Eastern Journal of European Studies

Statement of Retraction

The Editors of *Eastern Journal of European Studies* (EJES) have retracted the following paper:

> Derbali, A., Lamouchi, A. (2020), The Triple (T3) Dimension of Systemic Risk: Identifying Systemically Important Banks in Eurozone, *Eastern Journal of European Studies*, 11(1), pp. 87-122.

The publication in EJES followed the standard procedure envisaged by our journal: first, an anti-plagiarism check with Turnitin and, second, a double blind peer-review process. According to the aforementioned procedures the paper fulfilled all the necessary scientific and ethical criteria for publication.

Nevertheless, after publication, based on the documents provided by the editorial board of the International Journal of Finance and Economics, it appears we faced bogus claims of authorship. A similar paper, but having other authors, was in peer review process for a longer period of time at the 'International Journal of Finance and Economics'. One of the reviewers was Derbali, A. Meanwhile, the paper under review by Derbali A. was submitted for evaluation to EJES, by Derbali A. and Lamouchi A., as main authors.

The Editorial Board of the *Eastern Journal of European Studies* discourages unethical practices and infringements of professional ethical codes in academic research. We are interested and open to close cooperation with the authors, the reviewers, and also with the editorial and scientific boards of the other journals, in order to promote a high scientific level of the published papers, in a transparent, ethical and fully integrity approach.

In the current case, we mention that Derbali A. and Lamouchi A. did not show cooperation in clarifying this matter.

The retracted article will remain online, but it will be digitally watermarked on each page as "Retracted article".

Date: 14 January 2021

The triple (T3) dimension of systemic risk: identifying systemically important banks in Eurozone

Abdelkader DERBALI[*], Ali LAMOUCHI[**]

Abstract

The systemic importance of a financial institution is generally assessed by the effect on the banking system conditional on the bankruptcy of this financial institution and the creditworthiness of other financial institutions. This paper proposes a new systemic risk measure based on a multi-way analysis. The systemic risk is composed of two different components: the time and the cross- dimension. The first refers to the accumulation of banking risk and their interaction with the business cycle, while the second concerns the high-level concentration of the specific risk on relevant financial institutions. Then, we have empirically evaluated and compared Marginal Expected Shortfall, SRISK measure, and CoVaR on the basis of a representative sample of Eurozone institutions listed on the stock exchange for the period from June 2005 to May 2018. Our results show how these estimation methods produce very different systemic risk classifications for the same bank. The results, therefore, highlight the fragility and structural dependence of these measures, which may not be used for the estimation of a stable rank. Applying a three-way factorial analysis, we show how our measure gives a more stable score. Moreover, our index is the first one to be composed of both the cross-section and the temporal components, essential elements for a proper assessment of systemic risk. Finally, Regulatory authorities usually claim that one of the main reasons for regulating financial markets is precisely to reduce systemic risk. Thus, only the central banks, in their role of lender of last resort, would be able to remedy it when it materializes. But in reality, the regulation leads to a uniformity of practices which greatly increases the systemic risk.

Keywords: Systemic Important Bank, Systemic risk raking, Multi-way analysis, Banking supervisor, Composite Index

[*] Abdelkader DERBALI is Assistant Professor at the Taibah University, Medinah, Saudi Arabia; e-mail: derbaliabdelkader@outlook.fr.

[**] Ali LAMOUCHI is Assistant Professor at the Qassim University, Buraidah, Saudi Arabia; e-mail: ali_lamouchi@yahoo.fr.

Introduction

The Bank for International Settlements (BIS), the Financial Stability Board (FSB) and the International Monetary Fund (IMF) highlighted the two components of systemic risk: the cross-sectional and the time dimension (Financial Stability Board, 2011; Rhu, 2011; Derbali *et al*., 2015a; Derbali *et al*., 2015b; Derbali, 2016; Derbali, 2017a; Derbali, 2017b). The cross-sectional dimension concerns the interdependencies between financial institutions. This is the classic domino effect, from the risk in one financial institution which spreads to another compromising all or part of the system, due to direct and indirect contagion. The other component is the time dimension, which is linked to the financial cycle, i.e. the accumulation of risk over time. These two dimensions play a highly important role in estimating each institution's contribution to overall risk.

In addition, the same report (IMF/BIS/FSB, 2009) offers two clear insights into the concept of systemic risk and the definition of systemically important institutions. Systemic risk is defined as: "The risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy".

Meanwhile, systemically important institutions are defined as: "a financial institution is considered `systemically important' if its failure or malfunction causes widespread distress either as a direct impact or as a trigger for broader contagion".

The right identification of Systemically Important Financial Institutions (SIFIs) and Systemically Important Banks (SIBs) is crucial for the development and execution of macro-prudential stress testing procedures. Proper identification is important to correctly implement the systemically important surcharge policy, or the constraints related to the risk-intensive leverage ratio, i.e. in terms of balance sheet structuring. A method that automatically classifies in a transparent (non-discretionary) way would be ideal for regulators.

In the last years, since the global financial crisis, many market methods have been proposed to measure (cross-sections) interconnectedness and thus, systemic risk between financial firms[1]. Kuusk *et al*. (2011) investigate empirically the research question mark whether the US 2008 financial crisis spilled throughout contagiously to the Baltic States as small open markets. They find that stock returns' correlations among the US and Baltic States improved through crisis times, proving the financial contagion assumption. Bisias *et al*. (2012) were the first to try to classify the methodologies proposed to measure systemic risk. Since the document was written no later than 2012, it highlights the relative novelty of this discipline (Kemp, 2017). The number of methods has grown exponentially in recent years (Silva *et al.*, 2017). For example, Zhou (2010) proposed two measures to identify the SIFIs: the systemic impact index and the vulnerability index using the multivariate extreme

[1] For a comprehensive classification see Bongini and Nieri (2014).

value theory. The conditional value-at-risk (CoVaR), defined as the value-at-risk (VaR) (White *et al*., 2015) of the financial system when some specific event affects a single institution, and the ΔCoVaR, defined as the difference between CoVaR when a financial firm is under distress and when is not under distress, of Adrian and Brunnermeier (2016). The marginal expected shortfall (MES) and systemic expected shortfall (SES) of Acharya *et al*., (2017). The SRISK, of Brownlees and Engle (2016) which, considering the firm's balance sheet (such as size and leverage) extend MES, can quantify the effect of a systemic event on a financial institution's capital shortfall.

All the same, these methods can hardly be used for supervisory purposes due to their weak theoretical and inherently volatile basis in the rankings (Nucera *et al*., 2016). In fact, the main limitation of these market measures is that they only capture one aspect of the risk. Also, the structural diversity of methodologies leads to different results in terms of ranking.

Purposely, several measures have been proposed by the regulators to identify the SIFIs and the SIBs. For example, the Basel Committee on Banking Supervision (BCBS, 2011) proposed the application of an indicator-based measure[2]. The methodology framework assigns a score to each bank, by comparing 12 indicators. The indicators are i) size, ii) interconnectedness, iii) substitutability, iv) complexity and the v) cross-jurisdictional activity (Brunnermeier *et al*., 2009)[3]. The index, therefore, takes into account both qualitative and quantitative dimensions[4]. The Basel III agreement requires capital surcharges to be imposed on institutions identified as being at systemic risk based on their systemic importance (BCBS, 2011). In particular, the percentage of additional capital an undertaking is required to hold shall be determined by that institution's systemic risk classification and shall not be directly related to the extent of its contribution to systemic risk.

However, this methodology has some critical aspects and deficiencies both from an academic point of view (Masciantonio, 2015; Benoit *et al*., 2017), and from a professional point of view. In particular, BNP Paribas' Consultative Paper 201, Response to the BCBS[5], analyses a number of criticisms of the methodology. For example, the systemic scores are not made public and the G-SIB ranking only starts in 2010, well after the outbreak of the global financial crisis (Masciantonio and

[2] This methodology has been transposed in the EU regulatory framework (art. 131 of the Capital Requirements Directive IV (CRDIV)).

[3] For empirical and theoretical importance of these components of systemic risksee Lopez-Esinosa *et al*. (2012) for size; Allen and Gale (2000), Billio *et al*. (2012) for interconnection risk; Flannery *et al*. (2013) for complexity.

[4] (The) advantage of the multiple indicator-based measurement approach is that it encompasses many dimensions of systemic importance, it is relatively simple, and it is more robust than currently available model-based measurement approaches and methodologies that only rely on a small set of indicators" (BCBS, 2011)

[5] Available at www.bis.org/publ/bcbs201/bnpparibas.pdf.

Zanghini, 2017). Furthermore, importance assigned to size is not always empirical true (Moratis *et al*., 2017; Hautsch *et al*., 2014; Segoviano and Goodhart, 2009)[6] and the weights assigned to the characteristics are arbitrary (Benoit *et al*., 2017)[7]. However, this approach proved to be inadequate during the two crises (the US and sovereign debt crisis). Indeed, the crisis has shown that even small banks can jeopardize financial stability. As the banking system is interconnected by nature, small banks play a very important role in transmitting shocks. On the other hand, large banks are able to absorb more of the system's shocks.

Therefore, both dimensions appear to have both positive and negative effects on the stability of the system. For example, Bulow and Klemperer (2013) show how these regulatory measures based on capital have not perfective predictive power for bank default[8]. The authors show the imperfection of the regulatory capital measures. They note that if the 413 banks that went bankrupt between 2008 and 2011 (Tier 1 = 6%) each held 14%, this infusion would have been insufficient to offset the losses of the 372 banks (90%). For example, Lehman Brothers was well above a solid capital base (Tier 1 = 11.6%) immediately before its default in September 2008 (Sarin and Summers, 2016).

As well pointed out by Masciantonio and Zanghini (2017), "The literature has not yet adequately dealt with the integration between systemic risk and systemic importance measures, neither from an analytical nor from an empirical point of view". Therefore, the aim of our work is to try to bridge this gap.

The paper proposes a new method providing a robust combined ranking, for identifying these important financial firms in order to address systemic risk in a single framework where both time-dimension and cross-sectional dimension are considered simultaneously, by multi-way analysis. Our method is easy to apply, transparent, fast and produces intuitive results, important characteristics for quick and suitable banks ranking. Therefore, our findings support the discussion on the straightforwardness of regulation and the estimation of systemic risk. Haldane

[6] However, there are several empirical papers that show that the size is one of the important key drivers of systemic risks (see Vallascas and Keasey, 2012; Varotto and Zhao, 2014). These works, by different methodologies, confirm the positive impact of size on the systemic risk for European banks.

[7] In an effort to address these shortcomings, Masciantonio (2015) and Alessandri *et al*. (2015) provide a new methodology based on publicly available data.

[8] "The rapid collapse of Bear Stearns during the week of March 10, 2008, challenged the fundamental assumptions behind the Basel standards and the other program metrics. At the time of its near-failure, Bear Stearns had a capital cushion well above what is required to meet supervisory standards calculated using the Basel framework and the Federal Reserve's \well-capitalized" standard for bank holding companies. The fact that these standards did not provide enough warning of the near collapse of Bear Stearns, and indeed the fact that the Basel standards did not prevent the failure of many other banks and financial institutions, is now obvious" (Cox, 2008).

(2011) argues in favour of three driven principles of "good regulation": simplicity, robustness, and timeliness. The work of Rodriguez-Moreno and Pena (2013) highlight that policy-makers and regulators should emphasise on one or more simple indicators for monitoring the systemic risk.

The systemic risk is assumed to be an evolving latent weighted network, where nodes are banks and arrows are the measure of interconnection. The network can be defined by several weighted matrices (Core Matrix, H), each of which illustrates the state of the financial system at a given time. The matrices are thus combined into an object by three-way PCA. The Tucker Three exploits the connectivity information of the structure of the network and decomposes its variance (latent factors) as the product of three vectors, the banks' score (A-mode), the systemic measures score (B-mode) and the time score (C-mode). These vectors can be interpreted as indices of the systemic importance of the financial firms associated with each measure of risk in each period. The time dimension score, being a function of both the accumulation risk and of its distribution among firms, with different systemic importance, can perceive a change in systemic risk behaviour which occurred during the crisis. Indeed, results also indicate that, prior to a crisis, the time score highlights the increase of risk with respect to the measures of systemic risk. We recognize factors that make banks' co-movement and observable features that are related to them via cross-sectional and time-dimension.

In order to do that, first, we estimate the five "popular" measures of systemic risk proposed in the recent literature, such as, VaR, ΔCoVaR, MES, and SRISK. Also, we compute the measure of dynamics interconnection as Billio *et al*. (2012) to point out the high degree of dependency on the Eurozone banks. These types of market indicators contain a large set of information about systemic risk (Fang *et al*., 2017). However, these measures are not capable of identifying a reliable bank ranking in a consistent and stable manner. By factor analysis - as an information aggregation tool - we can resolve this problem. Combing these five measures in a multi-way factor analysis, we obtain a reliable systemic risk rating. We can decompose both information deriving through the price based and fundamental information, in order to find each directly systemic risk contribution, identifying the top Eurozone systemically important banks. The combined ranking is constructed from the A-mode proper value that explains most of the variance of the observed data. Different from the work of Nucera *et al*., (2016) and Fang *et al*., (2017), who only use principal components in the cross-section direction, our paper also estimates all factors in a time series context (C-mode). Our sample is composed of major listed Eurozone banks. In particular, we study N = 34 banks during T = 3380 days from June 2005 to May 2018.

We focus on the main empirical findings. First, we apply five popular methods to show an overview of systemic risk in the Euro-area and to analyze the systemic risk ranking for these banks. The results confirm the view that systemic risk is still present in the Euroland, mainly due to the consequences of the sovereign debt crisis.

By focusing on estimation methods, we find that there are very different systemic risk rankings for the same bank. These results show the fragility and structural dependency (Benoit *et al*., 2013) of these measures, which cannot be used for the estimation of a stable rank. An underestimation of systemic risk may spread the externalization of risk: belief in a safer banking system can lead to investing in riskier securities, while an overestimation can lead to disputes (e.g., high level of capital requirement) and lack of confidence in supervisory systems.

Applying the three-way factorial analysis, we show how our measure assigns a stable score. Also, our measure is the first to be composed of both the cross and the time components, essential elements for a correct systemic risk assessment.

The work contributes to the literature on the analysis of the systemic risk with multi-methods, focusing on the financial system of the Europe (Engle *et al*., 2014; Black *et al*., 2016; Derbali and Hallara, 2016a; Derbali and Hallara, 2016b). To the best of our knowledge, this is the first attempt to derive a measure of systemic risk in a cross-section and temporal dimension on a common framework. Our measure allows us to identify SIFIs (SIBs) in an unambiguous and transparent way, taking into account both dimensions of risk.

Also, our approach continues the line of research developed in Moreno and Pena (2013), Giglio *et al*. (2016), Nucera *et al*. (2016). The first use a Principal Component Analysis (PCA) to build a systemic risk index. The same approach is used by Giglio *et al*., (2016) who use PCA to build a systemic risk index, used to test its predictive power of future shocks on macroeconomic variables. Finally, Nucera *et al*., (2016) identify a stable ranking for SIFIs by PCA.

The remainder of this paper is organized as follows. Section 2 presents data and econometric methodology. In section 3, we present an overview of systemic risk in Euroland. In Section 4, we report the results of empirical analysis of systemically important banks in the Eurozone. Finally, section 5 concludes.

1. Methodology and data

1.1. Different measure of systemic risk

In order to measure the systemic risk of the Eurozone banking system, we compute five different methodologies proposed in the literature. We make the MES and ΔCoVaR as proposed by Acharya *et al*., (2012), and by Adrian and Brunnermeier (2016), respectively. Also, we apply the SRISK measure, proposed by Brownlees and Engle (2016), the classical Value-at-risk and the dynamic conditional Beta (Engle, 2016). Finally, to draw attention to the level of interconnection and the evolution of the interdependence between banks, we apply the model of Billio *et al*., (2012).

CoVaR measures the system loss conditional on each institution in distress, while MES and SRISK measure each institution’s loss when the system is in distress.

The MES expresses the expected loss of a financial company's share when the stock market records a loss of value below a certain threshold and over a given time horizon. The MES capturing the degree of interconnection between banks expresses the concept of "too interconnected to fail". To estimate the "short-term" MES of the individual company, Acharya *et al*. (2012), use a daily 2% threshold for the daily negative change in the stock market and a threshold of 40% over a six-month period, namely the Long-Run Marginal Expected Shortfall (LRMES). CoVaR expresses the "value at risk" of the financial system conditioned by a specific event that affects a specific financial firm. "Co" of VaR expresses the concept of co-movement, trying to capture the spillovers effects between financial institutions (Di Clemente, 2018). Instead, the ΔCoVaR, expressing the contribution to the systemic risk of a specific institution, is given by the difference between the CoVaR of the financial system when the institution in question is in a state of "distress" and the CoVaR of the financial system when the institution is in a state of "normality".

Finally, the SRISK measures the expected capital loss of institution conditional upon the occurrence of a crisis affecting the entire financial system. The institution with the highest expected capital loss will contribute more to the systemic crisis, which implies that this company should be considered more systemically risky. The SRISK takes into account the capitalization and liabilities of banks, it is in line with the definition of "too big to fail".

1.1.1. Value at Risk

The Value at Risk (VaR) measures the maximum potential loss that a financial institution may suffer, given a confidence interval and within a predetermined valuation time horizon. The VaR of banks *i* is equal to:

$$VaR = P\left(r_i^t \leq VaR_{q,t}^i\right) = q \qquad (1)$$

Where, r_i^t is the return of bank *i*, and $VaR_{q,t}^i$ is the value at risk bank *i* at the level of confidence q in a time period *t*. This measure indicates the maximum amount that a bank can lose when an event occurs with a (*1*-*q*) probability. We extrapolate the value of VaR directly from the calculation of ΔCoVaR.

1.1.2. MES - Marginal Expected Shortfall

The Marginal Expected Shortfall (MES) indicates the marginal contribution of a financial institution *i* to systemic risk which, in turn, is measured by the extreme expected loss of the financial system, ES (Expected Shortfall). The first version of Acharya *et al*. (2012) assumes a static correlation measure between individual institutions, while Brownlees and Engle (2012) model dependencies in a linear and stochastic way using a GARCH-DCC (Generalized AutoRegressive Conditional Heteroskedasticity) multivariate model to estimate the MES.

We consider *N* financial institutions *i* at time *t* and we indicate with r_{it} the i^{th} firm's stock log return and with r_{mt} the market log return on day *t*. The MES_i is the tail expectation of the $firm_i$ return conditional on a crisis event. Formally:

$$MES_{it}(C) = E_{t-1}[r_{it}|r_{mt} < C] \quad (2)$$

Where, C is the threshold value definite as a crash in market return. Following Brownlees and Engle (2012), we define -2% the market return threshold (the daily loss).

1.1.3 CoVaR and ΔCoVaR

The concept of CoVaR is linked to the VaR methodology. It represents the maximum loss that an institution can record, over a specific time horizon, at a level of probability equal to q. Given a probability distribution of returns, and given a Value-at Risk at the confidence level of 95%, the expected value of the area underlying the probability distribution to the left of the VaR is calculated, which represents 5% of the worst cases that may occur. The CoVaR is the expected value of losses occurring in the worst 5% of cases. Hence, CoVaR is the VaR of the financial system returns conditioned by the occurrence of a specific stress event $C_{(r_{it})}$.

$$P\left(r_{mt} \leq CoVaR_t^{m|C_{(r_{it})}} \middle| C_{(r_{it})}\right) = q \quad (3)$$

While the contribution of each firm i to systemic risk is equal to

$$\Delta CoVaR_{it}(q) = CoVaR_t^{m|r_{it}=VaR_{it}(q)} - CoVaR_t^{m|r_{it}=0.5(r_{it})} \quad (4)$$

We estimate unconditional and conditional CoVaR via quantile regressions on data.

1.1.4. SRISK

Capital Shortage depends on the degree of leverage, on the size and on the Marginal Expected Shortfall's (MES, i.e. the loss in value of equity as a result of negative shocks). Thus, SRISK measures the contribution of a financial institution to systemic risk and the aggregated systemic risk of the whole system. It is determined based on the expected capital shortfall that a financial company would have to face in the event of a significant market decline over a given time horizon (systemic event). Companies with the highest SRISK contribute most to the under capitalization of the financial sector during the crisis. The idea behind SRISK is that a bank will not be able to operate when the value of its assets decreases beyond the value of its liabilities. We calculate the SRISK as Brownless and Engle (2016):

$$SRISK_{it} = kD_{it} - (1-k)\big(1 - LRMES_{it}(C_{t:t+h})\big)W_{it} \quad (5)$$

Where, k is the prudential capital requirement (Basel Committee of Banking Supervision), D_{it} is the book value of the bank's debt at time t and W_{it} is the market value of the bank's equity at time t and the *LRMES* (Long-Run Marginal Expected Shortfall) is the expected loss of equity over a potentially long time period ($Ct{:}t+h$). The *LRMES* is calculating as follows:

$$LRMES_{i,t:t+h}(C_{t:t+h}) = 1 - exp(log(1 - C_{t:t+h})\beta_i) \quad (6)$$

Where, β_i represents the dependence between the stock market and *bank$_i$*, estimated by "Dynamic Conditional Correlation"(DCC).
The contribution of each financial firm *i* on aggregate SRISK can be written as:

$$SRISK\%_{it} = \frac{SRISK_{it}}{SRISK_t} \qquad (7)$$

Where, the denominator is the total amount of systemic risk in the banking sector.

1.1.5. Dynamic Conditional $\beta \times MV$

Beta is a statistical measure that represents the volatility of the returns of a specific asset relative to market returns. It is defined as the difference between the returns of an asset and market returns, divided by the change in market returns. The beta (β) coefficient is an important parameter of the single-factor Capital Asset Pricing Model (CAPM):

$$E[r_{i,t}] = \beta_{i,m}(E[r_{m,t} - r_f]) + r_f \qquad (8)$$

In this model, $\beta_{i,m}$ is a sensitivity measure that describes the relationship between the return on an asset and the return on a financial market or index. As Nucera *et al*., (2016), we calculate the $\beta \times MV$, namely the time-varying beta estimate times a bank's market capitalization. This gives an estimate of the specific risk of the bank's market capitalisation in the event of a market shock. Following Engle (2016), we estimate the time-varying beta in order to explain the cross-sectional section of average equity and market returns to capture the dynamics in terms of volatility (Adrian and Franzoni, 2005).

1.1.6. Granger Causality measure

Granger's causality test is a statistical hypothesis test to identify a causal link between two variables expressed in a Vector Autoregressive model (VAR). A variable *X* "Granger cause" *Y* if the past values of *X* provide significant information for predicting future values of *Y* above and beyond that contained in past values of *Y* alone. In the formula:

$$X_t = \sum_{i=1}^{n} a_i X_{t-i} + \sum_{i=1}^{n} b_i Y_{t-i} + \varepsilon_t \qquad (9)$$

$$Y_t = \sum_{i=1}^{n} c_i Y_{t-i} + \sum_{i=1}^{n} d_i X_{t-i} + \omega_t \qquad (10)$$

Where, *a*, *b*, *c* and *d* are the coefficients of the model, *n* denotes the maximum lag and ε_t and ω_t are two uncorrelated white noise processes.

To have causality in the Granger sense, it is necessary that *b* or *d* be $\neq 0$; specifically, when $b = 0$ then *Y* causes in the Granger sense the variable *X*; when $d = 0$, then *X* cause in the sense of Granger *Y*. If both coefficients (*b*,*d*) are statistically different from zero, then, in that case, each Granger variable causes the other and *vice versa*.

In line with Billio et al. (2012), we define the causality indicator as the following,

$$(X \to Y) = \begin{cases} 1 \; if \; (X \to Y) \\ 0 \; \boldsymbol{otherwise} \end{cases} \tag{11}$$

And assume that $(X \to Y) \equiv 0$, i.e. X and not Granger causes himself. As a result, we can build connectivity measures to identify the degree of risk and connectivity between banks. We calculate the Dynamic Causation Index (DCI) for each window as follows:

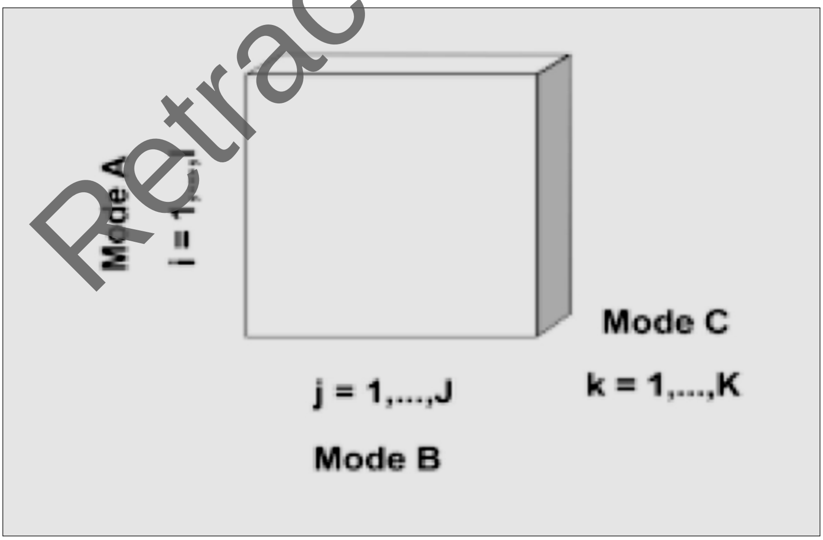
$$DCI_t = \frac{number\ of\ causal\ relationships\ in\ window}{total\ possible\ number\ of\ causal\ relationships} \tag{12}$$

Where the degree of the index directly indicates the level of interconnection of the banking system. Therefore, a higher DCI value suggests that the system is highly interconnected, the lower level indicates the contrary.

1.2. The three-way dimension of systemic risk

In three-way factor analysis (Tucker, 1966), information is specified by three indices (modes): A-mode identifies the cross-section component (i), B-mode identifies the variables and C-mode represents the time-dimension component (Figure 1). The elements of the three-way matrix X are denoted with x_{ijk} where the indices represent the different components. Graphically (Figure 2), a three-way matrix is tensor of $\mathbb{R}^{I \times J \times K}$.

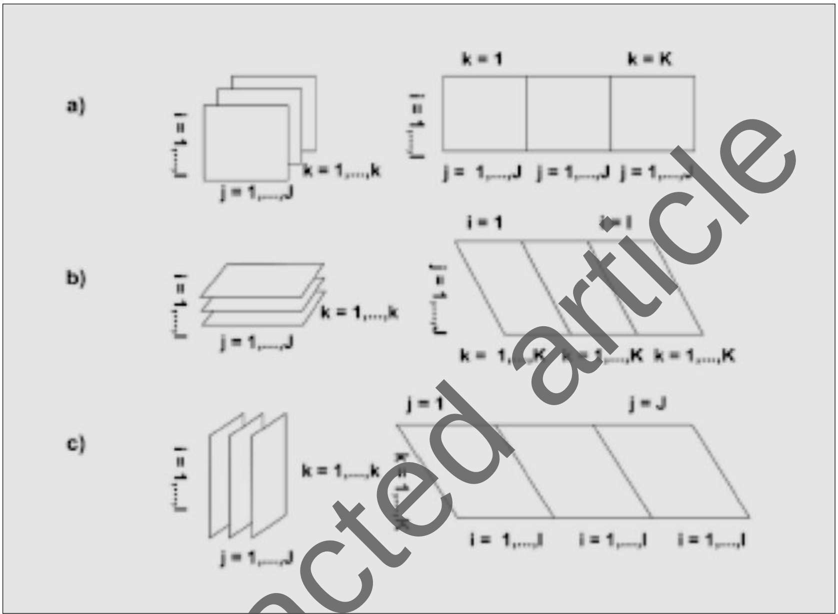
Figure 1. Modes of a Three-way matrix



Source: Authors' representation.

The high dimensionality of the modes requires the use of a procedure, called distribution or unfolding, based on the transformation or reordering of the arrangement into a single matrix.

Figure 2. Unfolding of Three-way matrix



Source: Authors' representation.

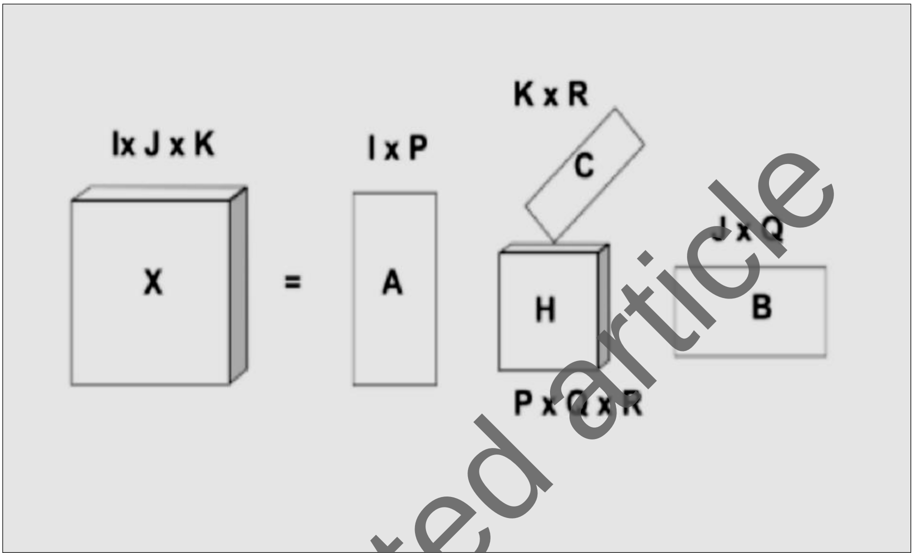
The Tucker3 (T3 - afterwards) method is one of the techniques designed for the analysis of three-way data and is a generalization of the analysis and decomposition of the main components into individual values. The T3 allows for the analysis of three ways to regularly refer to variable measurements on subjects at different times, by using reduction procedures that allow easy interpretation and representation in spaces which smaller than the original data array. The T3 analysis aims to define the fundamental structure of a data matrix by summarizing the information in a series of new dimensions known as factors. The matrix identifies the interactions between the three sources of variation. The model is defined in terms of a triple sum between the values of elements contained in each of the component matrices and in the central matrix, plus an error term:

$$x_{ijk} = \sum_{p=1}^{s} \sum_{q=1}^{t} \sum_{r=1}^{u} a_{ip} b_{jp} c_{kr} h_{pqr} + \varepsilon_{ijk} \quad (13)$$

Where a_{ip}, b_{jq} and c_{kr} are the mode array elements **A(I × P)**, **B(J × Q)** and **C(K × R)** while h_{pqr} is the core array element **H(P × Q × R)** and ε_{ijk} is the error term. The tensor **H(P × Q × R)** constitutes the most important contribution of the T3 method

(Tucker, 1966), showing the iterations between the different components. Figure 3 shows the decomposition of T3.

Figure 3. Tucker Three decomposition



Source: Authors' representation.

As suggested by Figure 3, the systemic risk can be described by means of a three-way factor, where the element on Core matrix represents the amount of risk by banks i, by measure b at time t. In nutshell, the core score is a weighted sum of risk executed in each period, where each risk is weighted by the joint systemic importance (A-mode).

Also, equation (13) shows that the scores of risk measures (the cross-sectional dimension) are influenced by the time score that provides additional weights, depending on whether financial institutions have more volatility in a period of low or medium systemic importance in the time dimension. Furthermore, the C-score is influenced by the cross-sectional dimension of systemic risk through the scores of risk measures. Therefore, the two dimensions of systemic risk are considered by three-way factorial analysis.

1.3. The banking sample

The analysis focuses on the Eurozone banking system. The choice to concentrate on these countries is due to our aim to ensure enough homogeneous banking regulation under one monetary policy by ECB. The sample periods cover the time span from June 2005 to May 2018. We select banks according to size. In particular, we only use listed bank companies in terms of total asset and capitalization according to Bankscope Country rank. Therefore, institutions with a significant systemic exposure to the banking system in the Euro area were included. However, many European banks are not listed on the stock exchange and the lack of balance sheet data makes it necessary to exclude them.

Table 1. Bank sample

Banks	**Ticker**	**Country**	**Tot. Asset**	**Market Cap.**	**Tot. Liabilities**
Erste Group Bank AG	EBS	Austria	220,659	15,068,789	206,788
Raiffeisen Bank International AG	RBI	Austria	135,146	9,032,682	124,565
BKS Bank AG	BKS	Austria	7,579	720,001	6,533
Oberbank AG	OBS	Austria	20,831	2,843,042	18,370
Dexia SA	DEXB	Belgium	180,938	9,706	175,946
KBC Groep NV	KBC	Belgium	292,342	27,401,396	273,539
National Bank of Belgium	BNB	Belgium	172,676	1,112,000	125,056
BNP Paribas SA	BNP	France	1,960,252	66,489,284	1,850,352
Credit Agricole	ACA	France	1,550,283	33,190,404	1,494,500
Societe Generale SA	GLE	France	1,275,128	29,036,562	1,215,800
Natixis SA	KN	France	519,987	19,030,687	500,192
Commerzbank	CBK	Germany	452,493	10,795,323	423,631
Deutsche Bank	DBK	Germany	1,474,732	19,427,667	1,526,043
Alpha bank	ALPHA	Greece	60,813	3,025,651	51,215
Piraeus Bank	BPIRF	Greece	67,417	1,327,444	51,330
Bank of Greece	BGC	Greece	125,441	291,021	124,847
Eurobank	EGFEY	Greece	60,029	2,109,489	48,020
National Bank of Greece	NBGIF	Greece	64,768	2,614,256	52,473
Allied Irish Banks	AIBG	Ireland	108,011	13,056	73,714
Bank of Ireland	BIRG	Ireland	146,979	7,865	111,650
Banca Monte Paschi Siena	BMPS	Italy	139,154	78,580	125,786
Banco BPM	BAMI	Italy	161,207	3,868,260	145,042
Mediobanca	MB	Italy	70,446	7,288,054	60,539
UBI	UBI	Italy	127,376	3,740,668	112,918
Unicredit	UCG	Italy	836,790	32,078,861	770,557
Intesa Sanpaolo	ISP	Italy	796,861	40,632,774	731,161
ING	ING	Netherlands	846,216	48,519,115	794,277
V Lanschot Kempen	VLK	Netherlands	14,659	1,027,825	13,310
Banco BPI	BPI	Portugal	71,939	4,035,435	26,411
Banco Comr.Portugues ‘R’	BCP	Portugal	29,640	2,112,540	61,622
Banco de Sabadell	SAB	Spain	221,348	7,964,969	201,595
Banco Santander	SAN	Spain	1,444,305	75,492,997	1,314,262
Bankiter ‘R’	BKT	Spain	71,333	7,654,744	66,787
BBV.Argentaria	BBVA	Spain	690,059	39,820,619	622,011

Notes: Total assets is the book value of total assets expressed in millions of EUR. Leverage is the book value of total liabilities expressed in million of EUR. The market capitalization is the average of May 2018.
Source: Datastream.

Table 1 lists all (34) banks included, from 10 countries (Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain). All data have been taken from Datastream. Table 2 shows the summary characteristic - financial and balance sheet information - of the entire sample.

Table 2. Summary statistics

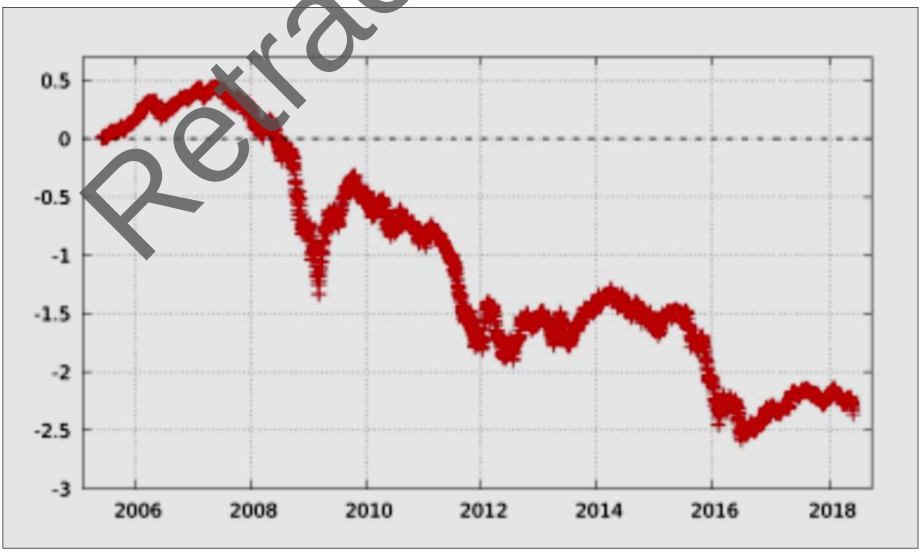
Statistics	Stock return	Market Capitalization	Total Liabilities
Mean	-0.0067	16 411	400 813
Std dev	0.0335	20 181	51 000
Min	-1.1982	9.47	4 334
5% perc.	-0.0451	481.80	15 859
95% perc.	0.0425	62 841	1 500 000
Max	0.6931	100 561	2 171 720

Notes: The time series of observations cover the period from June 2005 to May 2018 (3390 obs.). The stock market return is: $\log(r_{i;t}) = \log(r_{i;t}) - \log(r_{i;t-1})$.

Source: Authors' calculations.

The stock return over the sample period ranges from -1.19 to 0.69, highlighting how the two crises (financial and sovereign debt) had a strong impact on bank equity returns. The banks' total liabilities range from EUR 4*bn* to EUR 2,171*bn* across the sample period with a sample median of EURO 400*bn*.

Figure 4. Cumulative average return



Source: Authors' representation.

Figure 4 shows the cumulative average return of the Eurozone banking system. In the pre-crisis period (2005-2007), we can observe a growth of stock return. After the Lehman failure (September 2007), the stock market started to fall. The financial crisis affected the market sentiment as well as the solvability perceptions of the banking system. Since the spring of 2010, the increase in sovereign risks has been associated with the banking crisis due to the worsening of the financing conditions and to an increase of the long-term yield of the sovereign bond. The long weakness of the economy has had a heavy impact on the stock return of the Eurozone banking system. Also, the figure shows how, at the end of 2016, there is a new negative peak, which refers to the problem of NPLs, namely the consequences of the crisis.

2. An overview of systemic risk in Euroland

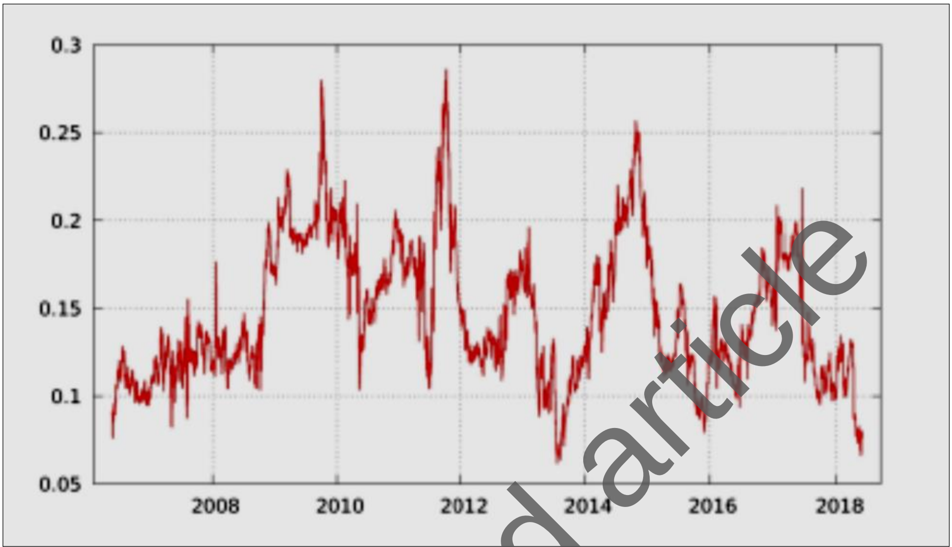
How did systemic risk measure change for Eurozone banks during the past 13 years? We start our study by making different risk measures for the sake of highlighting their evolution over years as well as their relations.

2.1. Linear Granger-causality test

We apply Granger causality to compute the dynamic causality index (Figure 5), in order to have a measure of the interconnection between Eurozone banks. Analyzing the graph, we can see a certain variability in the number of connections between the institutions. Periods in which the connections between banks of the network seem to be quite contained alternate with moments in which the system becomes much more interconnected, to then reach the end of our observation period when we can see a decline in the degree of connectivity.

The dynamic of the index clearly shows the three phases of the crisis: the global financial crisis, the sovereign debt crisis, and the consequences of the crisis, indicating strong interconnections and co-movement. The highest peak (0.30) coincides, as we expected, with the sovereign debt crisis. Indeed, during this phase, the Eurozone banks were highly exposed to sovereign risk and, therefore, given the strong interdependence between banks and sovereigns, the default risks materialized (Bratis *et al*., 2018). Although, after 2012 the DCI shows a downward trend, there are two local peaks that coincide with the key financial events, such as the problem of non-performing loans, the "new" Greek crisis, the introduction of bail-in and Brexit.

Figure 5. Dynamic Causality Index/ DCI captures the interconnection between 34 banks[9]



Source: Authors' representation.

In Figure 6, we report the network diagrams estimated via banks' daily returns, following Billio *et al*. (2012) approach. The networks show the significant at 5% Granger causality, between the 34 Eurozone banks. We report the results for the full sample and the sub-periods, to point out the evolution of the network. The lines (edges) connecting the banks represent the Granger-causality relationships. The bank *i* at date *t* that Granger-causes the stock returns of bank *j* at date *t + 1*.

These graphs present the network among the 34 banks of the sample without distinguishing the direction, therefore, the stock return of one bank influences those of the others, and *vice versa*. The size of the nodes is proportional to market capitalization. The plots suggest that the banking system became more interconnected during the crisis. Although the number of Granger's causal relationships decreased slightly after the crisis, it remained high compared to the pre-crisis period. This high interconnection between financial institutions is indicative of the potential systemic risk in the Euro area banking sector.

In addition, in Table 3, we report the summary statistics of centrality measures of the network for each period. These measures are good indicators for understanding how a single financial institution can influence the others to which it is connected. In more detail, the centrality indicators are suitable to comprehend if a shock due to

[9] Higher level stands for the banking system is highly interconnected. Rolling windows = 251 days.

a triggering event that affects a given bank can also spread to other banks, namely the spread of systemic risk and contagion (domino effects). Closeness centrality is used to calculate the distance of a node from all other nodes, considering the network as a whole. It measures the speed of information from top to bottom. This information shows that, while in `tranquil' periods, it can be positive for returns, during crisis periods it can be represented as a double-edged weapon. Bad information can spread to the entire system. Therefore, the higher the closeness centrality-index, the faster the danger of spreading an initial systemic shock. Degree centrality is the number of links that affect a node. It indicates how a node (bank) affects its system and *vice versa*. It can be interpreted in terms of the immediate risk that the node will hook up any information within the network. The eigenvector centrality shows the relative importance of a single node within a network. It assigns scores to all network vertices, based on the principle that connections to high-score vertices contribute more to the score of those nodes than equivalent connections to low-score vertices.

The mean measures of the indicators express how strong the network is connected. Indeed, these connections are crucial for the effects of the initial shock to be system-wide. Focusing on the *CloCen* measure, we can understand the rapidity of the influence of return of one bank on another. As seen in the Table, the value during the crisis period is much higher (0.35) than in the pre-crisis period (0.22) and post-crisis period (0.26), demonstrating that during periods of difficulty, the negative trend of stocks is spreading more rapidly. The same result can be seen for the average Degree Centrality measurement, which goes from 0.011 in the period due to the crisis, to 0.037 in the crisis and 0.021 in the post-crisis period. In the case of the European banking system, interconnection measures are higher during the crisis period and higher during the pre-crisis period. Therefore, a shock such as that of Lehman Brothers or the speculative attack on sovereign bonds could have an even greater effect on the entire European banking system.

In summary, measuring the network connections between individual banks, we find that the banking sector of the Eurozone has become progressively interconnected over the last decade. This implies a probable potential increase in systemic events.

Table 3. Centrality measures: Summary statistics

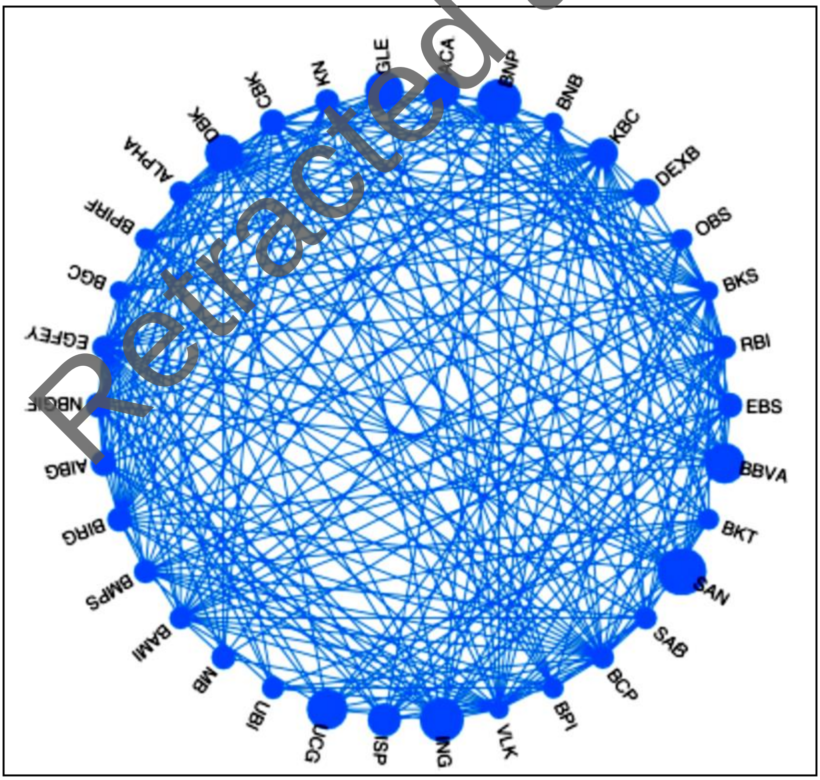
			PRE-CRISIS		
	Mean	Median	S.D.	Min	Max
CloCen	0.221	0.207	0.105	0.080	0.564
DegCen	0.011	0.006	0.012	0.003	0.046
EigCen	0.029	0.027	0.017	0.004	0.074
			CRISIS		
	Mean	Median	S.D.	Min	Max
CloCen	0.349	0.355	0.152	0.083	0.666

DegCen	0.037	0.022	0.034	0.000	0.130
EigCen	0.029	0.018	0.025	0.000	0.092
POST-CRISIS					
	Mean	Median	S.D.	Min	Max
CloCen	0.266	0.250	0.110	0.044	0.584
DegCen	0.021	0.015	0.020	0.007	0.098
EigCen	0.029	0.024	0.020	0.003	0.077
FULL-SAMPLE					
	Mean	Median	S.D.	Min	Max
CloCen	0.292	0.2937	0.054	0.180	0.411
DegCen	0.024	0.023	0.011	0.006	0.050
EigCen	0.029	0.029	0.010	0.013	0.057

Notes: The Table reports the summary statistics of centrality measure of bank network in di_erent periods. CloCen = Closeness Centrality; DegCen = Degree Centrality; EigCen = Eigenvector Centrality.

Source: Authors' calculations.

Figure 6. Banks Network / Network plot of linear Granger-causality relationships that are statistically significant at 5%, from June 2005 to May 2018 (full-sample)



Source: Authors' representation.

2.2. The systemic risk contribution

The systemic risk measures are estimated by using individual stock prices and a set of state macro-financial variables. These controlling variables are used to remove possible variations in tail risk not directly linked to the risk of the banking system (Adrian and Brunnermeier, 2016). In particular, we include the following state variables: 1) the VDAX, representing 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, and finally 4) the slope curve, as a difference between the 3-month and 10-years Germany bond yield. Table 4 provides the summary statistic of Eurozone state variables.

Table 4. State Variables Summary Statistics

Statistics	VDAX	3mE-3mG	d3mG	3m-10y
Mean	21.94	0.0255	-0.0007	0.889
Std Dev	8.592	0.0456	0.0435	0.8084
Min	10.98	-0.204	-0.345	-1.588
5% perc.	13.376	-0.043	-0.075	-0.559
95% perc.	39.31	0.105	0.065	2.442
Max	83.23	0.311	0.27	2.8565

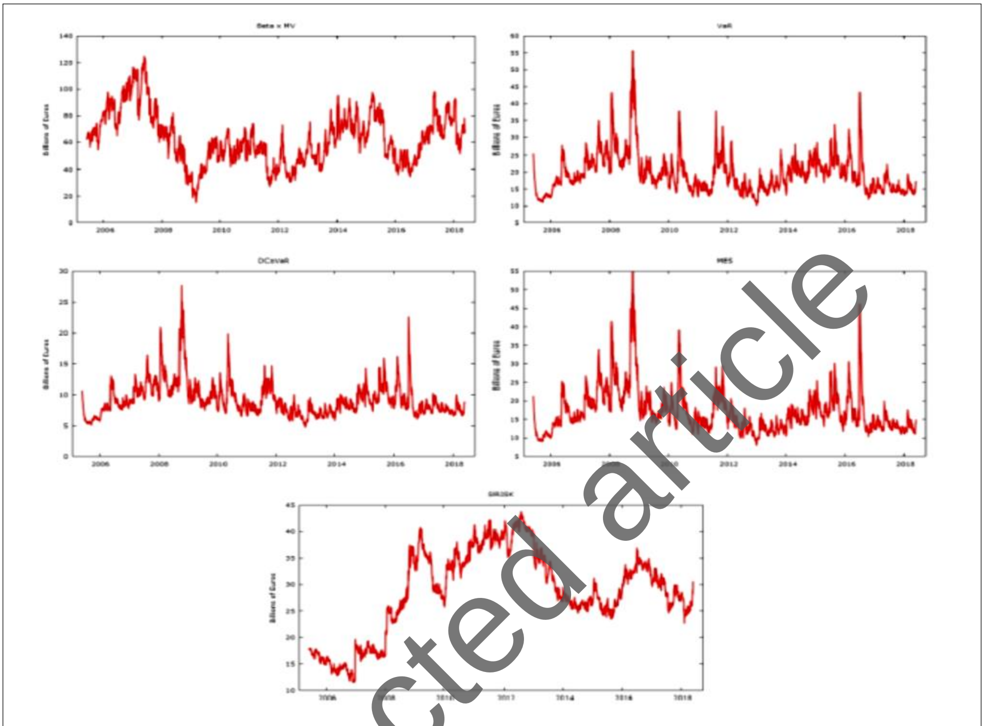
Notes: The time series of observations cover the period from June 2005 to May 2018 (3380 obs.). 3mE-3mG refers to the difference between 3-month Euribor and 3-month German government bond yield; d3mG refers to the first difference of 3-month German government bond yield; 3m-10y refers to difference between the 3-month and 10-years Germany bond yield.
Source: Authors' calculations.

To estimate the SRISK, we follow Brownlees and Engle (2016), and we use these sets of parametrization:

- *k = 5.5%* as a prudential capital fraction;
- *DAX_30* as a stock market with develop the model;
- *C = -40%* and *h = 132* trading days, as the market crash and time horizon over which it occurs, respectively.

Figure 7 shows the time series of cross-sectional averages (i.e. equity weighted) for each systemic risk measures ($\beta \times MV$, VaR, ΔCoVaR, MES, and SRISK) in order to evidence a panoramic view of the trend and the behavioural of risk on the systemic tension in the banking system, from June 2005 to May 2018.

Figure 7. Time evolution of systemic risk measures[10]



Source: Authors' representation.

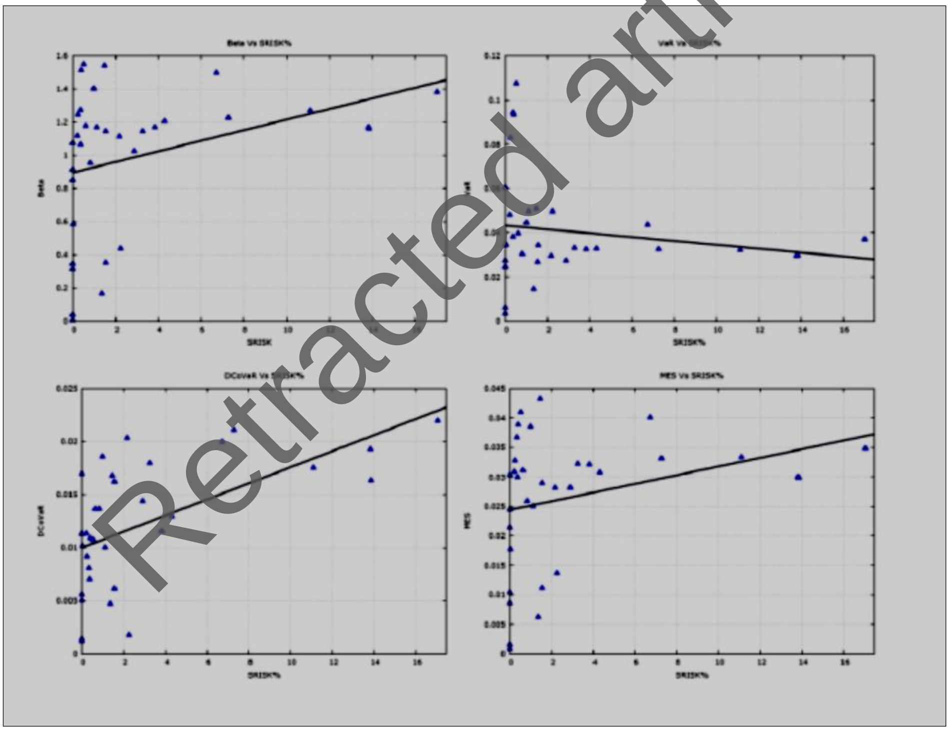
Focusing on $\beta \times MV$, VaR, ΔCoVaR and MES, banks' systemic risk measures strongly increase at the onset of the global financial crisis (2007), with a very high level due the Lehman Brothers' bankruptcy. Despite a decrease after 2009 – especially with regard to $\beta \times MV$ - the levels of other measures remain significantly higher than before the crisis. Following the European sovereign debt crises, levels show a further increase. The graph shows several peaks: the first at the beginning of the debt crisis (2010-2012), and the second at the beginning of 2016 during the NPLs problem (crisis consequences). In addition, another concern for the financial markets was the Deutsche Bank crisis, as the bank had deep links with other banking systems.

However, as the measures suggest, systemic risk is still much present in Europe (fourth peak, 2018). The SRISK shows a similar but different evolution. A low level on the pre-crisis period, high and persistent after the Lehman collapse. The

[10] The figure presents time series of daily 5 cross-sectional average risk measures covering the period from June 2005 to May 2018.

pattern clearly follows the phases of the sovereign debt crisis (2010-2012), with a slow and gradual reduction until the end of 2015. The ability of borrowers to repay their debt has declined, resulting in a further increase in the rate of new impaired loans and a further increase in their size. The SRISK clearly shows the high impact of NPLs on balance sheets and therefore, on banks' liabilities. In Figure 8, we present the cross-sectional scatter diagrams between SRISK and the other measures for the last period. In particular, we divide the sample into four periods. A pre-crisis period, from June 2005 to July 2007; a financial crisis period from August 2007 to September 2009, the sovereign debt crisis from October 2009 to December 2014, and the post-crisis period from January 2015 to May 2018[11].

Figure 8. Post-Crisis/Average value of time-varying measures and SRISK\% at each period[12]



Source: Authors' representation.

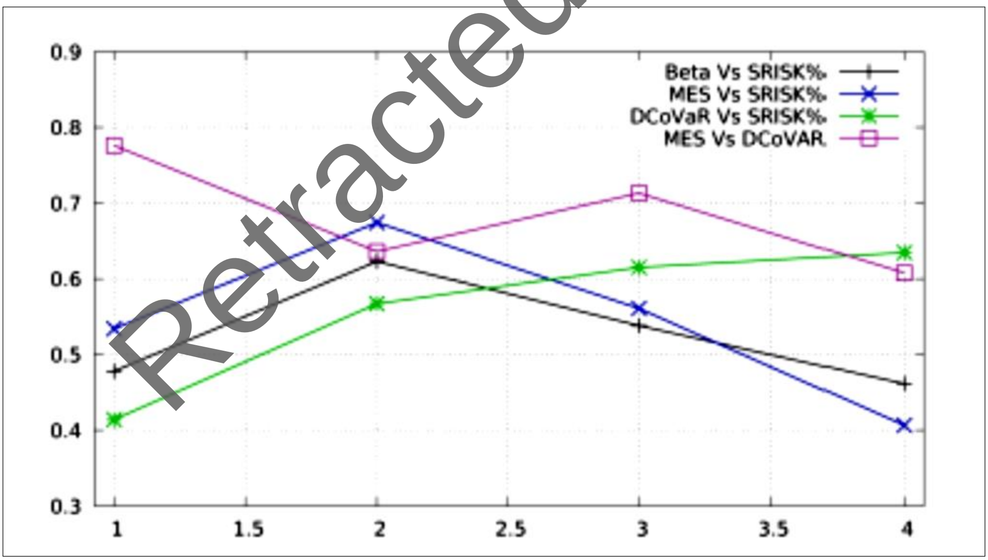
[11] The systemic risk value for each period is on average.

[12] SRISK is chosen as the benchmark in order to combine fundamentals-based rankings and market-based ones. Each measure is estimate at q= 95%, k=5%. Triangles denote to the 34 banks.

The scatter diagrams display that the β, ΔCoVaR, MES, evaluate each bank's systemic risk contributions is a very similar way showing a positive trend with SRISK%. Moreover, these relationships are respected in every period, while there is an opposite relationship between VaR and SRISK. This suggests that the financial institution that is the riskiest in terms of VaR does not necessarily appear to be riskier in terms of systemic risk and *viceversa* (Adrian and Brunnermeier, 2016).

In Figure 9, we report the time-varying Spearman rank cross-correlation for the systemic risk measures, in specific selected dates. We apply the Spearman rank correlations to show if the systemic risk measures compute a diverse rank of banks, i.e. if there is significant overlapping (Nucera *et al*., 2016). The correlation between β, MES with SRISK indicates a decrease from 2007 to 2018. On the other hand, we can see the positive increase in correlation in the overall period, between SRISK and ΔCoVaR. The results are quite consistent with Lin *et al*. (2016) who find a similar relationship for the Taiwan financial system. The results between MES and ΔCoVaR are rather stable, to prove that these measures can identify similar SIFI.

Figure 9. Spearman rank plot[13]



Source: Authors' representation.

[13] The numbers of X-axis stand for the 4 periods; 1 = Pre-crisis; 2 = GFC; 3 = SDC; 4 = Post-Crisis. The values of significant Spearman rank correlation in Y-axis.

Table 5. Top 10 Bank Rank

	Pre-Crisis					FC				
Rank	βxMV	VaR	ΔCoVaR	MES	SRISK%	βxMV	VaR	ΔCoVaR	MES	SRISK%
1	BMPS	BMPS	BNP	RBI	ACA	BMPS	BIRG	BNP	BIRG	DBK
2	CBK	RBI	DBK	CBK	BNP	KN	AIBG	ING	KN	BNP
3	RBI	EGFEY	BBVA	GLE	ING	AIBG	KBC	DBK	ING	ACA
4	GLE	NBGIF	ACA	ACA	GLE	BIRG	KN	KBC	AIBG	ING
5	ACA	BPIRF	SAN	UCG	KN	GLE	DEXB	GLE	KBC	CBK
6	BNP	ALPHA	RBI	BNP	DEXB	KBC	RBI	ACA	CBK	GLE
7	UCG	CBK	GLE	ING	CBK	ACA	CBK	BBVA	GLE	DEXB
8	DBK	EBS	MB	KN	UCG	CBK	ING	EBS	EBS	UCG
9	ING	KN	ISP	DBK	DBK	ING	EBS	SAN	RBI	KN
10	SAN	AIBG	EBS	BMPS	BMPS	RBI	NBGIF	UCG	ACA	ISP
	SDC					Post-Crisis				
Rank	βxMV	VaR	ΔCoVaR	MES	SRISK%	βxMV	VaR	ΔCoVaR	MES	SRISK%
1	BMPS	DEXB	BNP	GLE	BNP	BPIRF	BPIRF	DBK	BAMI	DBK
2	GLE	EGFEY	GLE	UCG	ACA	BAMI	EGFEY	SAN	BPIRF	ACA
3	UCG	AIBG	BBVA	ISP	DBK	NBGIF	NBGIF	BBVA	UCG	BNP
4	ISP	BPIRF	ISP	BIRG	GLE	UCG	ALPHA	UCG	NBGIF	GLE
5	BIRG	ALPHA	ACA	KBC	ING	UBI	AIBG	BNP	UBI	SAN
6	BAMI	NBGIF	UCG	BAMI	UCG	DBK	BAMI	UBI	EGFEY	UCG
7	ACA	BIRG	ING	ING	CBK	EGFEY	DEXB	ISP	DBK	CBK
8	KBC	BAMI	SAN	ACA	KN	GLE	BMPS	GLE	GLE	KN
9	UBI	UCG	DBK	UBI	SAN	ALPHA	BCP	MB	SAN	ISP
10	ING	BMPS	KBC	BNP	ISP	SAN	UBI	BAMI	ALPHA	ING

Notes: Top 10 rank of systemical riskies banks based on the 5 measure of risk. Bold indicates the same rank.
Source: Authors' calculations.

To summarize, in Table 5, we point out the top 10 banks according to their measures, by the 5 indicators, during each period. The risk measures produce different risk systems; this implies that the differences are linked to structural computational differences (Benoit *et al*., 2013). Overall, the findings support that these systemic risk measures cannot perfectly identify the most systemically important financial institutions over a certain period. This confirms the criticism of Danielsson *et al*. (2016) and Benoit *et al*. (2017), which show how these individual measures of systemic risk depend on the extreme distribution of stock return, and which, in turn, make heterogeneous in the risk ranking (Nucera *et al*., 2016).

3. T3-PCA ranking analysis

High "turnover at the top" (Nucera *et al*., 2017) of systemic ranking measures (Table V) can create problems to "right-way" formulation in macro-prudential policy from regulatory. Therefore, conclusions based on these metrics may not be adequate to provide well-timed policy decisions. In order to avoid these possible biases in evaluating ranking, we apply the Three-way factor analysis. By T3, we are able to specify the connections between the 3 different components, identifying the bank with an a-theoretical approach. T3 recognize the periods in which the banks (A-mode) are sizeable. We compute the loading of principal components for the two dimensions of systemic risk, cross-sectional and time dimension. In particular: A-modes are the banks (cross-sectional dimension), B-mode refers to five systemic risk measures (risk dimension), and C-mode stands for the periods (time-dimension). The power of T3 is that it identifies the financial companies in relation to the interaction matrix (H) and with the temporal importance. This allows us to highlight which are the banks that are more vulnerable to a systemic crisis.

To summarize the ranking ability, we compute the score for A and C-modes. The idea is to use the score as a measure of importance; therefore, the top scores allow us to identify the more vulnerability banks and *viceversa*.

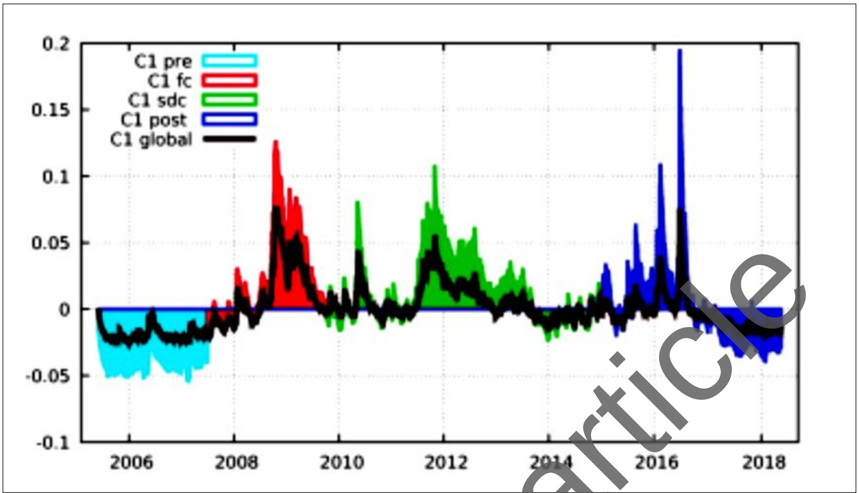
In our analysis, we first consider the complete sample measurement from June 2005 to May 2018 to identify the global pattern. In addition, we calculate the components in 4 sub-samples, according to the previous analysis. We select the combination via the convex hull procedure (Celeumans and Kiers, 2006). Especially, we select 3 components for A-mode, 2 for B-mode and 5 for C-mode. For the full sample, the optimal complexity explains approximately 60% of the data variance. All of the variables have been standardized, with mean 0 and variance 1, in order to ensure that factors' analyses are not influenced by the scale of units and the size of each measure.

3.1. The time dimension

In this section, we compute the temporal dimension of systemic risk. The results of the C1-score are plotted in Figure 10. The black line is the C1-score component for the full sample, while the colour bars are the C1-scores estimated for each sub sample periods (light blue is the pre-crisis period, red is the financial crisis, green is the sovereign debt crisis and finally, blue quantifies the post-crisis period). The time score follows more closely the dynamic of the VaR, ΔCoVaR and MES.

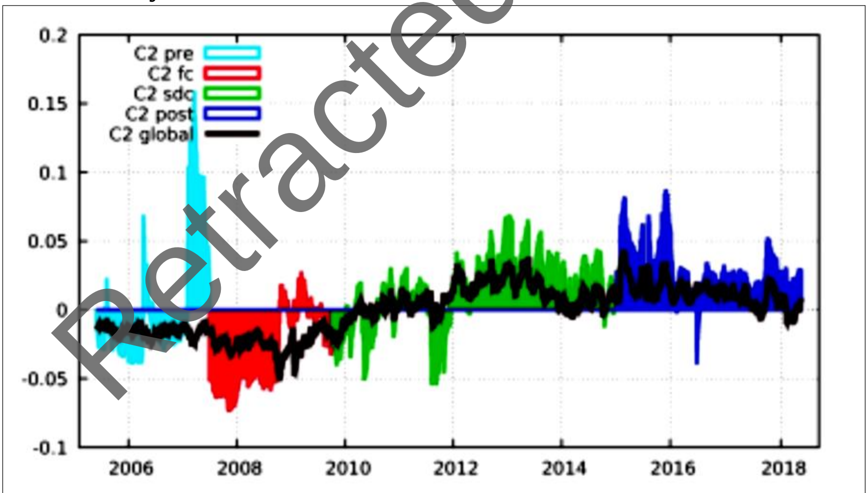
However, until 2015, C1-post outperform the other periods. This finding suggests that the time-dimension of systemic risk in Eurozone is made up of three parts: 1) spillover effect of US financial crisis, 2) sovereign debt crisis, and 3) the consequences of the crisis, which have a more relevant effect in term of accumulation of risk. The behaviour is accentuated by on the C2-score component (Figure 11). The shapes clearly identify the dynamic that affects the Euro area crisis. The blue-light box appears quite informative about the collapse of Lehman Brothers. The high level of the score due to the collapse immediately returns to its stable level. This because only a small sample of European banks (see Ireland, Germany, France) had a strong exposure to foreign markets and, therefore, were more affected by the US financial crisis.

Figure 10. The dynamic of C1-score[14]



Source: Authors' representation.

Figure 11. The dynamic of C2-score[15]



Source: Authors' representation.

[14] Daily estimated of C1 score. Black line is for full sample estimated; light-blue is the pre-crisis period; red is the financial crisis; green is the sovereign debt crisis; blue is the post-crisis period.
[15] Daily estimated of C2 score. Black line is for full sample estimated; light-blue is the pre-crisis period; red is the financial crisis; green is the sovereign debt crisis; blue is the post-crisis period.

Contrary to the evolution of classical measures estimated, the C2 component shows that the risk in Eurozone banks is always persistent from 2010. Looking at the dynamics of the DCI (Figure 5), we can see that, since the beginning of 2017, the total systemic connection has decreased substantially. However, focusing on the C2 component, we can observe the higher impact of the post-crisis period (from 2015 to 2018). Furthermore, we can see how the negative peak - a reduction of systemic risk -perfectly coincides with ECB intervention such as the “Whatever it takes” (WiT, July 2012) and ABSPP program (January 2015).

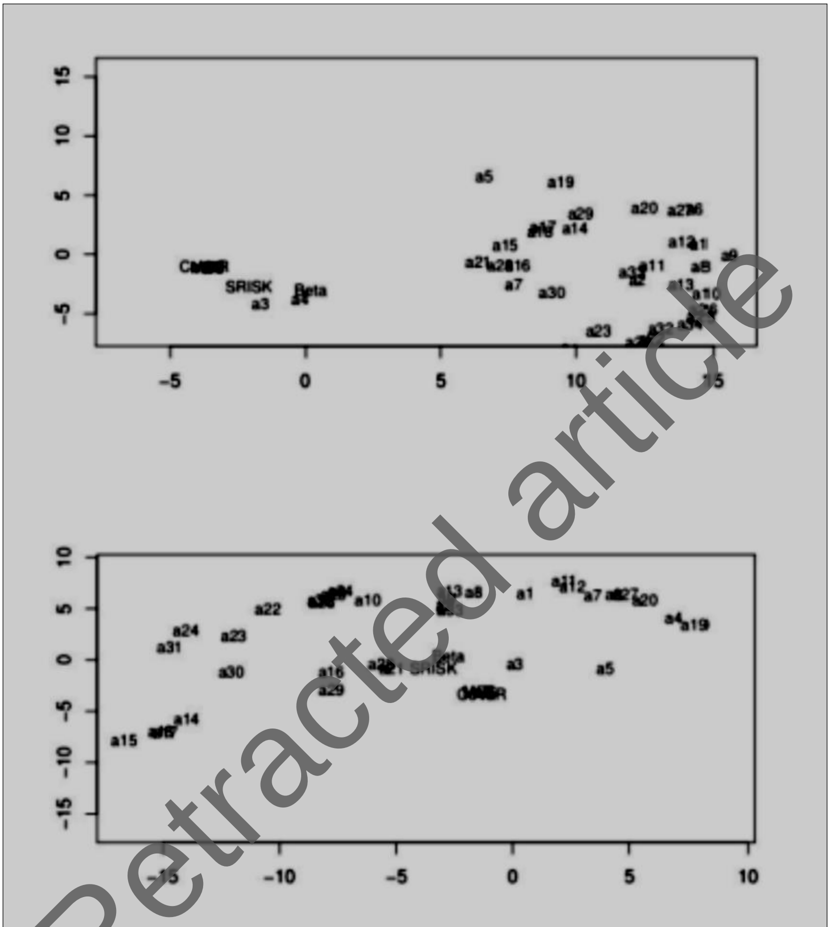
3.2. The cross-sectional dimension

Taking into account the structure of the cross-sectional dimension, the component for the A-mode provides a measure of the systemic risk measures and its time dimensional component, which affects the banks of Euro area. Thus, Figure 12 shows the banks (a1, a2,..., a34) and the systemic risk measures (Beta=B1, VaR=B2, MES=B3, CoVaR=B4, SRISK=B5) by joint plot for the C1 component. This class of plot is useful to interpret the relationship between the modes via the core matrix. The latter indicates the relationships between the 3 modes. The core matrix element ($h_{g,p,r}$) indicates the relationship among the g component with the other two modes (p,r). The h_{221} element, for example, indicates the mode 2-A and 2-B component with the 1-C-mode component. Through the core matrix, it is easy to identify these interdependencies between the modalities. For each combination of factors, we achieve the portion of variance that recognizes the \risk condition”. Therefore, we can obtain a much more accurate specification of systemic risk.

The left-panel of Figure 12 refers to the first component of the temporal dimension (the “fire” break path), while the second component (the Eurozone financial crisis) is shown in the right-panel. The graphs contain a lot of information about the transmission of risk and its impact on various banks. The plot also shows which risk measure is most suitable to represent the risk dimension of the bank, in fact, the distance between a-mode and b-mode indicates which risk measure is most significant. For example, for the a4 component, β (B1) is the perfectly right measure to evaluate its risk component, as a3 in the graph below.

It is interesting to note the clustering of banks by country of origin. Indeed, we can see that banks in the Core countries (Austria, Germany, France) are very close to each other as are banks in the non-core countries (such as Greece, Italy). Spain and Italy banks have been most affected by the risk due to their banking system in distress (extreme right side), while French and German banks suffered from their exposure to the sovereign debt of no-core countries. Greek and Portugal banks appear to be close off adapt the distribution of the system. This means that shocks from Greek banks remain partly confined within their banking system.

Figure 12. Joint-plot for the C-component[16]



Source: Authors' representation.

Focusing on the temporal dimension of the European financial crisis, we can see the almost perfect (vertical) distinction of the impact of risk. This implies that the closer the banks are to each other, the greater the degree of interconnection. Therefore, there are several more interconnected poles, especially during the sovereign debt crisis. These results show that the European banking system can be "too similar to fail". The activities of these banks are characterized by homogeneity. One bank default may result in a single risk exposure due to the similarity between banks, which, in turn, makes the joint risks easily transferable to another financial firm, causing shocks across the banking system, i.e. the "domino effect". In such

[16] Left-panel is the joint-plot for C1-component; right-panel is for C2- component.

cases, when several institutions act as one, authorities should consider and analyse them as one cluster.

The A-mode with the highest interconnections are *a8, a10, a25, a26, a27, a32, a34* respectively (BNP, GLE, UCG, ISP, ING, SAN, BBVA). This dynamic configuration is in line with the Granger-causality results (see section 4.1).

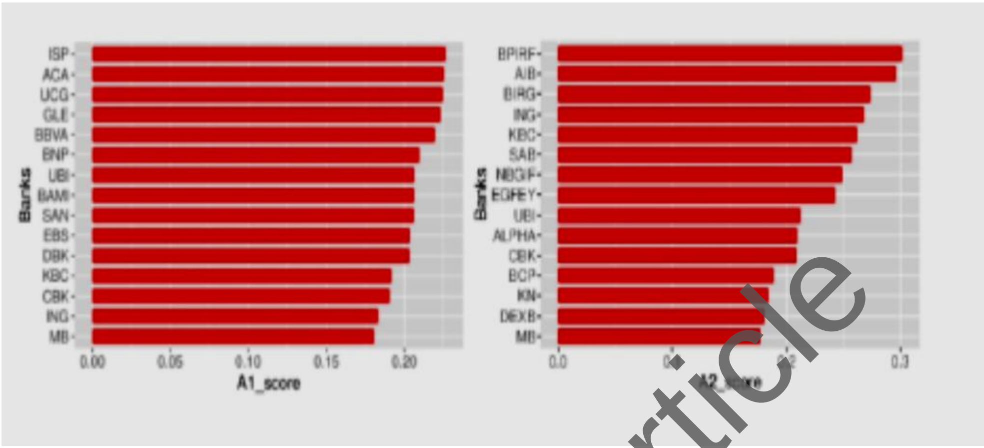
Thanks to the T3 factor analysis, we can examine these characteristics of the banking system. By using this approach, which combines the cross-sectional and temporal dimensions, it is necessary to discover previous changes in the dynamics of banks' behaviour and to achieve a multidimensional ranking. In that way, it could to help the banking authorities as a quantitative tool to figure out systemically important banks.

From Figure 13, we can see the top 15 Eurozone banks in terms of A-score for the entire period. It indicates the systemic, important score for each bank, i.e. they are systemically important banks. These results are comparable to Derbali and Hallara (2016a), Derbali and Hallara (2016b) and Moratis *et al*. (2017) who find a similar ranking by using diverse methodologies and datasets. Especially, in Moratis *et al*. (2017), the systemically important banks are captured by the degree of CDS spillovers.

Our approach is free of discretion because it does not assume any modelling of data and it provides a rank that combines the two important characteristics of systemic risk. By the way, it is remarkable that a bank's systemic importance is not only closely related to its risk but also, to its interconnectedness to other banks. Based on the findings, we can conclude that ISP, ACA, UCG, GLE, and BBVA are the systemically important banks. The bankruptcy of these SIBs could bring a great impact on the real economy, particularly on its potential enormous negative externalities and the fast spread of moral hazard. Hence, these banks should be paid more attention by policy-makers (authorities and regulators) due to their high level of the score. These results suggest a very important policy implication. High A-score banks should be closely monitored since they are, inherently, a potential threat to the financial stability, regardless of \too big to fail” policy. For example, the ISP (first) and the ACA (second) are the great-size banks but not in absolute value. Therefore, is evidence of the spread of systemic risk can be mitigated by a "too-interconnected to fail")[17] policy. By acting directly on these banks, it is possible to interrupt the cycle of self-fulfilling bank crisis, namely the domino effect of contagion, which is not essentially true due to the structural conditions (balance sheet) of the banks. Understanding the vulnerability of the Eurozone banking system to self-fulfilling bank runs is crucial for policymakers concerned about financial stability.

[17] See Acharya and Yorulmazer (2007).

Figure 13. Top 15 score banks rank[18]



Source: Authors' representation.

Therefore, relying on systemic risk measures alone would exclude the interconnection between cross-section and time-dimension, which are instead pertinent from the financial stability viewpoint. The overall assessment without considering the two dimensions would be below the current level of systemic fragility of the banking sector as a whole (see different ranking banks by Table IX). In addition, policy-makers should note that each ranking measure is inherent to the different C components. In other words, banks are riskier systemically depending on the reference time component. For example, if policymakers attribute a higher value to the spread and relevance of the Eurozone crisis (C2), they should focus their attention on the A2 component modes (Figure 13, right-panel), and on component A1 if they attribute a higher value to global systemic risk (C1).

3.3. One Index to rule them all, one Index to find them

We use the estimated systemic importance measures to build *a* index (T3R) which summarizes the 2 dimension-information of systemic risk. Then, we calculate the index as follows:

$$T3R = a_i(\sum_{i=1}^{n} b_i x_{it})c_t \qquad (14)$$

Where, *T3R* is the overall systemic risk conditions index at time *t* and x_{it} are n systemic risk measures at time *t*. The b_i's are weights attached to each of the variables, a_i is the cross-sectional weights, while c_t is the time-dimensional weights. In particular, a_i, b_i and c_t are the weighted loadings for each modes. In a nutshell,

[18] Top 15 banks ranking by the score of A1 component (left-panel), and A2 component (right-panel) for full-sample.

the index is built by summing the selected components weighted by the share of total variance explained by them (percent of _t).

The trend of the index is similar to that of the risk measures included (Fig.14). However, it can be observed that the indicator is almost always close to its average. This result is very important for the perception of systemic risk in Europe. Taking both components into account, the index suggests that, on average, the risk is rather low, meaning that the Euro area banking system is financially stable in means. The index varies strongly over time but most of them vary around their mean value. The high risks of some banks (A-mode components) are more than offset by the low risks of others over time (C mode components). The risk is limited to its average value (blue line). This means that bank rankings are stable over time.

The result is very controversial compared to our expectation and to the other risk measures pattern but is in line with Nucera *et al*. (2016) and Fang *et al*. (2017), who find the similarities stable loadings for the US market and China financial sectors, respectively. Obviously, the peaks are periods of crisis but, at the same time, we see a clear change in behaviour after 2012. In a non-volatile market context (the bank ranking is stable), there was a further peak at the end of 2016. This result is in line with the "paradox of volatility" (Brunnermeier and Sannikov, 2014). According to this paradox, financial corporations take on more risk in the event of episodes of low perceived volatility, making the financial system riskier when it appears safer. To summarise, our indicator offers a stable solution for the detection of SIBs.

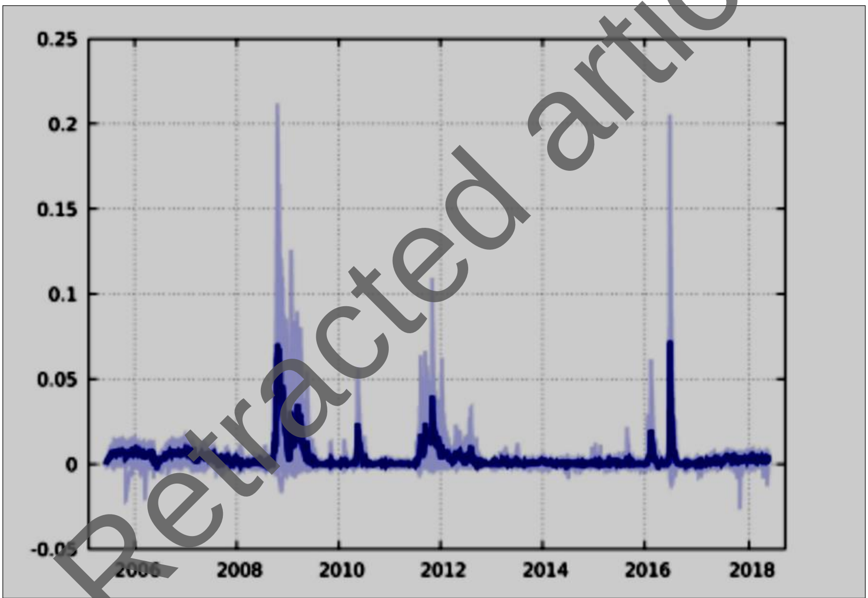
3.4. Discussion

The aim of systemic risk measures is not to quantify the amount of risk for each bank in relation to the total, but to ranking financial institutions (banks) as SIFIs (SIBs). SIBs have different attributes which we can classify according to the following characteristics. The size is associated with the number of transactions that the financial undertaking carries out in the market; therefore, a failure of the financial undertaking would have a negative impact on the whole system and therefore on the economy ("Too Big to Fail").

A second criterion is the interconnectedness between financial institutions within the financial system. A highly interconnected system results in a very likely risk of direct contagion. The propagation of an idiosyncratic shock of a bank influences another bank, which, in turn, will infect another bank and so on, given by the banks' reciprocal balance sheet exposure ("Too Interconnected to Fail"). Another criterion is the so-called "Too many to Fail" (Acharya and Yorulmazer, 2007). This criterion refers to the possibility that more than one financial institution may have similar balance sheet characteristics (e.g. claims on a common debtor or issuer, the concentration of loans in a single sector of the real economy and of assets). The similarity makes risks easily transferable to other banks (domino effect), causing shocks throughout the financial system (fire sales).

As already mentioned, indicator-based approaches (BCBS, 2011) are simple to compute and apply but have clear limitations, falling to capture these different characteristics. First, the specific weights for each category are arbitrarily decided and depend on the experience of the supervisory authorities (e.g. the five indicator categories used in the Basel's valuation approach are weighted by 20%). Secondly, they are not able to fully grasp the spillover effect, and the interconnectedness between banking institutions. One of the lessons emerging from the global financial crisis is that the regulatory model should include not only micro-prudential regulation, but also macro-prudential regulation based precisely on the possibility of risk transmission.

Figure 14. The T3R[19]



Source: Authors' representation.

Moreover, the indicators are based on annual balance sheet data and are therefore backward in nature. This implies that they are unable to detect the dynamics of systemic risk. Indeed, systemic risk is dynamic by nature and any change in the initial factors of the financial network would lead to a systemic risk of a "buttery effect" in the financial system (Wang *et al*., 2018). Market-based methods have the advantage of being timely, dynamic and based on readily available data.

[19] The T3 systemic risk index. Blue line is the mean; Light-blue lines are the index for the 34 banks.

These methods are forward-looking, reacting to market expectations and so, they carry information about potential systemic risks. To summarize, our work provides the following additional information for regulators. First, our multidimensional approach captures both dimensions of systemic risk, considering the entire network structure to identify banks of a systemic nature. Therefore, the distinctive feature of our analysis is the great emphasis we placed on the feedback mechanism between the transversal risk and the time dimension. Our methodology for estimating systemic risk considers the entire structure of the network to identify in a-theoretical way banks of a systemic nature.

The policy maker should monitor institutions with a high score in terms of A-mode to see if a change of the score leads to an increase in the fragility of the entire banking system. Secondly, our measurement meets the requirements of timeliness, ease of application and effectiveness. Having the right time means that the indicator signals must arrive sufficiently in advance so that policy measures can be implemented and have an impact. As regards the effective implementation of an early warning system, it is essential for policymakers to decide on the most appropriate time for its adoption.

Compared to the EBA assessment approach, our analysis suggests that additional banks should be included in the monitoring list, as they have a high level of connection to the system (Figure 12). Finally, the methodology could be incorporated into bottom-up stress testing. More precisely, the measure we are proposing could be used to generate estimates of the expected losses of entities, incorporating all the information both in the cross-section and in the time dimensions.

Conclusions

In this work, by using T3, we have built an index that can summarize these characteristics (cross-section and time dimension) of systemic risk, which is essential for a robust identification of SIFIs. Analysing the Eurozone banking system, our findings suggest that the systemic risk estimations ($\beta \times MV$, VaR, ΔCoVaR, MES, and SRISK) provide heterogeneity in bank rank. This heterogeneity precludes regulators and policy-makers to adopt policies and directives in the right direction. „Punishing” one bank instead of another can affect the entire financial system. Timely and correct identification of SIBs is of vital importance, both for the financial context and for the economic context.

Our measure allows us to identify SIFIs (SIBs) in an unambiguous and transparent way, considering both dimensions of risk. Therefore, it can help authorities to automatically and transparently identify the SIBs.

The main empirical findings confirm the view that systemic risk is still present in the Euroland, mainly due to the consequences of the sovereign debt crisis. We show the fragility and structural dependency of the used measures, which cannot be used for the estimation of a stable rank. Also, we find how our measure assigns a stable score. Also, our measure is the first to be composed of both the cross and the time component, essential elements for a correct systemic risk assessment.

Additionally, this paper contributes to the literature on the analysis the systemic risk with multi-methods focusing on the financial system of Europe. This study is the first attempt to develop a measure of systemic risk in a cross-section and temporal dimension on a common framework. Our measure allows us to identify SIFIs (SIBs) in an unambiguous and transparent way, considering both dimensions of risk.

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