Small but Dangerous: Measuring connectedness between Eurozone financial institutions

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Abstract

Keywords:

JEL Codes:

1 Introduction

In recent years there has been a clear "relationship" between banks, insurance companies and financial institutions that provide diversified financial services (called "shadow banking system"). This has led to much closer interconnections between different sectors than in the past. Just look of the "exchange" of activities between the different companies in the financial sector. For example, insurance has entered the investment management market, while banks have carried out insurance activities (Bernardi and Petrella, 2015). As regards shadow banking entities, they offer insurance, banking and investment products. These entities are structurally complicated enterprises, both in terms of the quality and quantity of services offered and from a regulatory point of view, providing banking services without access to central bank liquidity or public credit guarantees (Pozsar et al., 2013).

These intra-sectoral interdependencies between financial market participants have contributed to the spread of instability in the financial system by highlighting gaps in the assessment of these links (Abad et al., 2017). Therefore, to correctly specify the financial system, it is important to map these links (Fischer, 2015) in order to "set policies to limit possible instabilities associated with interconnectedness". The work aims at investigating (and bridging) the interdependencies of the tail-end risk between the three sectors

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mentioned above. This interconnection is a fundamental requirement for assessing the vulnerability of the market (and financial institutions) to systemic events (Glasserman and Young, 2016). As far as we know, this is the first attempt to consider the spillover effects of tail risk between banks, insurance companies and the shadow banking system[1], in the Eurozone contest.

Pioneering work in this field (connectivity measures), is the study of Nier et al. (2007), that analysed how systemic risk depends on the structure of the banking system. Using network theory (banks are connected by interbank linkages), the authors show how the financial system is resilience to contagious defaults. However, the crisis raised the awareness about the interactions and the connections between financial firms, therefore a considerable amount of works has been developed. Billio et al. (2012), by Granger causality measures, develop several measures of interconnectedness and systemic risk among banks, hedge funds, insurances, and brokers. The network is built on significant Granger causality test between the stock return. Diebold and Ylmaz (2014) propose a volatility spillover network model to estimate the interconnectedness among US financial companies. The direction of spillover (from, to) is based on vector autoregressive framework variance decomposition, which is estimated by a quantile regression in order to capture network spillover effects. The realized systemic risk beta of Hautsch et al. (2015) is based on tail risk interdependence network of financial institutions. Their measure capture and quantify the "impact on the risk of distress of the system induced by an increase in the risk of the specific company in a network setting". More recent, Wang et al. (2017) using Granger causality risk test, develop an extreme risk spillover network in order to analyse the interconnectedness among 84 US listed financial institutions. Bluhm and Krahnen (2014) build a system wide value at risk (SVaR) to study the contribution of individual banks to systemic risk. Different from previous work, their network model is based on bank balance sheets data. In more detail several empirical applications deal with the network measure and the risk spillover transmission over the U.S. financial market (for example see Diebold and Yilmaz, 2014; Härdle et al., 2016; Barigozzi and Brownlees, 2018) and the international prospective (e.g. Billio et al., 2012b; Drehmann and Tarashev, 2013; Bongini et al., 2018; Demirer et al., 2018)

Focusing on empirical findings on the European financial sector, Brunetti et al. (2015) show an increase of interconnectedness during the crisis period of market return network,

[1]We refer to "shadow banking" according to the definition of EESC (2012): "there are many ways in which shadow banks replicate traditional banks, and some shadow banks are part of traditional banks". Agree with Jeffers and Plihon (2016), this definition is functional to understand the European shadow banking, as it is closely linked to the universal banking model. In the same view the definition of Pozsar et al. (2013): "[F]inancial intermediaries that conduct maturity, credit, and liquidity transformation without access to central bank liquidity or public sector credit guarantees. Examples of shadow banks include finance companies, asset-backed commercial paper (ABCP) conduits, limited-purpose finance companies, structured investment vehicles, credit hedge funds, money market mutual funds, securities lenders, and government-sponsored enterprises."

in contrast to the physical network (based on interbank lending transactions) that decrease in the same period. The authors note that the correlation network is able to forecast the financial crisis, while physical forecast liquidity problems. Billio et al. (2012b), investigate the evolution of different measures of connection between European countries, and major European, U.S. and Japanese financial company. They find that the system of banks, insurance firms, and countries are highly connected. Also, they show the high impact of sovereign risk before the European debt crisis of 2010-12. Glasserman and Young (2015) analyse, in a theoretical framework, the interconnectedness, the diffusion and the effect of a shock. Their model is confirmed by an empirical example using data for the 2010 EBA stress tests. In particular, they find that the diffusion effects are high when the starting financial institution (node) has high leverage while the rest of the network have heterogeneous sizes. Betz et al. (2016) extend the model of Hautsch et al. (2015) and provide a new framework for estimating in presence of high-dimensional financial system, the time-varying systemic risk contributions. Their model is applied to 51 large European banks and 17 sovereigns, from 2006 to 2013, showing how the network's density increases during the financial crisis and decreases afterwards. Also, they find that the size, leverage and degree of interconnectedness increase banks' systemic importance.

A similarity in the studies cited is that the networks are usually weighted but not oriented, and that the spillovers are bivariate in pairs, thus not considering the effects of the complete system. Therefore, when trying to map the interconnections between the various sectors, not considering the risk in the system as a whole can lead to an underestimation of the risk, thus leading to sub-optimal policy reactions by the regulator. For this reason, a good understanding of the connections is advantageous, both for the policy-makers in order to manage, monitor the systemic risk and the financial stability, and for the investors in the determination of the price of the assets (asset allocation).

In an effort to consider these limits, the analysis is carried out using the TENET (Tail Event driven NETwork; Härdle et al., 2016) methodology, which is based on an extension of the CoVaR concept, introduced by Adrian and Brunnermeier (2016), that considers only the interaction between two financial institutions in an isolated environment. Following this approach, we are able to consider 1) a high dimension context, 2) the non-linearity between pairs of financial activities, 3) a weighted and direct network. The TENET is useful to show the contribution of a financial firm by taking into account its tail interconnects with other financial company and to analyse the spillover effect. Also, thank this method, we provide a measure of systemic risk for the entire financial system, for part of itself and each financial institution, taking into account the "too big to fail" and "too big to interconnected" concepts.

We analyse the financial system with a double point of view: at a 1) macro (aggregate) level and at 2) cross-section level. First, we compute the total connections and the spillover between the three financial sectors (banks, insurances, and others). Second,

we investigate the interconnectedness between 60 Eurozone (EZ) financial institutions to identify the SIFIs (Systemically Important Financial Institutions). This analysis offers a clear view and identification of the transmission of the systemic risk spillovers during the two financial crisis that affected the EZ countries.

Our results suggest that each financial sector has a significant impact on the other. By comparing the contribution of each sector, we show that banks are the largest emitters of risk, contributing more to the evolution of the total connection. In addition, we find that each sector in different periods contributes differently to the overall risk. Before the financial crisis, the "others" (shadow banking) sector is the one that emits (receives) the most tail risk to (from) other sectors, demonstrating the key role played in the transmission of the U.S. crisis. Also, we find that our estimates provide a meaningful classification of the systemic importance of financial institutions, consistent with the classifications of Global Systemically Important Banks (G-SIB), Other Systemically Important Institutions (O-SII) and Global Systemically Important Insurers (G-SII). However, small and medium-sized financial institutions are of systemic importance given their high level of connection, showing that these firms are "small but dangerous" to the system as a whole. The results suggest that policy-makers should focus not only on large financial companies but also consider the risk potential of small financial institutions.

The remainder of the paper is then organized as follows. In Section 2, we go through the TENET framework. In Section 3 the data are presented while in Sections 4 and 5 we discuss the empirical application. In Section 6 we draw our conclusions.

2 The TENET method

The Tail Event driven NETwork is a technique based on CoVaR methodology of Adrian and Brunnermier (2016). In this section we introduce the three steps of methodology for measuring systemic risk. Moreover, in the next sub-section the connectivity measures are describe.

2.1 VaR and CoVaR concepts

By definition, VaR is a measure of the maximum potential variation in the value of a portfolio over a given time horizon (t) and level of probability (P). The VaR of financial firms i at $\tau \in (0, 1)$ is the value, which can take the random variable $X_{i,t}$ (the log return) as:

$$P(X_{i,t} \leq VaR_{i,t,\tau}) \equiv \tau, \tag{1}$$

where τ is the quantile level of return distribution. The risk measure of $CoVaR_{j|i,t,\tau}$ (Conditional Value at Risk) is proposed by Arian and Bunnermeier (2016) to taking into

account the spillover effects and the state of economy. More specifically, $CoVaR_{j|i,t,\tau}$ is the VaR of financial firm j conditional to financial firm i at time t. It is defined as:

$$P\left\{X_{i,t} \leq CoVaR_{j|i,t,\tau}|R_{i,t}\right\} \equiv \tau. \tag{2}$$

Hence $R_{i,t}$ is the information set that includes some event of $X_{i,t} = VaR_{i,t,\tau}$ and M_{t-1} is a vector of macroeconomics variables that indicate the state of economy. In the first step, the CoVaR is estimated via linear quantile (tail event) regression of log return of firm i on macroeconomics variables as follow:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}, \tag{3}$$

$$X_{j,t} = \alpha_{j|i} + \gamma_{j|i} M_{t-1} + \beta_{j|i} X_{i,t} + \varepsilon_{j|i,t}. \tag{4}$$

The second step consist to estimate $VaR_{i,t,\tau}$ and $CoVaR_{j|i,t,\tau}$ of financial institutions i and j plugging the predictive values from the above estimates,

$$\widehat{VaR}_{i,t,\tau} = \hat{\alpha}_i + \gamma_i \hat{M}_{t-1} \tag{5}$$

$$\widehat{CoVaR}_{j|i,t,\tau} = \hat{\alpha}_{j|i} + \hat{\gamma}_{j|i} M_{t-1} + \hat{\beta}_{j|i} \widehat{VaR}_{i,t,\tau} \tag{6}$$

where $\hat{\beta}_{j|i}$ denotes the level of interconnectedness between firm i and firm j. Depending on that to set the subscript, j = return of system and i = return of financial firm, we capture the *contribution* CoVaR, while doing the reverse we obtain how a firm i is exposed to the risk of the system (*exposure* CoVaR).

2.2 TENET steps

The TENET model expands the CoVaR method of Adrian and Brunnermeier (2016) in three important aspects. One of the criticisms of CoVaR is that it not allows for considering the interaction effects in all system but only between two financial firms in an "isolated environment". Neglecting these effects may lead to an incorrect estimation of systemic risk. Härdle et al. (2016) modified this bivariate model to a high-dimensional framework by adding more variables. The second problem of CoVaR is that assumes a linear relationship between the financial company stock return and the system. However, as Chao et al. (2015) show, this relationship is non-linear, particularly during a crisis time. Therefore, the TENET framework using single-index quantile regression, allows estimating a nonlinear regression. Finally, the third innovation regards the building 2 indices of systemic risk. Härdle et al. (2016) propose two market capitalization weighted indices taking into account the connectedness structure of the system, namely the Systemic Risk Receiver (SRR) and Systemic Risk Emitter (SRE). These indices measure the systemic risk contributions for each financial firm with the purpose to identify the

systemically important financial institutions. To build a systemic risk network we need to proceed with two steps. First, we have to estimate the VaR for each individual institution using Eq. (5) and (6). Second, using the single-index quantile regression, we compute the interdependence network. The essential element of the network is the CoVaR calculated by Eq. (6). In this case, the CoVaR make allowance the risk spillover channel of liquidity and risk exposure. In fact, it estimated also uses the firm characteristic such as leverage, market-to-book. In formula, we have:

$$X_{j,t} = g(\beta_{j|R_j}^{\top}) + \varepsilon_{j,t}, \tag{7}$$

$$\widehat{CoVaR}_{j|\tilde{R}_j,t,\tau}^{TENET} \equiv \hat{g}(\hat{\beta}_{j|\tilde{R}_j}^{\top}\tilde{R}_{j,t}), \tag{8}$$

$$\hat{D}_{j|\tilde{R}_j} \equiv \frac{\delta\hat{g}(\hat{\beta}_{j|\tilde{R}_j}^{\top}R_{j,t})}{\delta R_{j,t}}|_{R_{j,t}=\tilde{R}_{j,t}} = \hat{g}'(\hat{\beta}_{j|\tilde{R}_j}^{\top}\tilde{R}_{j,t})\hat{\beta}_{j|\tilde{R}_j}. \tag{9}$$

$R_{j,t} \equiv \{X_{-j,t}, M_{t-1}, B_{j,t-1}\}$ is the information set that includes the following variables:

- $X_{-j,t} = \{X_{1,t}, X_{2,t}, ..., X_{N,t}\}$ is a vector of explanatory variables (log return) and N is the number of financial firms.
- M_{t-1} is the vector of economic state variables, t is the time
- $B_{j,t-1}$ are the company characteristics

The parameters $\hat{\beta}_{j|\tilde{R}_j}$ are defined as follow $\beta_{j|\tilde{R}_j} = \left\{\beta_{j|-j}, \beta_{j|M}, \beta_{j|B_j}\right\}^{\top}$. $\tilde{R_{j,t}} = \left\{\widehat{VaR}_{-j,t,\tau}, M_{t-1}, B_{j,t-1}\right\}$ where $\widehat{VaR}_{-j,t,\tau}$ is the VaRs for Eq. (5) for all financial firms exclude the firm j, while $\hat{\beta}_{j|\tilde{R}_j} = \left\{\hat{\beta}_{j|-j}, \hat{\beta}_{j|M}, \hat{\beta}_{j|b_j}\right\}^{\top}$. $g(.)$ indicates the shape of link function using to estimate the non-linearity relationship.

The marginal effects of explanatory variables are captured by the gradient measure $\hat{D}_{j|\tilde{R}_j}$, that includes $\hat{D}_{j|\tilde{R}_j} = \left\{\hat{D}_{j|-j}, \hat{D}_{j|M}, \hat{D}_{j|B_j}\right\}$. The key element of the TENET model is $\hat{D}_{j|-j}$ that a is able to measure the spillover effect from all network to financial institutions j [2]. Finally, the estimation results are put in a fashion of a $N \times N$ weighted adjacency matrix (total connect matrix), with a set of nodes ($V = \{1, 2, ..., N\}$, set of institutions) and edges (E) (see Eq. (10)).

$$A = \begin{bmatrix} 0 & |\hat{D}_{1|2}^{w}| & |\hat{D}_{1|3}^{w}| & \cdots & |\hat{D}_{1|N}^{w}| \\ |\hat{D}_{2|1}^{w}| & 0 & |\hat{D}_{2|3}^{w}| & \cdots & |\hat{D}_{2|N}^{w}| \\ |\hat{D}_{3|1}^{w}| & |\hat{D}_{3|2}^{w}| & 0 & \cdots & |\hat{D}_{3|N}^{w}| \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ |\hat{D}_{N|1}^{w}| & |\hat{D}_{N|2}^{w}| & |\hat{D}_{N|3}^{w}| & \cdots & 0 \end{bmatrix} \tag{10}$$

[2] As in Härdle et al. (2016), to construct the network, we use the partial derivatives of firms j to other financial firms, while the partial derivatives respect to $\hat{D}_{j|M}$ and $\hat{D}_{j|B_j}$ are not inserted.

The elements in the upper triangular matrix $\hat{D}^w_{j|i}$ allow to measure the impact from financial institutions i to j, while the elements in the lower triangular matrix $\hat{D}^w_{i|j}$ capture the level of risk tail spillover from firm j to i. w stands for the estimation window, while $||$ is the symbol of absolute value. By construction $\hat{D}_{j|i}$ is equal to zero when $j = i$. The rows represent the incoming edges, while the columns correspond to outgoing edges.

2.3 Measuring systemic risk contributions

Finally, in the third step of TENET, two indices of systemic risk are computed, with a focus on identifying the systemically important institutions. The two indices are the Systemic Risk Receiver (SSR) and the Systemic Risk Emitter (SRE). More precisely:

$$SRR_{j,w} = MC_{j,w} \sum_{i \in E^{IN}_w} (|\hat{D}^w_{j|i}| \cdot MC_{i,w}) \tag{11}$$

$$SRE_{j,w} = MC_{j,w} \sum_{i \in E^{OUT}_w} (|\hat{D}^w_{i|j}| \cdot MC_{i,w}) \tag{12}$$

Here $E^{(IN)}_w$ and $E^{(OUT)}_w$ are the set of financial companies linked with financial company j at window w. $M_{i,w}$ ($M_{j,w}$) is the market capitalization of firm i (j) at the start period w. $|\hat{D}^w_{j|i}|$ ($|\hat{D}^w_{i|j}|$) symbolize the incoming (row) and outgoing (column) interconnectedness of firm j. Taking into account both incoming and outgoing links and the market capitalization, these measures are able to link the "too big to fail" to "too interconnected to fail" issue (Wang et al., 2018).

2.4 Risk network measure

We now introduce the connectedness measures. To analyse the topological features of the network, we compute, as in Wang et al. (2017; 2018), two type of connectivity measure: 1) system-level connectivity and 2) sector-level connectivity.

1. Total Connectedness. TC measures the total level of tail risk spillovers. It is defined as:

$$TC = \sum_{j=1}^{N} \sum_{i=1}^{N} |\hat{D}^W_{j|i}|. \tag{13}$$

2. Sector-level connectivity measures. We calculate two measure of sector connectivity: the incoming ($GC^{IN}_{g,w}$) and outgoing ($GC^{OUT}_{g,w}$) connectedness. The first is the sum of incoming edges:

$$GC^{IN}_{g,w} = \sum_{j \in g} \sum_{i=1}^{N} |\hat{D}^w_{j|i}|, \tag{14}$$

while the latter is the sum of outgoing edges:

$$GC_{g,w}^{OUT} = \sum_{i=1}^{N} \sum_{j \in g} |\hat{D}_{i|j}^{w}| \tag{15}$$

where $g = 1, 2, 3$ correspond to the three sectors.

2.1 Sector-spillover level. We compute a measure of strength of cross sector (SCS), in order to study how sectors influence each sector. In particular, we investigate the spillover effect from sector m to another or itself n. The SCS is defined as follow:

$$SCS_{m \to n} = \frac{1}{N_m N_n} \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} |\hat{D}_{j|i}^{W}| \tag{16}$$

where m and n is the financial sectors (bank, insurances, and other), while N_m and N_n is the number of financial firms belonging to sector (n and m). When $m = n$, this implies in Eq. (16), $N_n = N_m - 1$.

2.2. Relative influence. We calculate the relative influence (RI) as the ratio between the difference and the sum of out-tail interconnectedness and in-tail interconnectedness, follow Kenett et al. (2010):

$$RI_{sector}(m) = \frac{\hat{D}_{out}^{W}(m) - \hat{D}_{in}^{W}(m)}{\hat{D}_{out}^{W}(m) + \hat{D}_{in}^{W}(m)} \tag{17}$$

hence $RI_{sector} \in [-1 : 1]$. This measure is allowed to capture the relative influence and the magnitude of risk spillover from this sector to other. For example a positive value means that this sector emits more systemic risk than it receives and *viceversa*.

3 Data

We apply TENET to main Eurozone financial firms in order to point out their contribution on systemic risk and their degree of interconnectedness. We divide the Eurozone financial institutions into three groups according to the list from Osiris database (Global industry classification standard: 40 - Financial): 1) banks, 2) insurance companies, and 3) others (such as Securities firm). We select the financial firms following two criteria: i) we choice top 20 firms in each group, according to the size (total asset) ranking; ii) the firm should be listed prior to 2005. For example, we reject inactive (delisted) firms. Our final data include 60 publicly traded Eurozone financial institutions. The period span from 2 December 2005 to 1 December 2017. The weekly observations (627 obs.) of the financial firm's equity indices and market capitalization were obtained from Datastream. Table I reports the complete list and the summary statistics of stock market returns. Following Wang et al. (2018) we defined the weekly returns of each financial firms as

$X_{i,t} = \ln \frac{P_{i,t}}{P_{i,t-1}}$ where $P_{i,t}$ is the closing price of firm i at week t.

As the Table I shows the mean return value for the banking sector is negative testifying to the great difficulties of the all major banks during the period under consideration. In fact, the stock returns of the banking sector are more volatile compared to the other two sectors, as the value of standard deviation suggests. Furthermore, we can observe as the minimum absolute value for the 71% of the sample is larger than the maximum. This implies that there is more risk in the left tail of the return distribution, meaning that a greater chance of extremely negative outcomes.

As in Härdle et al. (2016), we use several balance sheet variables to compute the following firm-specific attributes:

1. Total Asset/Total Equity ratio to capture leverage;
2. Market-to-book, as a measure of stock price performance;
3. Log(size), taking the firm size in terms of book value.

The quarterly balance sheet variables are obtained from Datastream and Bankscope Database. Cubic spline interpolation is applied in order to transform the quarterly variables into the weekly data. Following Adrian and Brunnermier (2016), we also collect six macro state variables taking into account the state of Eurozone economy:

1. VDAX, the option implied volatility for Europe market;
2. The short-term spread, as a difference between 3-month Euribor and 3-month German government bond yield;
3. The change in the 3-month Germany bond yield;
4. The slope curve, as a difference between the 3-month and 10-years Germany bond yield;
5. The weekly Euro Stoxx 50 market returns;
6. The weekly real estate sector returns form Euro Stoxx real estate.

4 How interconnected are financial firms?

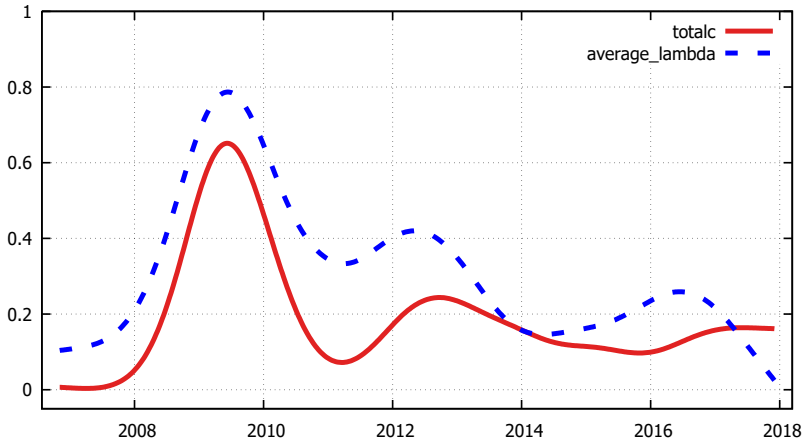
Following Härdle et al. (2016), we run the TENET analysis in 3 steps: 1) we estimate VaR and CoVaR, 2) we make the Network analysis and finally 3) we identify the SIFIs. In particular, we estimate the connectedness for the EZ financial system (60 listed financial institutions), i.e. the VaR and CoVaR models, setting $\tau = 0.05$, rolling window size equal to $w = 48$ (one year of weekly trading data), with the whole period $T = 627$.

Table I. Summary Statistics

	Financial institutions	Mean	S.D.	Min	Max
BANKS					
RAW	Raiffeisen bank intl	-0.0008	0.0699	-0.663	0.272
EBS	Erste group bank	-0.0002	0.0662	-0.551	0.297
DEXB	Dexia	-0.0138	0.1131	-0.538	0.693
KBC	KBC group	-0.0001	0.0820	-0.649	0.370
ACA	Credit agricole	-0.0008	0.0602	-0.316	0.241
BNP	BNP paribas	-0.0006	0.0567	-0.366	0.339
GLE	Societe generale	-0.0012	0.0654	-0.319	0.251
KN	Natixis	-0.0001	0.0654	-0.289	0.396
CBK	Commerzbank	-0.0041	0.0684	-0.414	0.480
DBK	Deutsche bank	-0.0022	0.0610	-0.512	0.412
BIRG	Bank of Ireland group	-0.0057	0.1101	-0.663	0.580
UBI	Unione di banche Italian	-0.0022	0.0551	-0.240	0.173
BMPS	Banca Monte dei Paschi	-0.0119	0.0878	-1.161	0.457
BAMI	Banco BPM	-0.0049	0.0743	-0.394	0.356
UCG	Unicredit	-0.0033	0.0687	-0.478	0.290
ISP	Intesa Sanpaolo	-0.0005	0.0552	-0.296	0.185
ING	ING groep	-0.0005	0.0686	-0.547	0.288
SAB	Banco de Sabadell	-0.0012	0.0503	-0.156	0.205
SANT	Banco Santander	-0.0002	0.0502	-0.261	0.212
BBVA	BBV.argentaria	-0.0007	0.0502	-0.274	0.168
INSURANCE					
MAP	Mapfre	-0.0003	0.0451	-0.289	0.163
VIG	Vienna insurance group	-0.0009	0.0461	-0.425	0.188
UQA	Uniqa insu gr ag	-0.0011	0.0398	-0.250	0.222
AGS	Ageas	-0.0026	0.0963	-1.821	0.390
CNP	CNP assurances	0.0002	0.0427	-0.224	0.143
SCR	Scor SE	0.0011	0.0359	-0.139	0.168
APR	April	-0.0011	0.0457	-0.393	0.217
AXA	Axa	-0.0005	0.0559	-0.363	0.244
HNR1	Hannover ruck	0.0021	0.0396	-0.240	0.173
NBG6	Nuernberger bets	-0.0002	0.0304	-0.162	0.138
ALV	Allianz	0.0007	0.0452	-0.337	0.343
FBH	FBD holdings	-0.0019	0.0484	-0.270	0.158
CASS	Cattolica assicurazioni	-0.0015	0.0452	-0.280	0.158
UIPN	Unipol gruppo finanziari	-0.0036	0.0583	-0.253	0.221
VAS	Vittoria assicurazioni	0.0014	0.0353	-0.145	0.165
ASG	Assicurazioni Generali	-0.0006	0.0394	-0.150	0.144
US	Unipolsai	-0.0047	0.0916	-1.031	0.121
AGN	Aegon	-0.0013	0.0669	-0.609	0.323
MUV2	Munich Re	0.0008	0.0335	-0.230	0.164
GCO	Grupo catalana occidente	0.0014	0.0456	-0.199	0.201
OTHERS					
MF	Wendel	0.0008	0.0551	-0.452	0.233
ROTH	Rothschild co	0.0004	0.0325	-0.148	0.248
VIL	Viel et Cie	0.0006	0.0378	-0.242	0.151
MONC	Moncey Financiere	0.0021	0.0435	-0.195	0.229
LTA	Altamir	0.0009	0.0533	-0.657	0.317
BSD	Bourse Direct	0.0006	0.0484	-0.182	0.362
BPCE	Credit foncier de Monaco	0.0002	0.0536	-0.316	0.498
ACKB	Ackermans Van haaren	0.0018	0.0340	-0.302	0.104
KBCA	KBC ancora	-0.0002	0.0877	-0.704	0.484
SOF	Sofina	0.0011	0.0280	-0.200	0.130
DB1	Deutsche boerse	0.0013	0.0424	-0.210	0.193
ARL	Aareal bank	0.0003	0.0675	-0.446	0.357
HSBC	HSBC trinkaus burke	-0.0002	0.0234	-0.256	0.127
COM	Comdirect bank	0.0006	0.0343	-0.157	0.147
MLP	MLP	-0.0018	0.0465	-0.238	0.297
CSV	Corporacion financiera Alba	0.0004	0.0380	-0.294	0.123
KA	KAS bank	-0.0009	0.0393	-0.238	0.234
BIM	Banca Intermobiliare	-0.0044	0.0516	-0.288	0.400
TIP	Tamburi inv partners	0.0017	0.0302	-0.108	0.176
ORE	Orey Antunes	-0.0023	0.0534	-0.270	0.305

Notes: This table shows the summary statistics of weekly returns, from 2005-2017 of 60 publicly listed financial institutions in Eurozone.

Figure 1. Dynamic TC and λ



Notes: The solid red line is the Total Connectedness while the dashed blue line is the average λ. To make it easy to interpret, i.e. to smooth the data, the spline function is applied.

4.1 The dynamic of total connectedness

Figure 1 shows the dynamic of total connectedness (solid red line) for the entire financial system and the average value of tuning parameter λ (dot blue line)[3]. The latter, since is computed by CoVaR estimations using SIM regression, express the evolution of systemic risk.

The system-wide connection increased substantially during 2008 (bankruptcy of Lehman), with a peak in 2009, while then it gradually decreased - never below pre-crisis levels - with two peaks associated with the two waves of the sovereign debt crisis (2011-13). Specifically, in the pre-Lehman period, the connection was low. However, the connection starts to increase more during the liquidity crisis of August 2007. During this period, European banks, too, had to make up for billions of dollars of losses because of their investments in mortgage-backed securities.

Lehman's default was an important event in terms of contagion, in fact, the interconnectedness gradually grew from its failure to its peak at the end of 2009 (the peak of the Great Recession). Over the months, Eurozone markets have calmed down and the connection has begun to decline. In fact, after the financial crisis, the density gradually declined until 2011 when Euroarea member countries were affected by the evolution of the banking markets and the sovereign debt problem of peripheral countries. The rise had at least two causes: 1) the sudden stops in 2008, and 2) the strong exposure of banks to sovereign bonds. The close interconnection has created a dangerous channel for the transmission and strengthening of shocks, called "the diabolical loop", which exposed the governments of the Euroarea to liquidity and solvency crises (Shambaugh, 2012). The ECB's announcement in 2011 of a three-year package of 1€trillion - Long Term Refinanc-

[3]To graphical comparison the two measures are standardized (0,1).

ing Operations (LTROs) - which provided liquidity to banks that had difficulty borrowing in the overnight market, significantly reduced the connections. Subsequently, the system connection jumped again (end of 2012), due to the spread of the sovereign debt crisis and the concerns of the banking sector in Spain and Italy. During this turbulence, the Eurostoxx 50 index fell by 33% (from February 2011 to May 2012), while the Eurostoxx bank index fell by 60%.

However, herd behaviour was not as strong as in the previous crisis, and connections gradually decreased. The efforts of the European Central Bank (ECB) and European governments have gradually reduced risks. A reduction in connection due to the announcement of "Whatever it takes", the establishment of the European Stability Mechanism (ESM) and the launch of the Quantitative Easing (QE) is consistent with evidence of a lower perception of market risk. These decisions have contributed to increasing confidence in the European banking system, thus preventing a potential collapse of the financial system.

It is interesting to note that the dynamics of systemic risk change follow the dynamics of interconnections: the two measures are highly complementary. One provides information on the nature of the interconnection of the financial system, the other on the ability to absorb a shock. When both measures are on the increase, the danger of a systemic event is high, and therefore greater interconnectedness implies a higher probability of risk spreading and *viceversa*. In fact, the highest values correspond to financial crises and the lowest values correspond to stable financial periods. The graph clearly shows that both indicators move in the same direction. Nevertheless, if we focus on the last two years (2016-2018), we can see that the change in systemic risk is the opposite. At the beginning of 2016, the connections decrease while λ increases (due to the consequences of the crisis, the Brexit effect, and the introduction of bail-in[4]), the opposite at the end of 2017. In addition, systemic risk levels have returned to pre-crisis levels while the interconnection measure shows a higher value than in 2006. This means that the financial system of the Eurozone, even if it is more interconnected, is much more resistant to systemic events, testifying to the positive effect of the latest monetary policies and of the still embryonic constitution of the Banking Union. In order to show there is a co-movement between λ and the Total Connected measure we conducted Granger causality test (Table II)

As we expected, the test results show that it is λ that granger causes the total interconnections (p-value is significantly smaller than 0.05, which indicates that the null hypothesis is rejected). These results are consistent with Härdle et al. (2017) that find the same relation between lambda and volatility connectedness index for US financial market. In conclusion, if the objective of monetary policy interventions was to stop the spread and amplification of the crisis that has occurred through the interconnection of

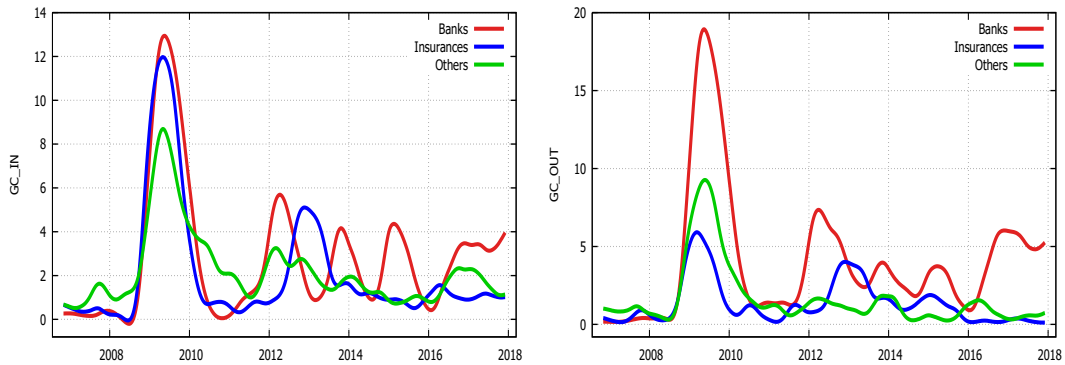
[4]According to De Grauwe (2013), as losses are distributed throughout the system, the bail-in can also have a contagious effect. This would appear to have happened in the Eurozone financial system.

Table II. Granger Test

Null Hypothesis:	Obs	F-Statistic	Prob.
λ does not Granger Cause TC	577	10.01	5.E-05
TC does not Granger Cause Lambda	577	1.187	0.305

Notes: We choose the VAR lag order according to SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion = 2.

Figure 2. Groups Connectedness



Notes: CG_{IN} (GC_{OUT}) measures the level of incoming (outgoing) connectedness for each sector. To make it easy to interpret, i.e. to smooth the data, the spline function is applied.

the financial sector, then this should be considered a success. Figure 2 shows the dynamic of incoming (left-panel) and the outgoing (right-panel) links for the 3 groups. Recall that TC is equal to $TC = \sum_{m=1}^{3} GC_{g,w}^{IN} = \sum_{m=1}^{3} GC_{g,w}^{OUT}$, i.e. the total connectedness is the sum of incoming and outgoing links between the three sectors.

Decomposition is interesting in order to explore the outgoing and incoming connections of the various sectors. Studying their temporal dynamics can help to better understand the dynamics of the global connection. The plot shows that most connection movements (both incoming and outgoing) at system level are due to the banking sector (red line). One of the reasons why banks issue and absorb more interconnections, therefore more risk, is because the European financial system is a bank-centered system. In fact, according to ECB "Report on financial structures" (ECB, 2017) the banking sector accounts for almost 60% of the total assets of the financial sector, while the insurance sector accounts for approximately 15% and the "other" for 25%. Also, the banking system plays a central role in financing the real economy. In 2017, bank loans accounted for just over 80% of the debt of non-financial corporations, while 20% came from the financial markets (Bank of France, 2018). Turning on the left-panel, we can see that during the financial crisis, the dynamics of the TC is caused more by the incoming edges of the banks and the insurance sector. The TC during the sovereign debt crisis reflects the incoming connectedness of banks and shadow banking. This may reflect the fact that

in liquidity crises, the insurance industry - by its nature - is less affected by liquidity shocks. From the end of 2012 to 2013, the largest interconnection is mainly due to the insurance sector, which peaked at the beginning of 2013. The greater interconnection in terms of incoming edges is due to the fact that in that period the insurance sector suffered a greater decline in liquidity and the "taper tantrum" of 2013 (IMF, 2015). Also, the increase in outgoing connections could be explained by the fact that during that period the International Association of Insurers Supervisors (IAIS) published the list of G-SIIs and their proposed methodology. These were considered by the markets to be weak and not sufficiently credible to contain systemic risk (Bongini et al., 2017).

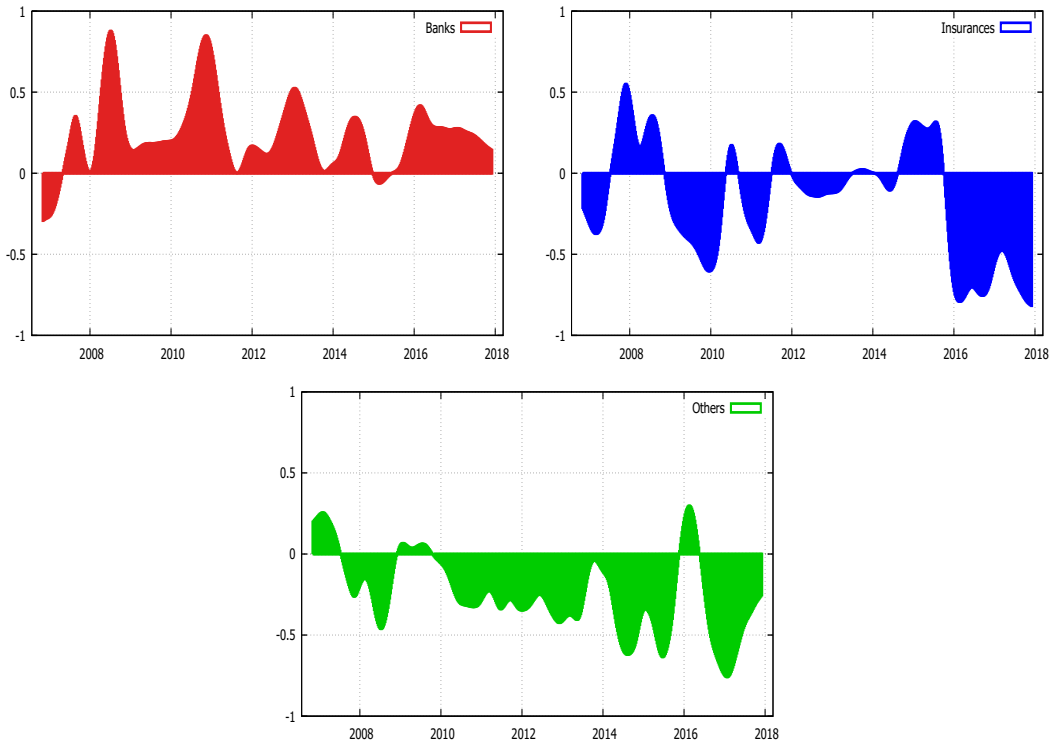
The TC in the last phase is caused to a greater extent by the incoming links in the banking sector. It is interesting to note the value of the connection for the "others" sector. In the pre-crisis period (2006-2008) and in the last period (2016-2018), the connection level is at an important value (in the initial period it is the highest). This result is not accidental, as the European shadow sector is strongly interconnected with the US shadow sector by credit securities, repo markets and counterparts in derivative (Jeffers and Baicu, 2013). For example, Abad et al. (2017) find that 60% of EU banks' exposures are to shadow banking entities domiciled outside the EU, with around 27% of total exposures to shadow banking companies domiciled in the US. This interconnection has amplified the negative effects and propagated the crisis from the United States to Europe. From the graph we can see how it was first influenced by the US crisis, and then by problems related to the consequences of the sovereign debt crisis (such as the NPLs).

Figure 2 (right-panel) shows the outgoing links for three sectors. The patterns of these group are similar to incoming links, except that the TC in the financial crisis period is caused in an order banks, others and insurances. In this case, for the "others" group, there are more links between 2009-2010end testifying to the key role in the transmission of initial and final shocks. As was intuitively predictable, during the full period the banks sector dominates the others in the emitter risk. By analysing the dynamics of Relative Influence (RI), we can highlight this result.

The Figure 3 shows the dynamic of relative influence (RI) for each sector. The RI of the banking sector (red) assumes (except for the pre-crisis period) positive values. This implies that the banking sector acts as the net sender of systemic risk spillovers. The RI for the insurance industry (blue) changes over time with positive and negative values, but in most periods, it assumes negative values especially during 2010 and 2016-18. The impact of Solvency II, the capital requirement regulation for insurers, which came into force in January 2016, is clear.

Focusing on the "others" sector, the graph shows (green) that shadow banking is almost always a net-beneficiary of systemic risk spillovers, except (i) in the pre-crisis period (ii) in 2009 and (iii) in 2016. Our analysis shows how the roles of net-sender and net-recipient for sectors can change at critical points of financial and macroeconomic

Figure 3. Relative Influence

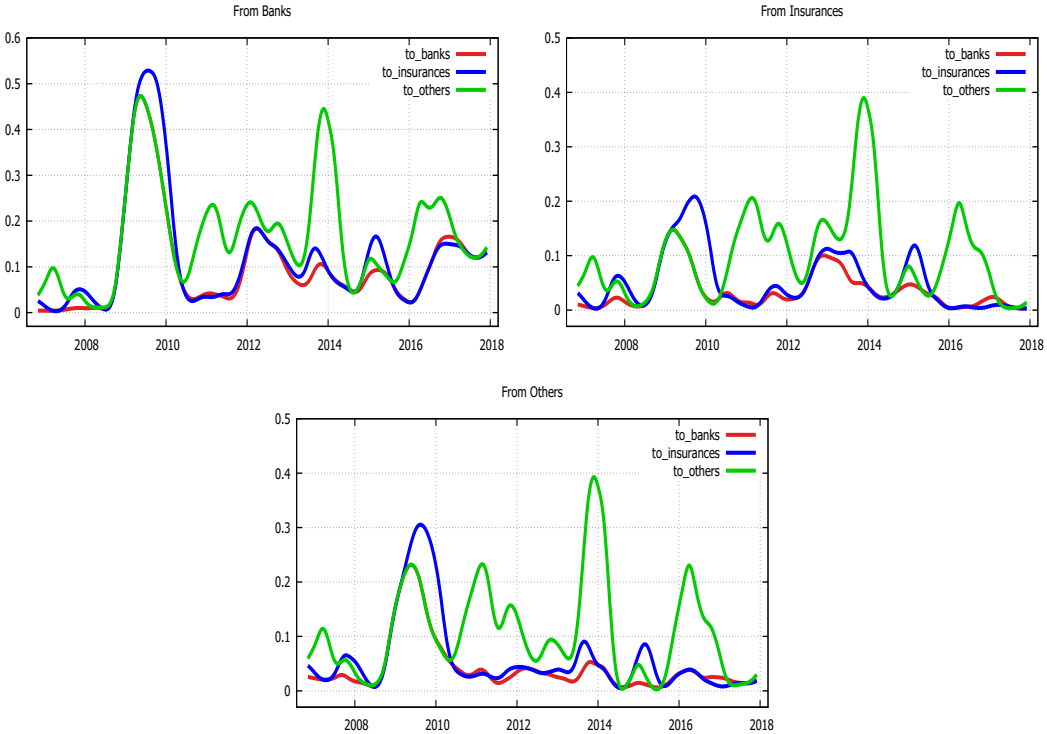


Notes: Dynamic relative influence of each sector. To make it easy to interpret, i.e. to smooth the data, the spline function is applied.

uncertainty. Therefore, the policy-maker should focus his attention according to the role assumed by the sector at that precise moment.

In Figure 4, we present the cross-section spillover from one sector to the others and or to itself. The purpose is to understand the directional connectedness. The patterns for bank and insurance sectors are similar to that evolution of TC. There is rapidly increasing during the first period and then there is a quick decrease, whit several jumps during the 3 and 4 phases. In particular, the behaviour (from/to) of the spillovers are very similar between the two sectors. However, the trend for the "others" sector is totally different. We can see four picks: 2008-2010 (financial crisis), 2010-2012 (sovereign debt crisis), 2013end-2014 and 2016-2017. After the financial crisis, the most of risk emitter and receiver are spilled over to "other" sectors followed by itself, insurance and banks. These results are quite informative of the evolution of the sovereign debt crisis, i.e. banking crisis. These results suggest how the sector "others" has become a very active sector in Europe. It is totally influenced primarily by banking risk and subsequently by insurance risk, due the interconnected whit commercial and depositories bank. Therefore, if a shock occurs, the banking sector and the insurance sector will infect shadow banking (and itself), causing "spillover chain" effects and endangering the stability of the financial system.

Figure 4. Tail Risk Spillover



Notes: SCS measures the level of the tail interconnectedness from one sector to another or itself. To make it easy to interpret, i.e. to smooth the data, the spline function is applied.

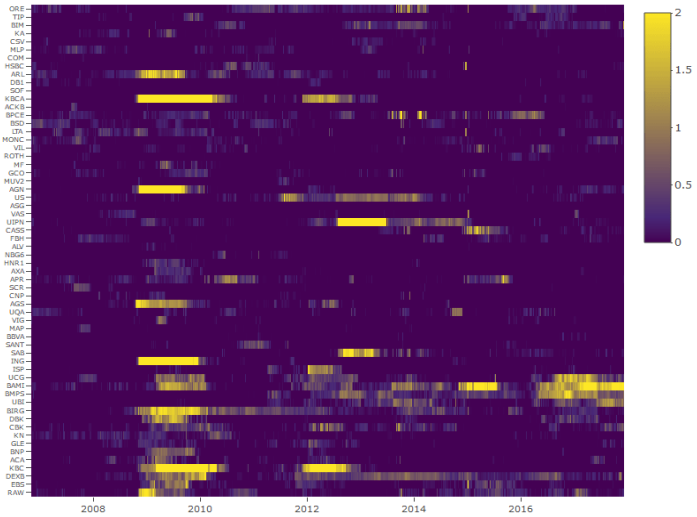
4.2 Cross-firms analysis

Here we focus our analysis on the evolution of the cross-firm incoming (CF^{IN}) and outgoing (CF^{OUT}) connectedness for each financial firm[5]. In-edges and out-edges are of interest because studying the bank origins of spillover may help to better highlight the dynamics of connectedness for each sector. Figure 5 and Figure 6 show the dynamics of the CF^{OUT} and CF^{IN} for each firm in each sector respectively.

By visually inspecting each Heatmap, we can see the evolution of connection. We divide the sample period into three phases: the financial crisis, the sovereign debt crisis and the consequences of the crisis. Let us first discuss of the financial crisis phase. Figure 6 shows that the bank that issued the highest level of out-edges was ING, followed by KBC, BIRG, RAW, DBK, DEXB, RAW, and BAMI. These results suggest that the global financial crisis has affected banks and thus countries that have had a strong exposure to foreign markets (such as the Netherlands, Germany, Ireland). Therefore, as these banks are most affected by the US crisis, they are the ones that have issued the most risk in Europe. In fact, three of these banks needed several billion of euro in bailout fund. In particular, ING received 10€billion in 2008 as well as 3.5€billion in interest, KBC

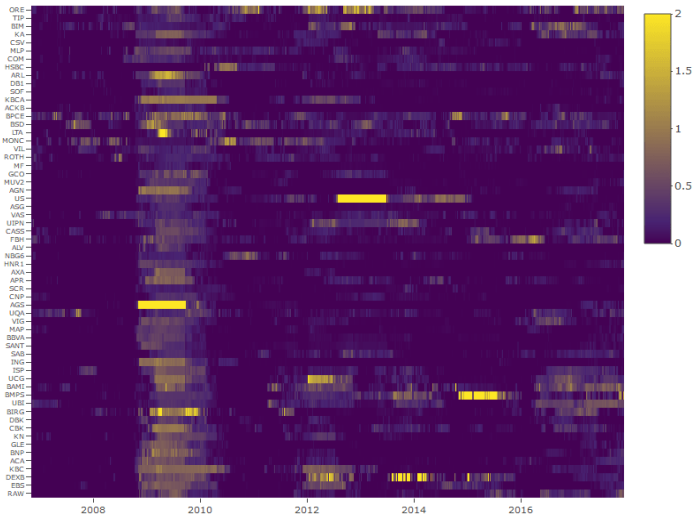
[5]The firm incoming edges is defined as: $CF^{IN} = \sum_{i=1}^{N} |\hat{D}^{w}_{j|i}|$; The firm outgoing edges is defined as: $CF^{OUT} = \sum_{i=1}^{N} |\hat{D}^{w}_{i|j}|$

Figure 5. CF^{OUT}



Notes: CF^{OUT} measures the level of outgoing connectedness of financial institutions.

Figure 6. CF^{IN}



Notes: CF^{IN} measures the level of incoming connectedness of financial institutions.

received 7€billion in 2008 and 2009, and DEXB required three bailouts totalling more than 15€billion. Concentrating on the insurance sector we can see that AGN and AGS are the insurers that have issued the most tail risk, while KBCA (high interconnection with parent company KBC) and ARL[6] for the "others" sector. Another interesting aspect that is worth mentioning regarding the out-interconnectedness of this sector is that they are nevertheless high before the financial crisis. In particular, financial companies such as BDS, ARL, LTA, MLP have played an important role in the transmission of tail risk before the crisis. In fact, these companies are very closely linked to the US financial sector, for example, ARL is a real estate company that was strongly affected by the 2006 real estate crash, while LTA and ML are investment companies. During the debt crisis, we observe that the banks that issued the most tail risk were SAB, ISP, UCG, BAMI, BMPS, KBC, and DEXB, showing how the debt crisis affected no-core countries. The same evidence can be found for the insurance sector with US and UIPN (Italian insurance companies), while ORE, BIM KBCA and BPCE for the "others" sector. During the 3 phase (consequences of the crisis) 10 institutions, including five banks (UCG, BAMI, MPS, UBI, and DEXB), three insurances firms (AGN, CASS, and FBH), and two "others" company (BIM and MONC) had larger FC^{OUT} values, implying that the financial Italy financial system and his NPLs problem played a key role in the emitter risk in these periods. This means that the Italian financial system is emitting financial spillovers from a growing number of companies, effectively increasing the fragility of the European financial system.

The dynamics of the CF^{IN} are similar to the CF^{OUT} (Figure 6). Here the levels are more homogeneous among financial institutions than the out-degree levels shown in Figure 5. However, it can be seen that the financial crisis has affected all banks indiscriminately (more or less). AGS stands out as the insurance company that received the most risk, while for the "others" sector ARL and BPCE are the institutions that received the most risk. As Shin (2011) pointed out, European banks have been very active in the U.S. financial system, taking advantage of concessional credit terms until 2007.

In the pre-period of the sovereign debt crisis, the others sector same to have high values of CF^{IN}. This is the consequences of the decision of US money market funds - concerned about overexposure to the Euroarea - to withdraw most of their funds from the French banks. As a result of the withdrawal of money market funds, the stock prices of the "others" sector collapsed. In the second phase, five firms (UCG, KBC, DEXB, US, ORE) had large CF^{IN} values. Very interesting is the pattern of SAB bank. In 2012, the bank has many outgoing connections and few incoming connections. This implies that a hypothetical collapse of the SAB during the sovereign debt crisis would have had a devastating effect on the entire European financial system. Exactly the opposite with regard to BMPS. In fact, after the second phase, BMPS received the highest tail risk. This means that it was receiving financial spillovers, increasing its fragility, but not that

[6] Aareal Bank received 525€million in 2009.

of the system. It is interesting to note that during 2015, the TC had a jump which can attribute to BAMI (largest emitter risk). In contrast, BMPS was the largest receiver, then we can conclude the high value of TC depended to spillover effect from BAMI to BMPS. At last, we see that at the final period we have UCS, BAMI, UBI, as the most in-edges institutions. Also, we see the high values for more of the companies of "others" sector, such as ORE, BIM, KA, BPCE, and BSD, which support the evidence that shadow banking triggered the recent "bear" market. In Figure A1 and A2 in Annex, we show the Systemic Risk Receiver (SRR) and Systemic Risk Emitter (SRE) for the full sample. Recall that these measures are able to capture the size and the interconnection, namely the concepts of "too big to fail" and "too interconnected to fail". Furthermore, we can identify the potential Systemically Important Financial Institutions over time.

The dynamic of SRE and SRR suggest that the financial system of Eurozone is bank-dominated. Almost all banks contribution to systemic risk transmission during the financial crisis, and the sovereign debt crisis. However, the last phase is marked by the systemic importance of Italian banks, due to the NPLs troubles.

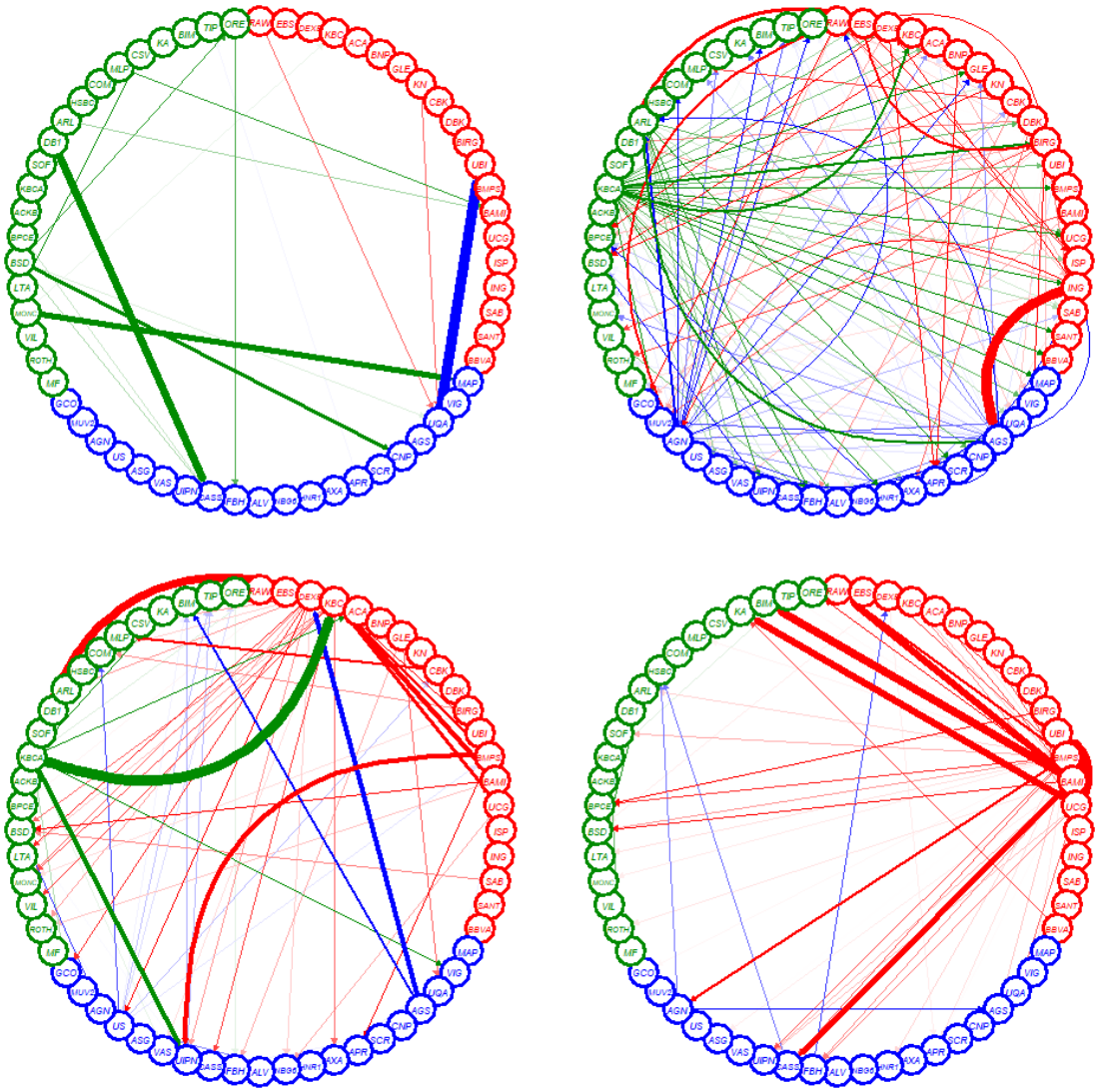
5 Identifying the contribution of systemic risk: Over-time Analysis

To evaluate the evolution of interaction between financial institutions, i.e. the dynamic of network, we split the analysis in four period (specific date): pre-crisis, financial crisis, Eurozone crisis, and after-crisis phase. Figure 7 visually the evolution of the network at 5% tail-risk level for these 60 Eurozone financial institutions. The colour of financial institutions indicates the sector to which they belong: red is the banking sector, blue is the insurance sector and green is the "others" sector. The networks show the firm level directional (emitter-receiver) connectedness. The main results can be summarized as follows.

We can see that the density of the network changes over time, hence there are different stages of the system. In particular, the density increases considerably between 2007 and 2009. During the climax of the financial crisis, the network reaches its strongest interconnection between financial institutions, as evidenced by the number of edges. In July 2012, in the midst of the sovereign debt crisis, interconnection is more fragmented, with in-out connections coming mainly from the banking sector. In the last period, the network structure clearly indicates a different picture. The interconnection between the rest of the system (others and insurances sector) is strongly decreasing, while the Italian banking system introduces greater tail risk (NPLs problem[7]). The negative effects of

[7] After reaching a record value of 341€billion at the end of 2015, the NPLs stock has fallen in the last two years, reaching 264€billion at the end of 2017 (PWC, 2017).

Figure 7. Dynamic of Network



Notes: Network representation of a weighted adjacency matrix. Left-top refers to pre-crisis period (2007-01-05); Right-top refers to financial crisis (2009-01-02); Left-down refers to sovereign debt crisis (2012-07-06); Right-down refers to the last period (2017-03-10). Bank sector in red, insurances in blue and "others" in green, $\tau = 0.05$, window size n = 48.

the NPLs on the banking sector led to a credit crunch, given the tighter credit policies for banks. The latter has affected the profitability of companies, which has led (1) the decline in industrial production, and (2) that it is more difficult for households to repay their loans (due to rising unemployment). This loop has led to a sharp increase in non-performing loans and a deterioration in balance sheets of Italian bank's.

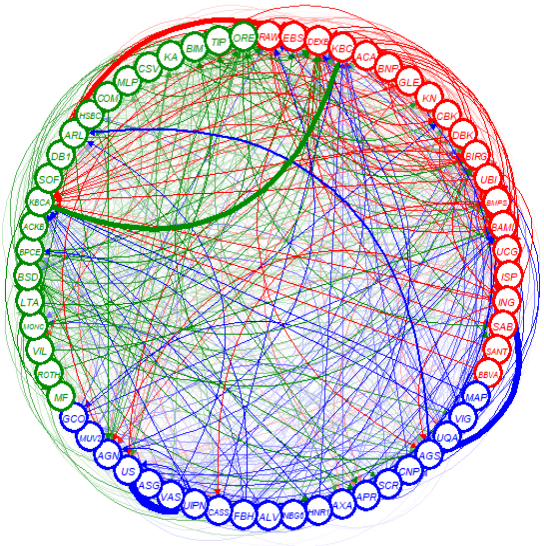
Focusing on the pre-crisis period, the companies that emit the most tail-risk spillovers are those of the "others" sector, highlighting the key role played in the transmission of the American sub-prime crisis. During the period of financial crisis, the banks emit the most risk in the insurance sector are ING to ASS while DEXB and BNP to APR. RAW issues risk to ARL ("others" sector). AGN is the insurance company that emit the most risk to the system, especially to the shadow banking system, while KBCA to the banking system. In 2012, the bank that emits the most intra-sector risk is ACA, while DEXB affects the entire "others" sector. The result is justified by the fact that Dexia was one of the leading banks with significant exposures to sovereigns and countries in difficulty[8](Enria et al., 2016). After the sovereign debt crisis, the network clearly highlights "national clusters" (Betz et al., 2016) showing strong intra and transnational links between the banks of the Italian banking system (home bias pattern).

Finally, the French banks BNP, ACA, GLE, as well as the German CBK and DBK are distinguished as interconnected banks. These results are consistent with the work of Betz et al. (2016), which highlight the role played by the bank-sovereign interconnection in the interconnection transmission of the European financial system.

The network in Figure 8 shows the directional connectedness for the entire period (total connectedness matrix aggregated over windows). There are some important links emitted for example by KBCA, KBC, US, AGS. In order to highlight these links in Table III we present the classification of the top 10 edges (directional connectedness), i.e. the transmitted link to other. The links are calculated by the sum of the absolute value of $\hat{D}^{w}_{j|i}$.

[8]Exposure to Sovereign Risk as percent of total bank value: 83.9% (see Groups of banks by exposure to sovereign risk (% of TBV), Deutche bank Research - available at http://www.asymptotix.eu/content/group-banks-exposure-sovereign-risk-tbv-includes-greek-irish-and-portuguese-sovereign-bonds)

Figure 8. Network over windows



Notes: Network representation of a weighted adjacency matrix aggregated during the period 20062017. Bank sector in red, insurances in blue and "others" in green, $\tau = 0.05$, window size n = 48.

Table III. Top 10 edges from firm i to firm j

Rank	From i	To J	Sum
1	UIPN	US	171.44
2	ING	AGS	124.32
3	KBC	KBCA	101.78
4	KBCA	KBC	100.58
5	BAMI	BMPS	76.11
6	BAMI	UBI	51.52
7	UCG	BAMI	43.79
8	SAB	US	37.21
9	ARL	AGS	36.27
10	UBI	BMPS	33.51

Notes: Top 10 directional edges from i financial institution to j. Follow Härdle et al. (2016) the ranking is calculated by the sum of absolute value of the partial derivatives, $\tau = 0.05$, window size n = 48, T = 627.

The strong links between banks (ING) and insurance companies (AGS) can be attributed to cross exposures: cross-sector loans, common investment exposure, customers, macroeconomic conditions, debt issuing activities (Malik and Xu, 2017). The strongest connection is between the UIPN insurance company and US (parent company), as well as KBC with KBCA. A possible explanation for the strong tail risk extending from banks to the shadow and *viceversa* is the business channel. For example, KBCA's core business is

Table IV. Top 10 firms - IN and OUT links

Rank	Firms	IN-links	MC rank	Firms	OUT-links	MC rank
1	US	249.47	30	KBCA	424.41	36
2	BMPS	201.79	56	BAMI	359.14	35
3	DEXB	189.26	59	KBC	334.24	12
4	AGS	180.71	24	ING	250.41	5
5	ORE	170.73	60	BIRG	212.09	27
6	BPCE	150.07	52	UIPN	200.12	38
7	BAMI	131.76	35	DEXB	199.99	59
8	UCG	117.94	10	BMPS	171.71	56
9	BSD	115.88	57	UCG	155.88	10
10	KBC	115.19	12	AGN	142.92	21

Notes: Top 10 financial institutions ranked by IN and OUT links, and the rank of market capitalization (MC rank) in 2017 (see Table A.1 in Annex).

"is the maintenance and management of its shareholding in KBC Group (the Group), as well as the shareholder stability, continuity and development of the KBC Group". This explains the strong spillover relationship between the two companies, including those belonging to different sectors.

It is interesting to note the spillovers between companies in different sectors does not seem to be so intense compared to the connection between the same, especially within the same country. In fact, most of tail risk spillovers are from banks to banks. BAMI is the bank that plays a very important role in the transmission of shocks within the financial system (see Table IV). Table IV shows the top 10 financial institutions classified by outgoing and incoming links respectively. Incoming links is defined as $CF^{IN}_{j,w} = \sum_{i=1}^{60} |\hat{D}^{w}_{j|i}|$, while outgoing links is $CF^{OUT}_{j,w} = \sum_{i=1}^{60} |\hat{D}^{w}_{i|j}|$. The largest enterprise with incoming links is US, while KBCA is the financial enterprise with the largest outgoing links. Most financial institutions have a moderate market capitalization (except ING). Therefore, these results show that the European financial system is the clear evidence of a system "too interconnected to fail". Small financial institutions have a strong inbound and outbound connection when the system is in difficulty (Wang et al., 2017).

However, the attribute "too connected to fail" is not a sufficient condition to identify the systemic importance firms (Härdle et al., 2016). To investigate the contribution of financial institutions to systemic risk, in Table V we classify the top 10 financial institutions according to the value of the SRR and SRE indices. These two indices incorporate both the concepts "too connected to fail" and "too big to fail". From a computational point of view, the indices are calculated taking into account the incoming and outgoing connections weighed for market capitalisation.

As we can observe, the top 10 list shows that 8 out of 10 are banks for both SRRs and SRRs, there are two insurance companies and one company in the "others" sector.

Table V. Top 10 firms - SRR and SRE indexes

Rank	Firms	SRR	MC rank	Firms	SRE	MC rank
1	UCG	1.8E+08	10	ING	3.8E+08	5
2	ISP	1.2E+08	7	KBC	2.1E+08	12
3	AGS	1.1E+08	24	UCG	1.2E+08	10
4	AXA	9.3E+07	4	DBK	8.4E+07	11
5	BNP	8.7E+07	3	ISP	8.4E+07	7
6	ACA	7.3E+07	8	ACA	7.3E+07	8
7	ING	6.7E+07	5	KBCA	6.2E+07	36
8	GLE	4.4E+07	9	BIRG	3.7E+07	27
9	BIRG	3.7E+07	27	AGN	3.4E+07	21
10	CBK	3.6E+07	17	GLE	2.8E+07	9

Notes: Top 10 financial institutions ranked by SRR and SRE indexes, and the rank of market capitalization (MC rank) in 2017 (see Table A.1 in Annex).

Looking on the SRE, we can see that even if the market capitalization of these institutions is moderate, they still rank among the top 10 systemic risk emitters, as they have strong outgoing links (high tail interconnection level). In order to validate the results, we compare the classification with the list G-SIB, O-SII and G-SII, drawn up respectively by the Financial Stability Report and the European Bank Authority[9]. The list shows that most financial institutions (except AGS and KBCA), both from the perspective of SREs and SRRs, are identified as systemically important. For example, ING is identified as G-SIB, while KBC as O-SII. However, our analysis suggests including AGS and KBCA as companies to be monitored by the authority, as even being "small" they can play an active role in financial instability (risk transmission). Their failure could jeopardize the entire financial system of the Eurozone.

5.1 Zooming in: Pre-crisis period

In this section, we would like to emphasize the role of the "others" sector in transmission risk in pre-crisis period, in particular we estimate the TENET model from 2 December 2005 to 28 December 2008. Table VI shows the ranking the 10 top financial institutions for total incoming and total outgoing links, while Table VII presents the ranking for the SRR and SRE value.

Table VI highlights some interesting insights. The "others" is the sector that receivers (emitters) most incoming (outgoing) links from (to) the other firms. The analysis provides that in the pre-crisis period the shadow banking system was very connected, mainly

[9]The lists are available here: http://www.fsb.org/wp-content/uploads/P211117-1.pdf (G-SIB); https://www.eba.europa.eu/risk-analysis-and-data/other-systemically-important-institutions-o-siis-/2017 (O-SII); http://www.fsb.org/wp-content/uploads/2016-list-of-global-systemically-important-insurers-G-SIIs.pdf (G-SII).

Table VI. Top 10 firms - IN and OUT links (pre-crisis)

Rank	Firms	IN-links	MC rank	Firms	OUT-links	MC rank
1	UQA	15.05	33	BSD	11.54	59
2	BSD	13.75	59	SCR	8.77	29
3	BPCE	12.22	51	MONC	7.54	42
4	MONC	11.62	42	MLP	6.89	50
5	ORE	6.05	60	LTA	6.07	58
6	ISP	5.06	10	ORE	6.01	60
7	VIL	5.01	56	ARL	5.12	44
8	UBI	4.82	30	UQA	5.09	33
9	CASS	3.72	39	UCG	4.92	12
10	BIM	3.66	52	BPCE	4.82	51

Notes: Top 10 financial institutions ranked by IN and OUT links, and the rank of market capitalization (MC rank) in 2008 (see Table A.1 in Annex).

Table VII. Top 10 firms - SRR and SRE indexes (pre-crisis)

Rank	Firms	SRR	MC rank	Firms	SRR	MC rank
1	ISP	2.0E+07	10	UCG	2.0E+07	12
2	UQA	1.2E+06	33	KN	7.4E+05	21
3	MONC	6.6E+05	42	UQA	5.9E+05	33
4	UBI	5.1E+05	30	MAP	3.9E+05	20
5	CASS	2.0E+05	39	RAW	3.3E+05	26
6	KN	1.9E+05	21	DB1	3.3E+05	14
7	EBS	1.6E+05	22	MONC	2.8E+05	42
8	ARL	1.4E+05	44	AXA	1.9E+05	4
9	MAP	7.5E+04	20	BAMI	1.8E+05	25
10	BAMI	7.2E+04	25	CBK	1.2E+05	19

Notes: Top 10 financial institutions ranked by SRR and SRE indexes, and the rank of market capitalization (MC rank) in 2008 (see Table A.1 in Annex).

between itself. These sectoral interconnections were a source of risk given the close relationship with the banking sector. Bakk-Simon et al. (2012) show as the activities of these intermediaries grew at high rates in the run-up to the crisis. In fact, between 2000 and 2007, European securitisation issues rose from 78.2€billion to 453.7€billion (Jeffers and Baicu, 2013). According to Table VII the ISP is the biggest bank risk receiver, while UCG is the largest bank risk emitter. Hence the classification is more heterogenous between sector (the bank sector with 5 firms wins), on the other hand three shadow firms (MONC, ARL, DB1) are systemic important, i.e. "small but dangerous" firms.

5.1.1 Discussions about the Shadow Banking

We now debate how the "other" sector has contributed to the growth of the interconnection of the Euroarea financial system and its spillover effects of interconnection to the banking system. We address the matters with the following interpretations. According to the FSB (2011), the shadow and ordinary banking systems are strongly interconnected, for two main reasons: (i) banks can support the shadow sector by temporarily supporting exposures in order to transform maturities; (ii) banks can invest in products issued by the shadow banking system. This interconnectedness between the two systems can therefore intensify the accumulation of leverage and thus risk. Therefore, shadow banking financial institutions, even if they are not "large" in terms of market capitalisation (or assets), can give rise to systemic risk given their interconnectedness (Lysandrou and Nesvetailova, 2015) and their structural characteristics. Transformations of assets may act as a stress accelerator, or tensions experienced by some shadow banking firms may quickly turn into potential liabilities for their sponsors (backstops). However, the latter may not have the liquidity to absorb them by feeding the risk into the system (Bank of France, 2017). These vulnerabilities are amplified by the fact that: 1) intermediation activity takes place through a heterogeneous chain of entities and 2) agents have an incentive to exploit regulatory gaps in the sector. During the period analysed, 2006-2017, the "others" sector played a decisive role in risk transmission. In the Eurozone, there has been rapid growth in this sector, driven mainly by the demand for "safe" (non-zero returns) and non-regulated investment strategies. The enormous growth in assets management has led to a strong expansion of this sector, becoming the alternative sector for the traditional one. This substitution has been a source of moral hazard, fuelling the expectation of public intervention in favour of these financial institutions. The potential risks to financial stability are associated with the business models and structural characteristics of these firms. More specifically, the "other" sector, being very heterogeneous (it includes securities, financial company, real-estate company ect), is a carrier of risk for the whole financial system (Abad et al., 2017). Securitizations (credit intermediation based on securitizations) played a very important role during the crisis. Covitz, et al. (2013)

show how traditional banks can be exposed to liquidity problems through their support to shadow banking firms. Indeed, during the financial crisis, most securitisation vehicles suffered losses, which were then absorbed by the sponsoring banks, fuelling interconnections and thus the riskiness of the financial system. As regards financial companies (such as leasing companies), Grillet-Aubert et al. (2016) highlight the risky nature of these entities, being particularly interconnected with the ordinary banking system. Moreover, the financing is mostly short-term and therefore more susceptible to racing and liquidity draining.

Our work provides an empirical mapping of these interconnections between the various systems, adding information to different types of approaches, such as indicator-based approaches. In fact, through the TENET approach we can capture spillover and contagion effects from credit (leverage), structural (business model) and market (stock return) exposures. Our empirical analysis shows that one key factor in the evolution of interconnections and therefore systemic risk was the shadow sector. Through its in and out-links, mainly with the banking sector, it was the vehicle of transmission of the sub-prime crisis that broke out in the US. Securitisation has supported credit growth (especially mortgage lending). This helped to strengthen systemic risk before and after the financial crisis. As well pointed out by Bakk-Simon et al. (2011) "the interconnection between the shadow banking system and the regulated banking system, [...] have increased considerably over the last decade, presumably increasing the risk of contagion through transmission of shocks across institutions". These close links between the US and European shadow banking systems have played an important part in the rapid spread of the crisis around the world. Ten years after the failure of Lehman Brothers, the European financial system is undoubtedly safer. The efforts of international (Financial Stability Board) and European (European Systemic Risk Board) regulation seem to have had a positive effect on financial stability. However, the exponential growth of the shadow banking sector, in terms of assets and thus risk transmission, could again jeopardise financial stability. According to the FSB (2017), systemic risks associated with new forms of market-based shadow banking activity outside the regulatory prudential framework may lead to new spill-over effects on other sectors. An international cooperation between the competent authorities would be necessary to reduce the risks of instability associated with global shadow banking.

6 Concluding Remarks

The detailed presentation of the total and inter-sector interconnections of the Eurozone financial system presented in this study is an important contribution. In our empirical survey, we found that the contribution of each sector changes over the period, increasing (decreasing) the level and reversing the order of importance. In addition, the

banking sector contributes relatively more to systemic risk in the Euroarea. However, the "other" sector played an important relative role in the pre-crisis periods. In fact, it is interesting to note that the risk dynamics (Figure 3) suggest that, before 2007, the shadow banking is the most active, introducing risk into other sectors. The work provides a clear view on the spread of spillovers and interconnection dynamics during the crisis, which can be particularly important for risk management and supervision in the Eurozone. According to Aristotle "The whole (the financial system) is more than the sum of its parts (financial institutions)".

Other areas of work could address how a network structure interacts with other financial structures to investigate global risk spillovers, potential sources of global contagion, in order to understand what network characteristics could be taken into account in preventing contagion mechanisms.

Annex

A Tables

Table A.1. Ranking market capitalization

MC rank	Firms	2008	MC rank	Firms	2017
1	SANT	50,289.70	1	SANT	88,409.99
2	BNP	36,654.91	2	ALV	84,606.74
3	ALV	33,933.45	3	BNP	77,741.50
4	AXA	33,102.71	4	AXA	59,986.28
5	BBVA	32,753.42	5	ING	59,549.05
6	ASG	27,082.62	6	BBVA	47,422.01
7	DBK	26,945.99	7	ISP	43,931.61
8	MUV2	22,611.54	8	ACA	39,276.24
9	ING	21,296.06	9	GLE	34,780.86
10	ISP	19,982.37	10	UCG	34,676.29
11	GLE	13,352.46	11	DBK	32,768.69
12	UCG	12,364.34	12	KBC	29,730.17
13	ACA	10,891.37	13	MUV2	28,106.56
14	DB1	8,192.92	14	ASG	23,739.49
15	CNP	7,703.17	15	KN	20,694.03
16	BIRG	7,654.25	16	DB1	18,669.86
17	AGS	7,226.40	17	CBK	15,635.68
18	AGN	7,141.48	18	EBS	15,517.93
19	CBK	6,662.80	19	CNP	13,220.84
20	MAP	6,424.44	20	HNR1	12,627.12
21	KN	5,992.08	21	AGN	11,138.37
22	EBS	5,308.57	22	RAW	9,933.98
23	KBCA	4,345.72	23	SAB	9,318.25
24	SAB	4,075.77	24	AGS	8,525.72
25	BAMI	3,969.78	25	MAP	8,247.04
26	RAW	3,922.81	26	NBG6	7,963.63
27	KBC	3,483.51	27	BIRG	7,654.25
28	VIG	3,087.36	28	MF	6,678.96
29	SCR	3,013.57	29	SCR	6,490.97
30	UBI	2,815.02	30	US	5,509.46
31	HNR1	2,758.06	31	ACKB	4,862.08
32	BMPS	2,720.06	32	SOF	4,491.89
33	UQA	2,378.01	33	GCO	4,432.80
34	MF	1,782.98	34	UBI	4,172.06
35	SOF	1,750.18	35	BAMI	3,969.78
36	CSV	1,746.73	36	KBCA	3,353.25
37	GCO	1,741.20	37	VIG	3,297.92
38	HSBC	1,413.90	38	UIPN	2,805.32
39	CASS	1,277.84	39	CSV	2,782.08

Continued on next page

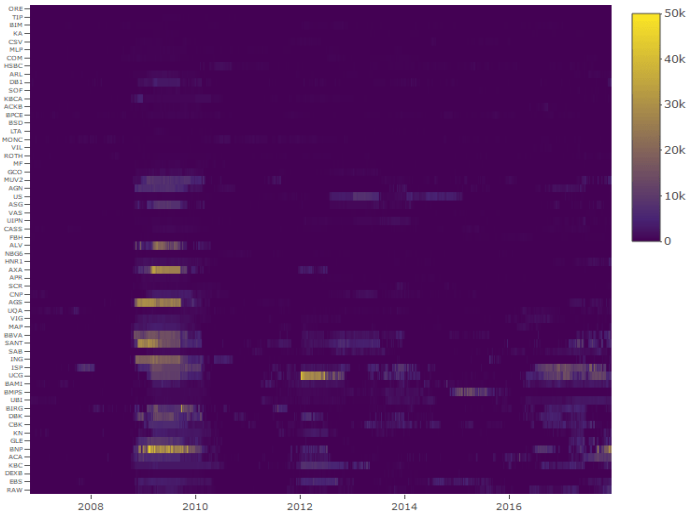
Table A.1 – *Continued from previous page*

MC rank	Firms	2008	MC rank	Firms	2017
40	ACKB	1,219.29	40	UQA	2,725.38
41	COM	1,043.34	41	ROTH	2,358.60
42	MONC	960.07	42	ARL	2,261.59
43	US	873.62	43	COM	1,612.74
44	ARL	834.41	44	CASS	1,577.36
45	APR	738.67	45	HSBC	1,573.05
46	UIPN	674.87	46	MONC	1,152.09
47	NBG6	648.85	47	TIP	889.14
48	ROTH	625.01	48	VAS	803.16
49	DEXB	578.85	49	MLP	607.35
50	MLP	566.14	50	APR	601.29
51	BPCE	532.00	51	LTA	556.45
52	BIM	432.38	52	BPCE	532.00
53	TIP	311.55	53	VIL	416.61
54	VAS	250.25	54	FBH	229.02
55	FBH	242.87	55	KA	156.50
56	VIL	173.56	56	BMPS	114.76
57	KA	134.23	57	BSD	91.21
58	LTA	92.38	58	BIM	73.68
59	BSD	57.07	59	DEXB	19.37
60	ORE	20.88	60	ORE	7.80

Notes: Rank of market capitalization, years = 2008; 2017.

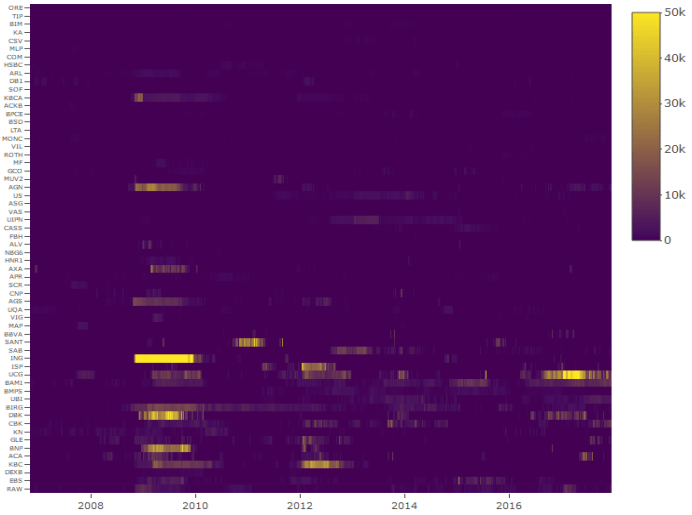
B Figures

Figure B.1. Systemic Risk Receiver (SRR)



Notes: SRR index for each financial institutions.

Figure B.2. Systemic Risk Emitter (SRE)



Notes: SRE index for each financial institutions.

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