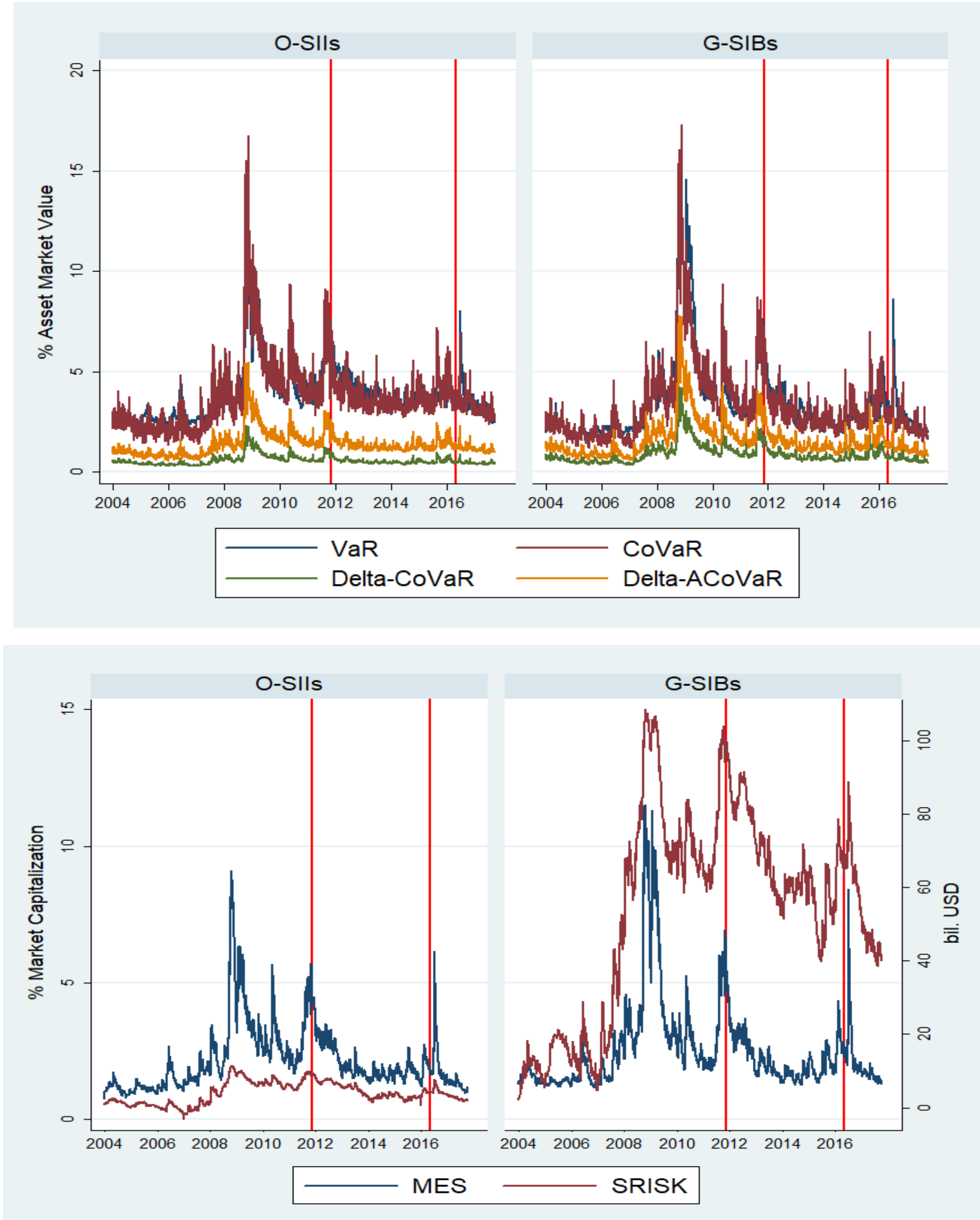


Figure 1 The evolution of systemic and individual risk measures for G-SIBs and O-SIIs

In the aftermath of the GFC all risk indicators increased in tandem, with greater spikes for G-SIBs, and therefore increased the spillover effects from G-SIBs and O-SIIs to system. The area between the two vertical red lines on each graph represents the period between the first release of G-SIBs list (4 November, 2011) and the first release of O-SIIs list (25 April, 2016). One can observe an increase in systemic and individual risk when these designation lists were made public (the so-called *stigma* effect). However, in the post-event days we can note a decrease in idiosyncratic and systemic risk which is associated with a *safety* perception by the investors as the banks were subject to a tighter macro-prudential supervision (Andrieș et al., 2017).

5.2 Dynamic Causality Index Evolution and measures of connectedness

The evolution of the DIC, we can note that the highest values are reached at the end of 2008 and 2011, confirming our previous results documenting an increase in interconnectedness between G-SIBs and O-SIIs, even though at that time (2008) the lists of G-SIBs and O-SIIs were not published yet. The first list of G-SIBs was made public by the FSB of November 4, 2011 and the first list of O-SIIs was released by the EBA on 25 April, 2016 – and one can observe an increase in the DCI following these announcements. However, the subsequent list announcements of new G-SIBs and O-SIIs did not increase the interconnectedness between the two groups.

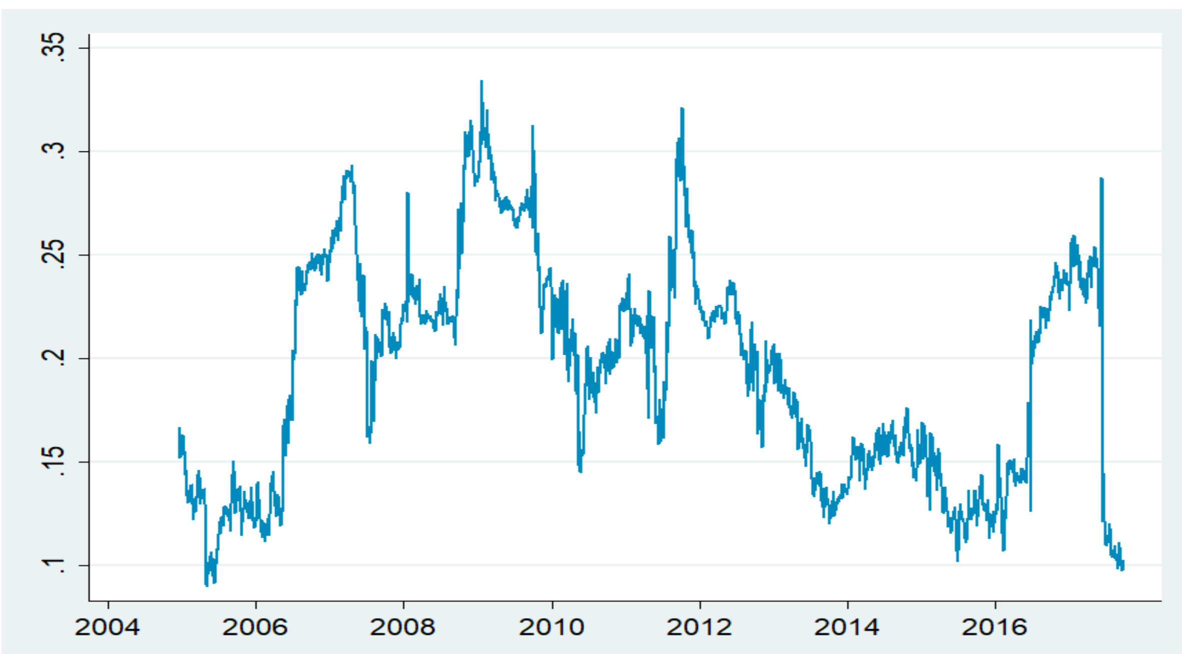


Figure 2. Dynamic Causality Index

Note: This graph exhibits the Dynamic Causality Index (DCI) which denotes the ratio of statistically significant Granger-causality relationships among all N(N-1) pairs of N financial institutions over the period January 1, 2004 – September 29, 2017.

In Figure 3 we illustrate the network diagram of linear Granger-causality relationships between G-SIBs and O-SIIs over the whole period, indicated as straight lines connecting an institution that at time *t* Granger-causes the return of another institution at time *t+1* .

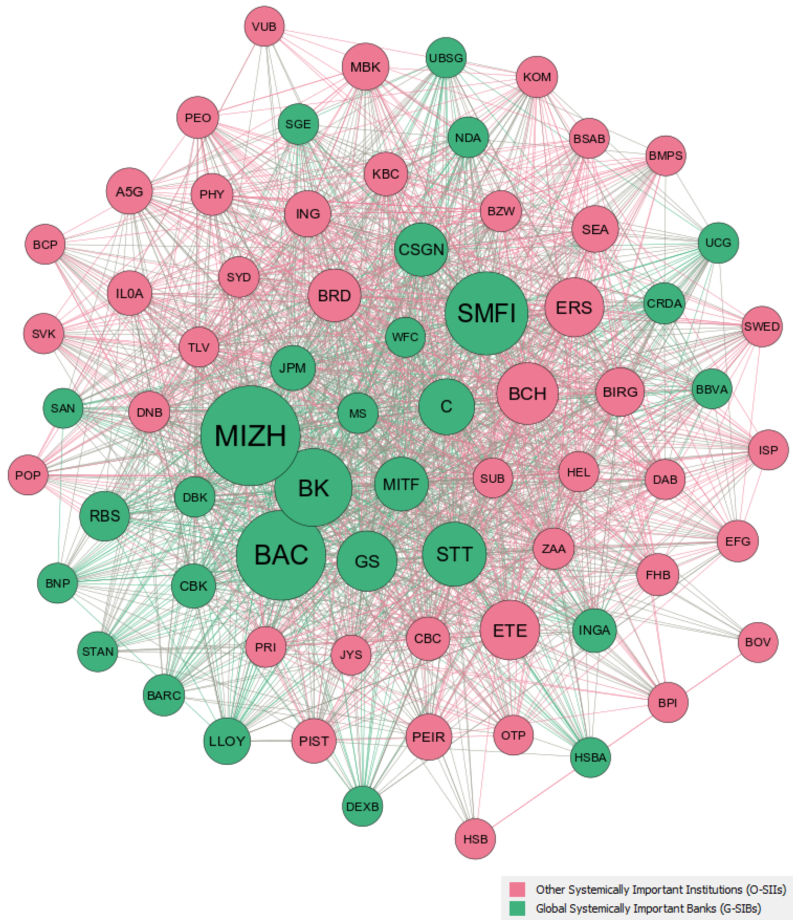


Figure 3. Network graph of Granger-causality relationships between G-SIBs and O-SIIs

Note: This diagram represents the Granger-causality relationships between G-SIBs (29 institutions) and O-SIIs (41 institutions) that are significant at 5% level over the period January 1, 2004 – September 29, 2017. The size of the nodes is proportional to betweenness centrality measure. The estimation is performed over a rolling-window of 252 trading days (one business year).

Additionally, we perform the same analysis over two sub-periods: 2004-2007 and 2008-2011[13]. These are pre-crisis and crisis periods and the latter also includes the sovereign debt crisis in Europe. The number of Granger-causality relationships significant at 5% over the whole period was 1,593, whereas during 2004-2007 – 1,689 and during 2008-2011 – 1,789. We remark an increase in the number of connections between G-SIBs and O-SIIs, G-SIBs and G-SIBs and O-SIIs and O-SIIs during the crisis period compared to the pre-crisis period. More importantly, during 2008-2011 the number of connections between the groups (G-SIBs and O-SIIs) was higher than within the groups (G-SIBs and G-SIBS and O-SIIs and O-SIIs) and one can associate

[13] The network diagrams for these two sub-periods are presented in the Appendix section of this paper.

this with an increase in the interconnectedness between the two groups. Furthermore, the biggest nodes in terms of betweenness centrality which takes into account both direct and indirect linkages capturing the position of a node in the overall network appear to be banks from G-SIBS group, i.e., Mizuho Financial Group (MIZH), Sumitomo Mitsui Financial Group (SMFI), Bank of America (BAC) and Bank of New York Mellon (BK). Hence, they are the most susceptible to shocks that propagate through the network.

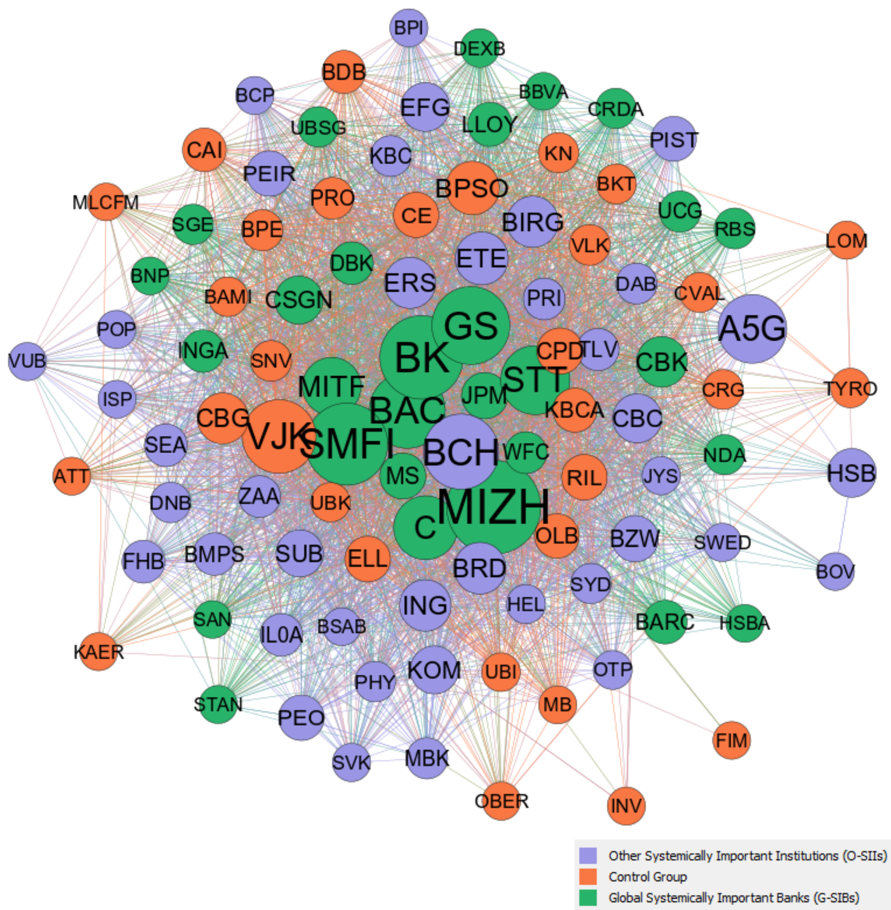


Figure 4. Network graph of Granger-causality relationships between G-SIBs, O-SIIs and control group

Note: This diagram represents the Granger-causality relationships between G-SIBs (29 institutions), O-SIIs (41 institutions) and a control group of banks from the EU (30 institutions) that are significant at 5% level over the period January 1, 2004 – September 29, 2017. The size of the nodes is proportional to betweenness centrality measure. The estimation is performed over a rolling-window of 252 trading days (one business year).

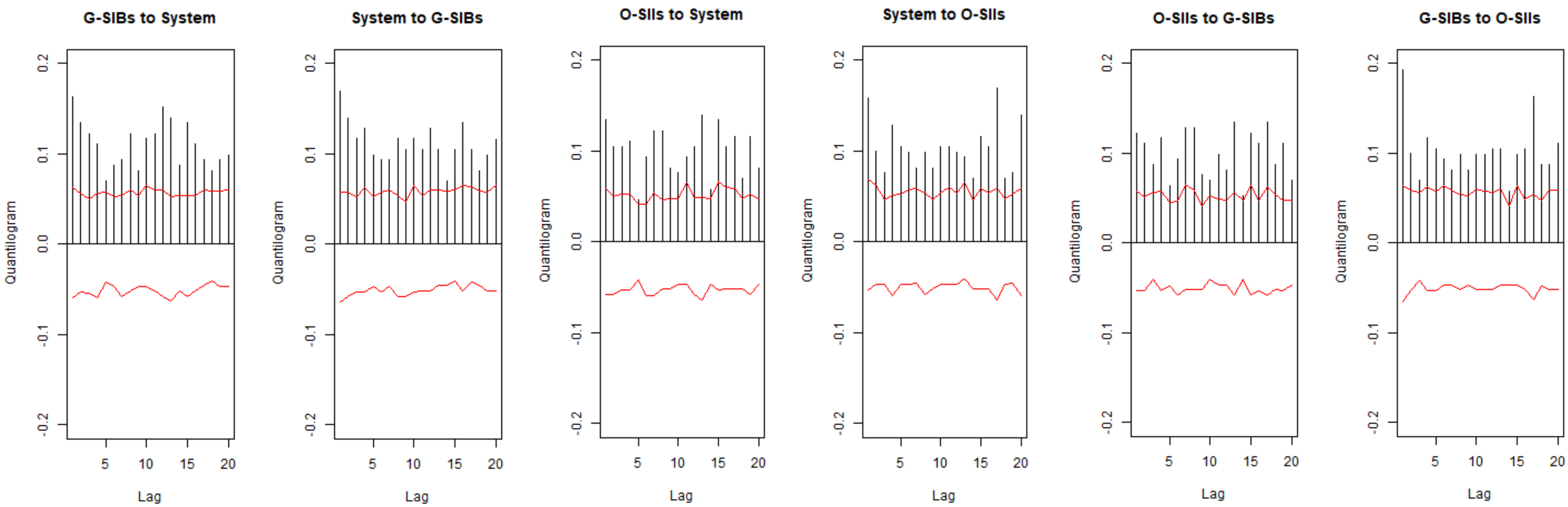
Adding a control group of 30 banks[14] from the EU, the number of Granger-causality relationships significant at 5% increases from 1,593 to 3,485, more than double. However, as it can be observed in Figure 4, the connections are more pronounced between O-SIIs and the control group than between G-SIBs and O-SIIs or between G-SIBs and the control group which is what we would expect given the fact that O-SIIs are financial institutions from Europe.

5.3 Cross-quantilogram Results

The regulators and supervisory authorities should be interested in the quantile dependence between G-SIBs and O-SIIs, O-SIIs and G- SIBs, G-SIBs and system, system and G-SIBs, O-SIIs and system and system and O-SIIs, over time. The cross-quantilogram from G-SIBs to system (first graph in Figure 5a) has the highest value for a lag of k = 1 (0.1636), meaning that it takes only one day for the systemic risk from G-SIBs to reach its peak once G-SIBs are in distress. This is also equivalent to G-SIBs contribution to systemic risk (spillover effects). On the other hand, the exposure of G-SIBs to systemic risk (system to G-SIBs, second graph in Figure 5a) is the highest (0.1694) for a lag of one. Therefore, as the system gets distressed, G-SIBs are instantly exposed. Concerning the O-SIIs, there is evidence of a reduced contribution and exposure to system-wide distressed as compared to G-SIBs. For O-SIIs to system, the cross-quantilogram takes the highest value (0.1400) for k = 13, which means that the systemic risk from O-SIIs reaches the peak in approximately two weeks once the O-SIIs encounter systemic problems (see Figure 5b).

However, O-SIIs get exposed to systemic risk much faster, i.e., in one day, the value of cross-quantilogram being 0.1636, comparable to the value of system to G-SIBS. Indeed, if we look back at Table 1, it showcases that on average, G-SIBs contribute more to systemic risk and at the same time are exposed more to systemic risk than O-SIIs. Therefore, the cross-quantilogram may constitute a useful and easy to implement tool for assessing systemic risk of individual financial institutions based only on their equity returns.

[14] The list of banks was taken from Thomson Reuters Datastream, with the symbol G#LBANKSEU. We initially started with 119 banks, but we eliminated all the banks that are either G-SIBs or O-SIIS, keeping only those with full data availability over January 1, 2004 – September 29, 2017. We thus ended up with 30 banks.



(5a) **(5b)** **(5c)**

Figure 5. The cross-quantilograms between G-SIBs, O-SIIs and system

Note: These figures exhibit the bivariate cross-quantilograms between G-SIBs, O-SIIs and system. Bars are the cross-quantilograms and the red lines are the 95% bootstrap confidence intervals centered at zero based on 1,000 iterations.

Finally, the spillover effects from G-SIBs to O-SIIs are higher and propagate more rapidly than from O-SIIs to G-SIBs (one day comparing to 13 days, respectively for a maximum value of cross-quantilogram of 0.1928 comparing to 0.1342, respectively, as depicted in Figure 5c).

5.4 Bivariate copula with Markov-switching regimes

In Table 4 we present the estimation results of the marginal distributions of the conditional variance (mean omitted) for the two groups of banks derived from a ARMA(1,1)-GARCH(1,1)-skewT model. ν and ξ are the degrees-of-freedom parameter and the asymmetry parameter of Hansen's (1994) skewed Student's t distribution, respectively.

Table 4. Marginal distribution results

Coefficient	G-SIBs	O-SIIs
Intercept	0.0003	0.0004
	(0.0002)	(0.0005)
AR(1)	0.0818	0.2368
	(0.1203)	(0.7401)
MA(1)	0.0230	-0.1778
	(0.1201)	(0.7133)
ARCH(1)	0.0773	0.0777
	(0.0103)	(0.0155)
GARCH(1)	0.9195	0.9215
	(0.0100)	(0.0111)
ν	6.9330	7.8324
	(0.7647)	(1.9036)
ξ	-0.0316	-0.0377
	(0.0217)	(0.1038)
Kolmogorov-Smirnov test	0.0003	0.0003
Kolmogorov-Smirnov test p-value	1.0000	1.0000
Berkowitz test	0.5336	0.3605
Berkowitz test p-value	0.9115	0.9483

This table presents the results of the marginal distributions of the conditional variance (mean omitted) derived from a ARMA(1,1)-GARCH(1,1)-skewT model. ν and ξ are the degrees-of-freedom parameter and the asymmetry parameter of Hansen's (1994) skewed Student's t distribution, respectively.
Kolmogorov-Smirnov test is the test of goodness-of-fit with the null hypothesis that the probability integral transform is uniform in the interval (0,1). Berkowitz'test is similar to Kolmogorov-Smirnov test but instead uses Berkowitz's (2001) transformation to a univariate normal distribution. Standard errors in parentheses.

Table 5 presents the estimation results for the SJC copula and Normal copula. The values of p and q, which are the probabilities for the two regimes (high and low, respectively) are very high, which indicates that both regimes are persistent.

Table 5. SJC and Normal copula estimation results

Coefficient	SJC copula	Coefficient	Normal copula
$\omega_{c,U}^{0}$	1.4329	ω_{c}^{0}	-0.2959
	(0.4835)		(0.0021)
$\omega_{c,U}^{1}$	2.2126	ω_{c}^{1}	0.2593
	(0.3810)		(0.2547)
$\beta_{c,U}$	-1.4474	β_{c}	2.7620
	(0.5356)		(0.0010)
$\alpha_{c,U}$	3.6625	α_{c}	0.0972
	(0.2949)		(0.0335)
$\omega_{c,L}^{0}$	-1.6257	p	0.9470
	(0.2445)		(0.0385)
$\omega_{c,L}^{1}$	-1.6613	q	0.9767
	(0.2532)		(0.0097)
$\beta_{c,L}$	-6.7991	$\mathrm{Log-likelihood}$	1401.5822
	(1.8694)		
$\alpha_{c,L}$	-0.9359	AIC	-2803.1506
	(0.5759)		
p	0.9986	-	-
	(0.0045)		
q	0.9983	-	-
	(0.0041)		
$\mathrm{Log-likelihood}$	1358.6119	-	-
AIC	-2717.2182	-	-

Copula estimation results corresponding to Eq. (26), (28) and (29). U and L represent lower and upper tail, respectively whereas p and q are the probabilities in being in state 0 (high dependence) and state 1 (low dependence), respectively. Standard errors in parentheses.

Further, Figure 6 shows the filtered probabilities, that is, probabilities computed using past and contemporaneous information for the two regimes, high and low, concerning the dependence between G-SIBs and O-SIIs. We consider a change in the dependence regime once the probability is greater than 0.5. Thus, one can observe persistence in the high dependence regime especially between 2005-2006, when we faced an energy crisis. The crisis regime starts again in 2008 and lasts until de end of 2009. This period is associated, as we know well, with the GFC that has its roots in Lehman Brothers collapse from September 15, 2008.

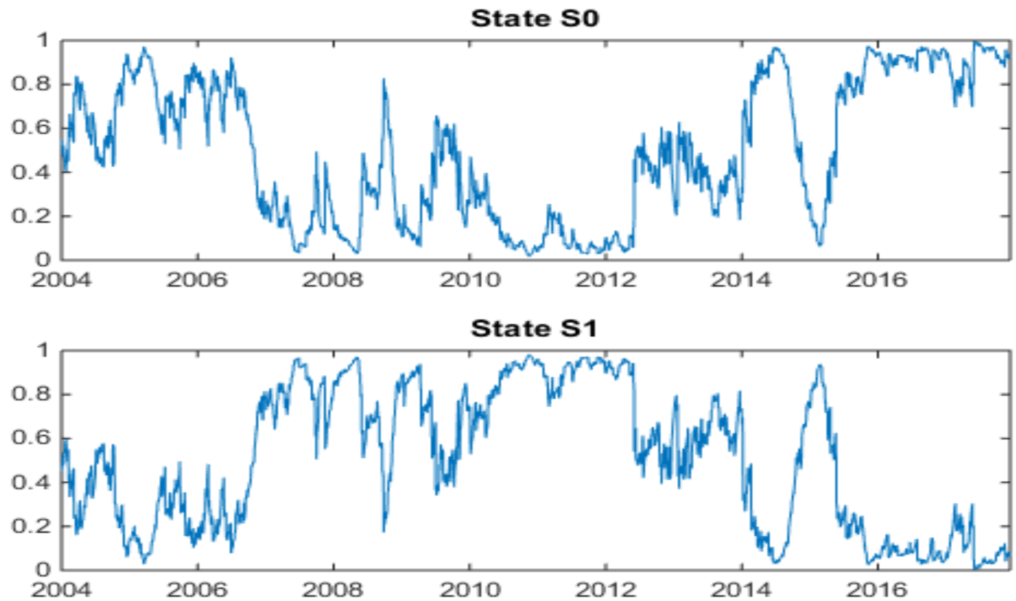


Figure 6. Filtered probabilities for the two regimes derived from a SJC copula

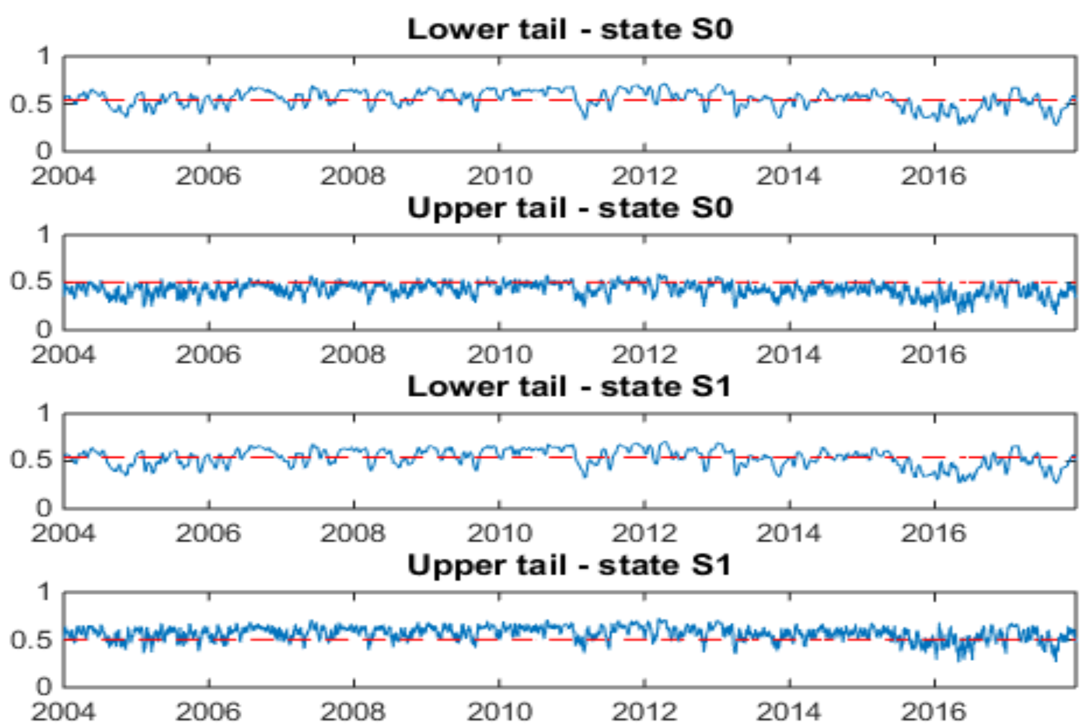


Figure 7. Dependence dynamics from a SJC copula

Note: Red lines describe constant tail dependence whereas blue lines describe time-varying tail dependence.

In Figure 7, showing the dependence dynamics from fitting a SJC copula model for both regimes, high (state S0) and low (state S1), we can observe the evolution of the lower and upper tail parameters with respect to the two regimes. The lower and upper tail parameters appear to be higher in the high dependence regime than in the low dependence regime that suggests a greater dependence during crisis times than during tranquil times between G-SIBs and O-SIIs. As hinted by Bekaert et al. (2005) this can be associated with a contagion effect, but in our case it is about contagion between institutions and not between markets.

6. Concluding remarks

In this paper we investigated the spillover effects and the systemic relevance of two particularly important groups of financial institutions: global systemically important banks (G-SIBs) and other systemically important institutions (O-SIIs). These institutions are designated by the Financial Stability Board (FSB) at the global level and by the European Banking Authority (EBA) at the European level. Because of their size, complexity, and systemic interconnectedness, in the case of a default these institutions are more likely to affect financial system (or even to drive it to the collapse) and the real economy as a whole, generating negative and expensive externalities.

As we expected, G-SIBs were, on average, the main contributors and the main exposed financial institutions to systemic wide distress. However, O-SIIs were more risky in terms of individual risk as measured by VaR and it highlights the idea that individual supervision is not without shortcomings.

From a network Granger-relationship perspective there is evidence of an increase in interdependence between G-SIBs and O-SIIs especially during 2008-2011, a period associated with the subprime crisis and debt crisis in Europe. In addition, spillover effects seem to be more pronounced within the group rather than between the groups.

Overall, our findings document that G-SIBs are more systemic relevant than O-SIIs and that there has been an increase in spillover effects between the two, especially during the global financial crisis.

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APPENDIX

Table 2. Financial institutions used in systemic risk analysis

Name	Ticker DS	Country of origin	Activity	Type	Total Assets as of end of 2004 (mil. USD)	Total Assets as of end of 2016 (mil. USD)	Date of inclusion
BANK OF CHINA 'A'	BCL	CHINA	Banks	G-SIB	513582.27	2764987.10	4 November, 2011
INDUSTRIAL & COML.BK.OF CHINA 'A'	ITL	CHINA	Banks	G-SIB	611410.48	3679954.16	11 November, 2013
AGRICULTURAL BANK OF CHINA 'A'	ABC	CHINA	Corporate Banks	G-SIB	NA	2974457.61	6 November, 2014
CHINA CON.BANK 'H'	CCBN	CHINA	Banks	G-SIB	472395.43	3195138.40	3 November, 2015
BNP PARIBAS	BNP	FRANCE	Banks	G-SIB	1113023.40	2242316.65	4 November, 2011
CREDIT AGRICOLE	CRDA	FRANCE	Corporate Banks	G-SIB	1001909.35	1647639.77	4 November, 2011
SOCIETE GENERALE	SGE	FRANCE	Banks	G-SIB	739018.43	1490910.77	4 November, 2011
COMMERZBANK	CBK	GERMANY	Banks	G-SIB	516139.74	516926.87	4 November, 2011
DEUTSCHE BANK	DBK	GERMANY	Banks	G-SIB	1028614.50	1712849.95	4 November, 2011
UNICREDIT	UCG	ITALY	Banks	G-SIB	325656.06	915517.94	4 November, 2011
MITSUBISHI UFJ FINL.GP.	MITF	JAPAN	Banks	G-SIB	960840.15	2617311.16	4 November, 2011
MIZUHO FINL.GP.	MIZH	JAPAN	Banks	G-SIB	1237418.96	1697801.82	4 November, 2011
SUMITOMO MITSUI FINL.GP.	SMFI	JAPAN	Banks	G-SIB	911884.18	1636690.97	4 November, 2011
ING GROEP	INGA	NETHERLANDS	Banks	G-SIB	1065304.88	914708.52	4 November, 2011
BANCO SANTANDER	SAN	SPAIN	Banks	G-SIB	700767.83	1426971.80	4 November, 2011
BBV.ARGENTARIA	BBVA	SPAIN	Banks	G-SIB	376604.89	774701.11	1 November, 2012
NORDEA BANK	NDA	SWEDEN	Banks	G-SIB	330036.32	680854.93	4 November, 2011
CREDIT SUISSE GROUP N	CSGN	SWITZERLAND	Banks	G-SIB	841442.19	813685.97	4 November, 2011
UBS GROUP	UBSG	SWITZERLAND	Investment Management & Fund Operators	G-SIB	1343550.63	921468.00	4 November, 2011
BARCLAYS	BARC	UNITED KINGDOM	Banks	G-SIB	964977.09	1698624.26	4 November, 2011
HSBC HDG.	HSBA	UNITED KINGDOM	Banks	G-SIB	1227024.51	2702048.62	4 November, 2011
LLOYDS BANKING GROUP	LLOY	UNITED KINGDOM	Banks	G-SIB	517233.81	1146419.75	4 November, 2011
ROYAL BANK OF SCTL.GP.	RBS	UNITED KINGDOM	Banks	G-SIB	1078422.05	1120773.64	4 November, 2011

STANDARD CHARTERED	STAN	UNITED KINGDOM	Banks	G-SIB	136174.71	736187.03	1 November, 2012
BANK OF AMERICA	BAC	UNITED STATES	Banks	G-SIB	1110457.00	2168476.00	4 November, 2011
BANK OF NEW YORK MELLON	BK	UNITED STATES	Investment Management & Fund Operators	G-SIB	94529.00	333469.00	4 November, 2011
CITIGROUP	C	UNITED STATES	Banks	G-SIB	1484101.00	1742387.00	4 November, 2011
GOLDMAN SACHS GP.	GS	UNITED STATES	Investment Banking & Brokerage Services	G-SIB	530753.00	854615.00	4 November, 2011
JP MORGAN CHASE & CO.	JPM	UNITED STATES	Banks	G-SIB	1157248.00	2490972.00	4 November, 2011
MORGAN STANLEY	MS	UNITED STATES	Investment Banking & Brokerage Services	G-SIB	775410.00	814949.00	4 November, 2011
STATE STREET	STT	UNITED STATES	Investment Management & Fund Operators	G-SIB	94040.00	242488.00	4 November, 2011
WELLS FARGO & CO	WFC	UNITED STATES	Banks	G-SIB	427849.00	1930115.00	4 November, 2011
ERSTE GROUP BANK	ERS	AUSTRIA	Banks	O-SII	171430.01	225213.86	25 April, 2016
RAIFFEISEN BANK INTL.	RAI	AUSTRIA	Banks	O-SII	35496.58	120972.08	25 April, 2016
KBC GROUP	KB	BELGIUM	Banks	O-SII	306522.07	295552.92	25 April, 2016
CB CENTRAL COOP.BANK	CBC	BULGARIA	Corporate Banks	O-SII	NA	2871.78	15 March, 2017
CB FIRST INVESTMENT BANK	CBF	BULGARIA	Corporate Banks	O-SII	NA	5032.33	15 March, 2017
ZAGREBACKA BANKA SER A	ZAA	CROATIA	Corporate Banks	O-SII	NA	18204.12	25 April, 2016
PRIVREDNA BANKA	PRI	CROATIA	Banks	O-SII	NA	11675.05	25 April, 2016
BANK OF CYPRUS	BCH	CYPRUS	Banks	O-SII	NA	23519.90	25 April, 2016
HELLENIC BANK	HEL	CYPRUS	Corporate Banks	O-SII	NA	7611.11	25 April, 2016
KOMERCNI BANKA	KOM	CZECH REPUBLIC	Banks	O-SII	17234.96	36941.83	25 April, 2016
DANSKE BANK	DAB	DENMARK	Banks	O-SII	307707.03	505637.61	25 April, 2016
SYDBANK	SYD	DENMARK	Banks	O-SII	12920.15	21286.55	25 April, 2016
JYSKE BANK	JYS	DENMARK	Banks	O-SII	20624.99	85173.35	25 April, 2016
NATIONAL BK.OF GREECE	ETE	GREECE	Banks	O-SII	65031.48	79534.46	25 April, 2016
ALPHA BANK	PIST	GREECE	Banks	O-SII	40482.84	65350.10	25 April, 2016
OTP BANK	OTP	HUNGARY	Banks	O-SII	19932.16	39419.65	25 April, 2016
FHB SHARE	FHB	HUNGARY	Retail & Mortgage Banks	O-SII	1993.03	2058.10	25 April, 2016
BANK OF IRELAND GROUP	BIRG	IRELAND	Banks	O-SII	130895.10	131917.86	25 April, 2016
AIB GROUP	A5G	IRELAND	Banks	O-SII	125497.25	100476.77	25 April, 2016
PERMANENT TSB GHG.	IL0A	IRELAND	Corporate Banks	O-SII	56952.79	25172.79	15 March, 2017
BANCA MONTE DEI PASCHI	BMPS	ITALY	Banks	O-SII	158235.55	162290.97	25 April, 2016

INTESA SANPAOLO	ISP	ITALY	Banks	O-SII	335974.04	773081.25	25 April, 2016
SIAULIU BANKAS	SUB	LITHUANIA	Corporate Banks	O-SII	NA	2014.66	25 April, 2016
BANK OF VALLETTA	BOV	MALTA	Corporate Banks	O-SII	NA	11537.89	25 April, 2016
HSBC BANK MALTA	HSB	MALTA	Corporate Banks	O-SII	NA	7886.86	25 April, 2016
DNB	DNB	NORWAY	Banks	O-SII	100881.95	304867.77	25 April, 2016
HANDLOWY	PHY	POLAND	Corporate Banks	O-SII	8552.28	11254.48	15 March, 2017
ING BANK SLASKI	ING	POLAND	Corporate Banks	O-SII	8843.15	29314.29	15 March, 2017
MBANK	MBK	POLAND	Banks	O-SII	8102.45	33305.42	15 March, 2017
BANK ZACHODNI WBK	BZW	POLAND	Banks	O-SII	6876.73	37146.63	15 March, 2017
PKO BANK	PKB	POLAND	Corporate Banks	O-SII	22503.90	70958.52	15 March, 2017
BANK POLSKA KASA OPIEKI	PKA	POLAND	Banks	O-SII	15021.47	43309.06	15 March, 2017
GETIN NOBLE BANK	GNB	POLAND	Corporate Banks	O-SII	NA	16545.34	15 March, 2017
BANK BGZ BNP PARIBAS	BGZ	POLAND	Banks	O-SII	NA	17946.35	15 March, 2017
BANCO BPI	BPI	PORTUGAL	Banks	O-SII	29490.57	40975.03	25 April, 2016
BANCO COMR.PORTUGUES 'R'	BCP	PORTUGAL	Banks	O-SII	88154.42	73716.48	25 April, 2016
BANCO POPULAR ESPANOL	POP	SPAIN	Banks	O-SII	76893.07	154859.68	25 April, 2016
BANCO DE SABADELL	BSAB	SPAIN	Banks	O-SII	51742.01	222765.76	25 April, 2016
SWEDBANK 'A'	SWED	SWEDEN	Banks	O-SII	135530.31	249361.00	25 April, 2016
SVENSKA HANDBKN.'A'	SVK	SWEDEN	Banks	O-SII	179176.81	304068.26	25 April, 2016
SEB 'A'	SEA	SWEDEN	Banks	O-SII	211181.32	303223.06	25 April, 2016

This tables exhibits the financial institutions used in systemic risk analysis. Ticker DS stands for to the ticker from Datastream and Date of inclusion refers to the first time when the financial institution was included in G-SIBs or O-SIIs list. So far, there were six updates of G-SIBs list and one update of O-SIIS list. NA stands for non available information.

Table 3. Rank of G-SIBs and O-SIIs by VaR, ΔCoVaR and MES

Ranked by	Name	Type	VaR	Name	Type	ΔCoVaR	Name	Type	MES
1	PERMANENT TSB GHG.	O-SII	5.98	DEUTSCHE BANK	G-SIB	1.16	RAIFFEISEN BANK INTERNATIONAL	O-SII	2.97
2	AIB GROUP	O-SII	5.51	BBV.ARGENTARIA	G-SIB	1.08	SOCIETE GENERALE	G-SIB	2.87
3	ALPHA BANK	O-SII	5.28	NORDEA BANK	G-SIB	1.06	COMMERZBANK	G-SIB	2.76
4	GETIN NOBLE BANK	O-SII	4.49	BNP PARIBAS	G-SIB	1.06	BANK OF IRELAND GROUP	O-SII	2.75
5	SIAULIU BANKAS	O-SII	4.16	SVENSKA HANDBKN.'A'	O-SII	1.05	CREDIT AGRICOLE	G-SIB	2.70
6	RAIFFEISEN BANK INTERNATIONAL	O-SII	4.13	SOCIETE GENERALE	G-SIB	1.05	UNICREDIT	G-SIB	2.69
7	BANK OF IRELAND GROUP	O-SII	3.89	UBS GROUP	G-SIB	1.04	DEUTSCHE BANK	G-SIB	2.67
8	BANK OF CYPRUS	O-SII	3.78	HSBC HDG.	G-SIB	1.02	ING GROEP	G-SIB	2.60
9	BANCO COMR.PORTUGUES 'R'	O-SII	3.75	BANCO SANTANDER	G-SIB	1.01	ROYAL BANK OF SCTL.GP.	G-SIB	2.56
10	BANCA MONTE DEI PASCHI	O-SII	3.75	GOLDMAN SACHS GP.	G-SIB	1.00	INTESA SANPAOLO	O-SII	2.54
11	CB FIRST INVESTMENT BANK	O-SII	3.64	CREDIT SUISSE GROUP N	G-SIB	0.99	BNP PARIBAS	G-SIB	2.52
12	MBANK	O-SII	3.63	ING GROEP	G-SIB	0.97	BARCLAYS	G-SIB	2.52
13	OTP BANK	O-SII	3.63	INTESA SANPAOLO	O-SII	0.96	BANCA MONTE DEI PASCHI	O-SII	2.49
14	UNICREDIT	G-SIB	3.60	CREDIT AGRICOLE	G-SIB	0.93	BANCO DE SABADELL	O-SII	2.46
15	BANCO DE SABADELL	O-SII	3.58	ERSTE GROUP BANK	O-SII	0.92	BANCO POPULAR ESPANOL	O-SII	2.43
16	ZAGREBACKA BANKA SER A	O-SII	3.50	JP MORGAN CHASE & CO.	G-SIB	0.91	BANCO SANTANDER	G-SIB	2.41
17	COMMERZBANK	G-SIB	3.48	UNICREDIT	G-SIB	0.88	PERMANENT TSB GHG.	O-SII	2.40
18	HELLENIC BANK	O-SII	3.45	DNB	O-SII	0.87	ERSTE GROUP BANK	O-SII	2.38
19	BANK POLSKA KASA OPIEKI	O-SII	3.42	SYDBANK	O-SII	0.84	BBV.ARGENTARIA	G-SIB	2.33
20	CB CENTRAL COOP.BANK	O-SII	3.41	SEB 'A'	O-SII	0.81	MORGAN STANLEY	G-SIB	2.31
21	BANK ZACHODNI WBK	O-SII	3.37	MORGAN STANLEY	G-SIB	0.80	BANCO COMR.PORTUGUES 'R'	O-SII	2.29
22	BANCO POPULAR ESPANOL	O-SII	3.34	BANK OF NEW YORK MELLON	G-SIB	0.80	KBC GROUP	O-SII	2.29
23	PRIVREDNA BANKA	O-SII	3.33	OTP BANK	O-SII	0.80	ALPHA BANK	O-SII	2.26
24	SOCIETE GENERALE	G-SIB	3.32	SWEDBANK 'A'	O-SII	0.80	CREDIT SUISSE GROUP N	G-SIB	2.24
25	PKO BANK POLSKI	O-SII	3.32	BARCLAYS	G-SIB	0.79	GETIN NOBLE BANK	O-SII	2.24
26	INTESA SANPAOLO	O-SII	3.30	STANDARD CHARTERED	G-SIB	0.77	BANK OF AMERICA	G-SIB	2.21
27	ROYAL BANK OF SCTL.GP.	G-SIB	3.30	BANCO POPULAR ESPANOL	O-SII	0.76	SEB 'A'	O-SII	2.21
28	ERSTE GROUP BANK	O-SII	3.30	DANSKE BANK	O-SII	0.75	CITIGROUP	G-SIB	2.16

29	BANCO BPI	O-SII	3.30	KBC GROUP	O-SII	0.74	UBS GROUP	G-SIB	2.15
30	FHB SHARE	O-SII	3.28	STATE STREET	G-SIB	0.74	STANDARD CHARTERED	G-SIB	2.12
31	CREDIT AGRICOLE	G-SIB	3.17	BANK OF AMERICA	G-SIB	0.74	NORDEA BANK	G-SIB	2.09
32	HANDLOWY	O-SII	3.13	RAIFFEISEN BANK INTERNATIONAL	O-SII	0.73	MBANK	O-SII	2.08
33	BARCLAYS	G-SIB	3.12	WELLS FARGO & CO	G-SIB	0.71	PKO BANK POLSKI	O-SII	2.08
34	DEUTSCHE BANK	G-SIB	3.10	JYSKE BANK	O-SII	0.71	OTP BANK	O-SII	2.07
35	ING GROEP	G-SIB	3.07	PKO BANK POLSKI	O-SII	0.70	LLOYDS BANKING GROUP	G-SIB	2.03
36	KBC GROUP	O-SII	3.03	BANK ZACHODNI WBK	O-SII	0.70	SWEDBANK 'A'	O-SII	2.01
37	NATIONAL BK.OF GREECE	O-SII	2.98	LLOYDS BANKING GROUP	G-SIB	0.67	DNB	O-SII	2.00
38	DNB	O-SII	2.96	CITIGROUP	G-SIB	0.67	AIB GROUP	O-SII	2.00
39	KOMERCNI BANKA	O-SII	2.94	KOMERCNI BANKA	O-SII	0.65	STATE STREET	G-SIB	1.99
40	ING BANK SLASKI	O-SII	2.89	COMMERZBANK	G-SIB	0.63	NATIONAL BK.OF GREECE	O-SII	1.95
41	BANCO SANTANDER	G-SIB	2.88	BANK POLSKA KASA OPIEKI	O-SII	0.61	GOLDMAN SACHS GP.	G-SIB	1.92
42	BNP PARIBAS	G-SIB	2.88	MBANK	O-SII	0.61	SVENSKA HANDBKN.'A'	O-SII	1.90
43	CREDIT SUISSE GROUP N	G-SIB	2.86	HANDLOWY	O-SII	0.59	BANK POLSKA KASA OPIEKI	O-SII	1.83
44	SWEDBANK 'A'	O-SII	2.85	BANCO BPI	O-SII	0.59	BANK OF NEW YORK MELLON	G-SIB	1.82
45	MITSUBISHI UFJ FINL.GP.	G-SIB	2.84	ING BANK SLASKI	O-SII	0.54	BANCO BPI	O-SII	1.80
46	STANDARD CHARTERED	G-SIB	2.84	ROYAL BANK OF SCTL.GP.	G-SIB	0.54	JP MORGAN CHASE & CO.	G-SIB	1.79
47	BBV.ARGENTARIA	G-SIB	2.83	NATIONAL BK.OF GREECE	O-SII	0.53	FHB SHARE	O-SII	1.78
48	SEB 'A'	O-SII	2.82	BANCO COMR.PORTUGUES 'R'	O-SII	0.52	DANSKE BANK	O-SII	1.68
49	MORGAN STANLEY	G-SIB	2.82	CHINA CONSTRUCTION BANK	G-SIB	0.50	HSBC HDG.	G-SIB	1.66
50	SUMITOMO MITSUI FINL.GP.	G-SIB	2.81	BANCO DE SABADELL	O-SII	0.48	WELLS FARGO & CO	G-SIB	1.61
51	LLOYDS BANKING GROUP	G-SIB	2.81	FHB SHARE	O-SII	0.44	JYSKE BANK	O-SII	1.61
52	MIZUHO FINL.GP.	G-SIB	2.75	GETIN NOBLE BANK	O-SII	0.43	BANK ZACHODNI WBK	O-SII	1.60
53	BANK BGZ BNP PARIBAS	O-SII	2.74	SIAULIU BANKAS	O-SII	0.32	HANDLOWY	O-SII	1.59
54	NORDEA BANK	G-SIB	2.72	ZAGREBACKA BANKA SER A	O-SII	0.29	SYDBANK	O-SII	1.56
55	BANK OF CHINA	G-SIB	2.64	MITSUBISHI UFJ FINL.GP.	G-SIB	0.27	KOMERCNI BANKA	O-SII	1.49
56	UBS GROUP	G-SIB	2.58	PRIVREDNA BANKA	O-SII	0.27	ING BANK SLASKI	O-SII	1.31
57	AGRICULTURAL BANK OF CHINA	G-SIB	2.55	BANK OF CYPRUS	O-SII	0.27	BANK BGZ BNP PARIBAS	O-SII	1.25
58	SVENSKA HANDBKN.'A'	O-SII	2.52	CB FIRST INVESTMENT BANK	O-SII	0.26	BANK OF CYPRUS	O-SII	1.25

59	CHINA CONSTRUCTION BANK	G-SIB	2.51	INDUSTRIAL AND COMMERCIAL BANK OF CHINA	G-SIB	0.25	CB FIRST INVESTMENT BANK	O-SII	1.20
60	BANK OF AMERICA	G-SIB	2.50	MIZUHO FINL.GP.	G-SIB	0.23	HELLENIC BANK	O-SII	1.15
61	DANSKE BANK	O-SII	2.50	SUMITOMO MITSUI FINL.GP.	G-SIB	0.21	CHINA CONSTRUCTION BANK	G-SIB	1.14
62	STATE STREET	G-SIB	2.46	CB CENTRAL COOP.BANK	O-SII	0.20	SUMITOMO MITSUI FINL.GP.	G-SIB	0.92
63	CITIGROUP	G-SIB	2.44	BANK BGZ BNP PARIBAS	O-SII	0.19	MITSUBISHI UFJ FINL.GP.	G-SIB	0.90
64	GOLDMAN SACHS GP.	G-SIB	2.43	AGRICULTURAL BANK OF CHINA	G-SIB	0.17	CB CENTRAL COOP.BANK	O-SII	0.90
65	JYSKE BANK	O-SII	2.38	BANCA MONTE DEI PASCHI	O-SII	0.17	MIZUHO FINL.GP.	G-SIB	0.90
66	SYDBANK	O-SII	2.36	BANK OF VALLETTA	O-SII	0.13	PRIVREDNA BANKA	O-SII	0.82
67	BANK OF NEW YORK MELLON	G-SIB	2.24	HSBC BANK MALTA	O-SII	0.13	SIAULIU BANKAS	O-SII	0.73
68	INDUSTRIAL AND COMMERCIAL BANK OF CHINA	G-SIB	2.23	BANK OF CHINA	G-SIB	0.12	ZAGREBACKA BANKA SER A	O-SII	0.69
69	JP MORGAN CHASE & CO.	G-SIB	2.15	HELLENIC BANK	O-SII	0.01	BANK OF CHINA	G-SIB	0.52
70	WELLS FARGO & CO	G-SIB	2.01	ALPHA BANK	O-SII	0.01	AGRICULTURAL BANK OF CHINA	G-SIB	0.48
71	HSBC HDG.	G-SIB	1.97	AIB GROUP	O-SII	0.01	BANK OF VALLETTA	O-SII	0.45
72	BANK OF VALLETTA	O-SII	1.84	BANK OF IRELAND GROUP	O-SII	0.01	INDUSTRIAL AND COMMERCIAL BANK OF CHINA	G-SIB	0.44
73	HSBC BANK MALTA	O-SII	1.83	PERMANENT TSB GHG.	O-SII	0.00	HSBC BANK MALTA	O-SII	0.39

The table presents the rank of G-SIBs and O-SIIS by VaR, ΔCoVaR and MES based on median daily values. All risk measures are expressed in percentage.

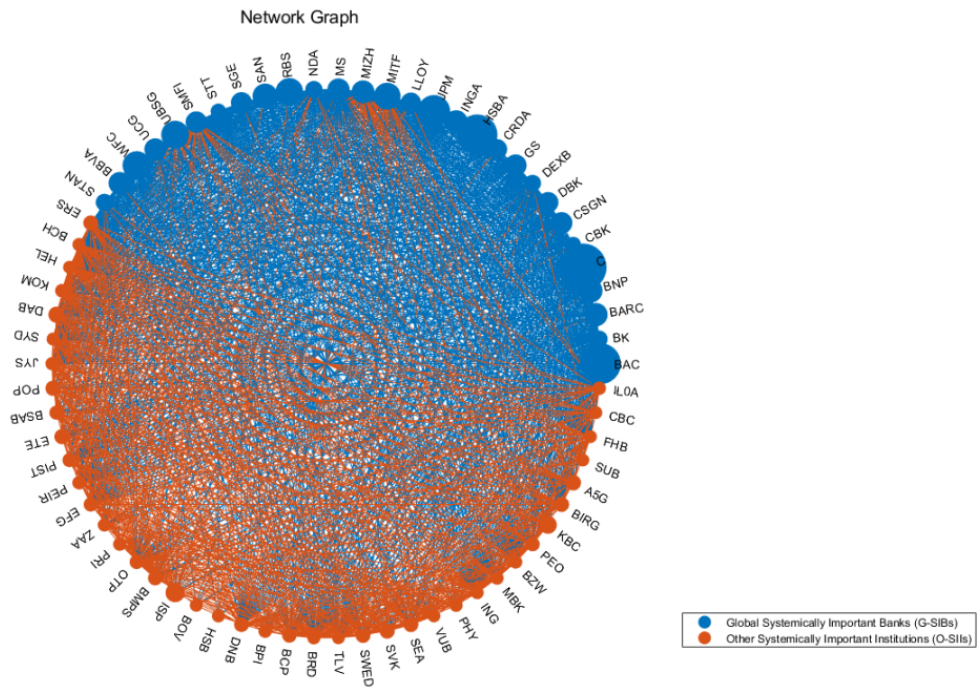

Figure 1. Network graph for 2004-2007 period

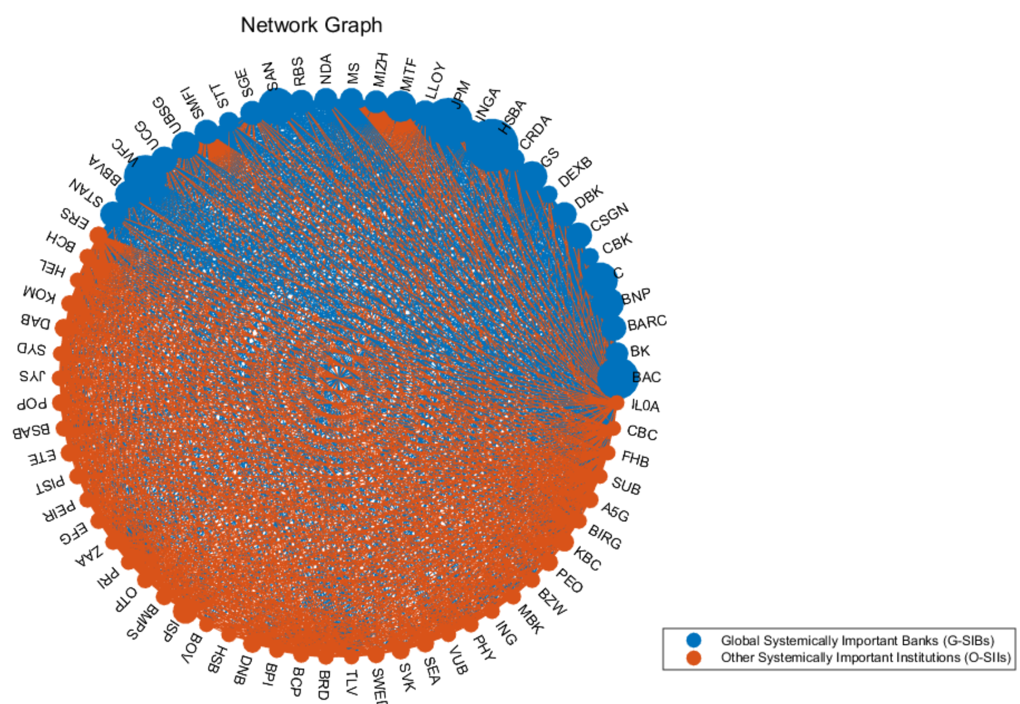

Figure 2. Network graph for 2008 - 2011 period