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Too-systemic-to-fail: Empirical comparison of systemic risk measures in the Eurozone financial system

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ABSTRACT

This paper quantifies the Too-Systemic-To-Fail (TSTF) paradigm in the Eurozone since the introduction of the Euro through three primary dimensions: Too-Big-To-Fail (TBTF), Too-Interconnected-To-Fail (TITF), and Too-Many-To-Fail (TMTF). We apply prominent systemic risk measures based on public data, including the Granger-causality network (GCN), Delta Conditional Value-at-Risk (ΔCoVaR), Marginal Expected Shortfall (MES), and Systemic Risk Index (SRISK). Financial interconnectedness and systemic risk exposure within the 17-member states of the Eurozone are measured on two levels: (i) identifying which financial sectors (banking, diversified financials, insurance, and real estate) are most exposed to systemic risk in the Eurozone at the union level; and (ii) identifying which member state is most exposed to systemic risk within each financial sector at the country level. We extend the original ΔCoVaR, MES and SRISK models by incorporating the bootstrap Kolmogorov-Smirnov stochastic dominance test to rank institutions based on their exposure to systemic risk formally.

1. Introduction

The 2007 global financial crisis (GFC) has brought systemic risk measurement and management to the forefront of academic research and supervisory policy agendas. The Basel Committee and the Financial Stability Board are continuously working to establish new regulatory requirements for Systemically Important Financial Institutions (SIFIs). These efforts aim to reach an agreement on the specific factors that make certain financial institutions more susceptible to system-wide shocks (systemic resilience or participation) or more likely to spread these shocks to other institutions, magnifying the overall effect (systemic contribution).

Furfine (2003) analyzed two dimensions of systemic risk: first, the simultaneous inefficient functioning of a group of markets or institutions due to a financial shock, and second, the risk that the failure of one or more institutions could spread to others because of their substantial interconnectedness. Several factors contribute to systemic risk in the financial system: (1) financial institutions becoming more interconnected through derivative contracts that transfer interest rate or exchange rate risk; (2) financial institutions investing in correlated assets and maintaining a high-level capital structure that is vulnerable to risk above the optimal level (Acharya, 2009); and (3) asymmetric information, particularly during periods of confidence loss, which can magnify an institution's distress and lead to an illiquidity crisis.

The Financial Stability Board (2011) defined SIFIs as "financial institutions whose distress or disorderly failure, because of their size, complexity, and systemic interconnectedness, would cause a significant disruption to the wider financial system and economic activity." Systemic risk is prominent when the distress of a single institution can cause the entire financial system to break down, subsequently affecting the real economy through cascading, chain-reaction, and contagion effects. This paper focuses on the financial institution of interest or the entire financial sector. Based on the above definitions, systemic risk can be examined under the Too-Systemic-To-Fail (TSTF) paradigm, where the imminent failure, incompetence to operate, and disorganized wind-down of certain institutions can disrupt the financial system and adversely affect the real economy (Thomson, 2009). TSTF can be examined in three primary dimensions: (1) Too-Big-To-Fail (TBTF),[1]

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[1] Mitchell (1997) originally defined the "Too-Many-To-Fail" paradigm, corresponding to a situation where it is less costly to rescue banks than to close large numbers of banks. Brown and Dinç (2014) have empirically illustrated this problem in emerging market countries, whereas Acharya and Yorulmazer (2007) are the first to argue that this phenomenon gives banks incentives to herd and increases the risk that many banks may fail together. The issue "Too-Big-To-Fail" was initially used in a 1984 U.S. congressional hearing to explain the decision to bail out Continental Illinois National Bank at a cost of $1.1 billion to the Federal Deposit Insurance Corporation (FDIC) and the potential need to save ten other large U.S. banks in the event of failure (Carrington, 1984).

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measured by an institution's relative size to the whole market; (2) Too-Interconnected-To-Fail (TITF), measured by the likelihood of an institution's failure generating negative externalities that affect the entire economy; and (3) Too-Many-To-Fail (TMTF),[2] measured by the likelihood of financial institutions gathering ex-ante to take more risk and increase bailout chances in the event of a systemic crisis.

During periods of distress, interdependence among financial institutions becomes substantially more significant as losses naturally extend to different institutions, making the entire financial system vulnerable. In this context, systemic risk refers to the simultaneous default of multiple large institutions. If financial instability leads to a systemic crisis, the entire economy and society could face significant costs and repercussions. Financial institutions often experience contagion episodes during financial crises, and regulators must account for this when evaluating the financial system's health. As central banks work to increase the financial stability of the domestic economy, analyzing and monitoring systemic risk is an essential element of their activities. While the GFC has promoted greater systemic analysis, it has also driven improvements in systemic risk indicators that central banks and other regulatory authorities can use as monitoring tools. Measuring the financial system's systemic risk is a crucial component of assessing its stability.

This paper makes several contributions to the academic literature on financial interconnectedness and systemic risk. Firstly, it is the first attempt to apply systemic risk measures within an economic union. The empirical analysis measures which sectors (member states) display a higher degree of interconnectedness during stress periods and assesses systemic risk exposure within the 17 member states of the Eurozone at both the union and sector levels. At the union level, the paper identifies which Eurozone financial sector and member state is most exposed to overall systemic risk. At the sector level, it detects which member state is exposed to systemic events when a specific sector is in distress. The paper compares the exposure of the main components of the financial system (banking, diversified financials, insurance, and real-estate sectors) to systemic risk rather than focusing solely on the exposure of individual financial institutions.

Secondly, the paper assesses the robustness of four prominent systemic risk measures: the Granger-causality network (GCN) of Billio et al. (2012), Delta Conditional Value-at-Risk (ΔCoVaR) by Adrian and Brunnermeier (2016), Marginal Expected Shortfall (MES) by Acharya et al. (2017), and Systemic Risk Index (SRISK) by Acharya et al. (2012) and Brownlees and Engle (2012). These measures, which are widely used due to their reliance on public data, have been developed within different frameworks. To avoid discrepancies caused by different estimation strategies, the paper unifies the theoretical framework of Brownlees and Engle (2012). Thirdly, the paper extends the original ΔCoVaR, MES, and SRISK models to include the bootstrap Kolmogorov–Smirnov dominance test developed by Abadie (2002), providing a formal ranking of the financial sectors (member states) with respect to their exposure to systemic risk. Finally, the paper links macro-prudential measures (ΔCoVaR, MES, and SRISK) with micro-prudential measures (systematic risk, tail risk, and correlation, as well as firm characteristics such as leverage and market capitalization). As a result, some systemic risk measures can be expressed as transformations of market risk measures. The approach presented in this paper is likely to be highly relevant to regulators, policymakers, and academicians.

The remainder of the paper is organized as follows. Section 2 reviews the literature on interconnectedness and systemic risk measures. Section 3 proposes a methodological analysis of the Granger Causality Network, MES, SRISK, and ΔCoVaR measures and presents the common framework used for comparison. Section 4 describes the data and summary statistics. Section 5 presents the main empirical findings on interconnectedness and systemic risk exposure at the union and sector levels during the sub-periods of analysis (before, during, and after the crisis). Section 6 reports the results of the robustness check, and Section 7 discusses limitations and future research. Section 8 summarizes and concludes with policy implications.

2. Literature review on systemic risk measures

Billio et al. (2012) demonstrated that several systemic risk indices can be used to determine the connectedness of financial institutions by applying Granger-causality networks and Principal Components Analysis (PCA) to monthly returns of financial institutions from various sectors. Rodriguez-Moreno and Pena (2013) utilized the Gonzalo and Granger metric, three Granger Causality test measures, and the systemic events index to correlate policy actions of two groups with high-frequency market-based systemic risk measures between 2004 and 2009, using U.S. and EU interbank rates data, stock prices, and credit derivatives at both individual bank and aggregate market levels.

Three notable systemic risk measures derived from public data are the Marginal Expected Shortfall (MES) by Acharya et al. (2017), the Systemic Risk Index (SRISK) by Acharya et al. (2012) and Brownlees and Engle (2012), and the Delta Conditional Value-at-Risk (ΔCoVaR) by Adrian and Brunnermeier (2016)[3]. These measures are well-known concepts that build upon popular methods of Value-at-Risk (VaR) and Expected Shortfall (ES) and have substantial economic interpretations. MES represents the expected equity loss of a financial institution when the market falls below a given threshold within a certain time period, specifically a 2 % drop within the market in one day for short-run MES and a 40 % drop in the market in six-month for the long-run MES (LRMES). Generally, financial institutions with higher absolute values of MES contribute more to market declines; therefore, these financial institutions indicate greater contributions to systemic risk. SRISK measures an institution's expected capital shortfall during a financial crisis, with institutions having the largest shortfalls being considered the most systemically risky. CoVaR captures the change in the financial system's VaR contingent on a financial institution experiencing a certain event. The financial system's systemic risk (ΔCoVaR) contributions are the change between the financial institution's CoVaR when it is under financial distress and its median state. Greater $\Delta CoVaR$ (in absolute values) indicate higher systemic risk contributions (or exposures).[4]

Several studies have proposed alternative methods to address systemic interrelations using various variables and procedures (Adams et al., 2014; Drehmann and Tarashev, 2011; Cao, 2013; Singh et al., 2013; Lopez-Espinosa et al., 2013; Allen et al., 2016).[5] Benoit et al. (2013) compared two commonly cited systemic risk measures, MES and SRISK, with ΔCoVaR using the same sample from Acharya et al. (2017) and Brownlees and Engle (2012). They found that under specific conditions, market risk measures (e.g., ES, VaR, Beta) can represent systemic risk measures. MES coincides with the product of the market's ES (market tail risk) and the institution's beta (institution systemic risk), while ΔCoVaR coincides with the product of the institution's VaR (firm tail risk) and the linear projection coefficient of the market return on the institution's returns.

Zhang et al. (2015) analyzed the efficiency of four market-based

[2] Adrian and Brunnermeier (2016) justified the phrase "Too-Many-To-Fail" as "systemic as part of a herd," where a group of institutions behaving similarly to each other can be risky and dangerous to the system as a large merged entity.

[3] The New York University's Volatility Lab is formulating the common systemic risk measures for numerous international financial institutions. The outcomes are renewed weekly via http://vlab.stern.nyu.edu/.

[4] Note that ES, MES, VaR_q^i, CoVaR and ΔCoVaR are typically negative numbers, in practice, the sign is often switched, which is followed in this paper. While $SRISK$ is typically a positive number.

[5] A thorough research of the main systemic risk measures and analytical frameworks formed over the previous couple of years is conducted in Bisias et al. (2012).

systemic risk measures, including ΔCoVaR and SRISK, during three financial crises: the 2007–2009 financial crisis, the 1997 Asian crisis, and the 1998 Ruble crisis. They investigated whether these measures provide early warning signs in addition to signals from traditional risk drivers. ΔCoVaR was found to be the best market-based systemic risk measure for forecasting realized systemic risk during the 2007 financial crisis but did not consistently predict realized systemic risk during the late 1990s Asian and Ruble crises. SRISK has been proposed as a meaningful measure for regulators to monitor the financial sector's vulnerability, as it is capable of predicting capital shortfalls over long crisis periods (Zhang et al., 2015; Acharya et al., 2014; Brownlees and Engle, 2012; Boucher et al., 2014). This indicates that SRISK is a meaningful measure used by regulators to observe the financial sector's vulnerability.

The SRISK measure was enhanced by applying the Structural GARCH (SGARCH) model (Engle and Siriwardane, 2018; Dungey et al., 2010), which enables accurate modeling of equity volatility fluctuations as the capital structure of financial institutions changes. Although the differences compared to the standard SRISK are small, the SGARCH-based SRISK appears to provide earlier signs of capitalization changes. Engle et al. (2015) introduced a multifactor model to justify the return dynamics of financial institutions, which could be interesting to apply in sub-markets, such as European banks, to separate specific shocks (e.g., to European banks) from more general shocks (e.g., PIIGS growth prospects[6]).

Modeling the joint distribution of market and financial institution returns while considering the nonlinear dependence of each return is crucial for calculating ΔCoVaR and MES. Under financial contagion, markets may exhibit greater dependence during adverse downward movements compared to upward movements (King and Wadhwani, 1990; Forbes and Rigobon, 2001, 2002; Bekaert and Harvey, 2002; Roesch and Scheule, 2014). Research expanding upon ΔCoVaR and MES suggests various estimation methods to account for potential nonlinear dependence return structures, aiming to model the relationship between institutions and market returns more precisely under extreme situations. These methods often involve sophisticated estimation procedures, such as quantile regression for modeling tail dependence (Adrian and Brunnermeier, 2016), nonparametric tail estimators (Brownlees and Engle, 2012), and Student-t copula (Acharya et al., 2012). Chuanliang (2012) proposed using different copula functions to measure ΔCoVaR, MES, and SRISK more accurately, while Straetmans and Chaudhry (2015) and Balla et al. (2014) suggested using extreme value theory to assess systemic risk. However, the main question remains whether these efforts are justified given the intended purpose.

Systemic risk in financial markets has been a topic of significant interest, particularly in the aftermath of the 2007 GFC. The review of systemic risk covers the pricing of systemic risk, the implications of various factors, the relationship between systemic risk and aspects of the financial system, and quantifying and modeling systemic risk arising from interconnectedness and network effects. Several studies have examined the pricing of systemic risk in interbank markets, with mixed results on whether counterparty and systemic risks are adequately priced in lending and deposit rates (Sigmund and Siebenbrunner, 2024). Siebenbrunner et al. (2024) proposed a framework to assess the systemic impact of bank bail-ins, finding that they can reduce systemic risk in moderate crises but may be inadequate for systemic events. Meuleman and Vander Vennet (2020) investigated the effectiveness of macroprudential policies in containing systemic risk in European banks, finding a generally downward effect with heterogeneous impacts across banks and instruments. Jin and De Simone (2020) examined the effects of monetary policy on systemic risk-taking in the Eurozone investment fund industry, finding evidence of increased contagion and vulnerability, particularly following conventional monetary policy shocks.

Various factors have been explored for their implications on systemic risk. Andrieş et al. (2024) found that banks can reduce their systemic risk exposure when their host countries improve their net international investment positions and maintain creditor status. Mies (2024) examined the impact of bank opacity on European financial stability, finding that bank opacity significantly influences systemic risk, while regulatory measures to improve risk disclosure have a positive effect. Xiao et al. (2023) presented a theoretical framework showing that the impact of asset securitization on systemic risk is non-monotonic and depends on factors such as banking asset structures and risk retention. Kanas et al. (2023) provided evidence for a positive link between CO2 emissions and systemic risk in the U.S. banking sector.

The relationship between systemic risk and various aspects of the financial system has been examined in several studies. Curcio et al. (2023) found that extreme weather and climate disasters can exacerbate systemic risk in the U.S. banking and insurance sectors and that the performance of green and brown market indices affects systemic risk differently. Pellegrini et al. (2022) evaluated how accounting and financial variables affect systemic risk in traditional and shadow banks, as well as real-estate finance services in China, finding that systemic risk increases with the size of large financial institutions, particularly shadow entities. Ellis et al. (2022) discussed various definitions and challenges in addressing systemic risk, conducting a literature review of systemic risk measures. Morelli and Vioto (2020) assessed the contribution of China's financial sectors to systemic risk, finding that the banking sector contributed the most, followed by real estate and insurance/brokerage industries.

Quantifying and modeling systemic risk arising from interconnectedness and network effects has been the focus of several studies. Chen and Zhang (2024) used knowledge graphs to study systemic risk in the banking industry, representing financial institutions as vertices and their connections as edges. Zhang et al. (2021) examined the impact of bank liquidity creation on systemic risk, finding that excessive liquidity creation increases systemic risk with a U-shaped relationship and that the network connectedness of banks strengthens this relationship. Bakkar and Nyola (2021) investigated the impact of bank internationalization and geographic complexity on systemic risk, finding that complexity reduced systemic risk before the 2007 GFC, but this relationship was inverted during and after the GFC. Poledna et al. (2021) quantified systemic risk arising from overlapping portfolios of financial institutions, showing that focusing only on direct interbank exposures underestimates total systemic risk. Pichler et al. (2021) presented an optimization procedure to minimize systemic risk in financial markets by rearranging overlapping portfolio networks. Andrieş et al. (2022) gauged the interconnectedness and linkages between global systemically important banks (G-SIBs), other systemically important institutions (O-SIIs), and the global financial system, documenting increased interconnectedness during the global financial crisis. Leong et al. (2020) evaluated the contribution of shadow insurance to global systemic risk, finding that the practice of shadow insurance is a significant driver of systemic risk.

3. Estimation methodology

This paper considers N financial institutions with r_{it} denoting the return of financial institution i at time t. The market return (or union return or financial sector return), calculated as the value-weighted average of all institutions' returns, is given by:

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t} \tag{1}$$

where w_{it} represents the relative market capitalization of financial institution i, defined as $w_{i,t} = \frac{ME_{i,t-1}}{\sum_i^N ME_{i,t-1}}$, and $ME_{i,t-1}$ is the market capi-

[6] PIIGS countries refer to countries of Portugal, Ireland, Italy, Greece and Spain.

talization of an institution *i*. By construction, index weights are time-varying and known given the information set at the time $t = 1$. Due to the Jensen Inequality, a market log-return is typically greater than the value-weighted firm log-return, particularly when handling extreme returns far from zero.

While volatile stock returns can impact systemic risk measures, it is not a given that systemic risk will always increase during market turmoil. The degree to which systemic risk is affected by volatile stock returns depends on factors such as diversification (Acharya et al., 2017), leverage (Adrian and Brunnermeier, 2016), interconnectedness (Acemoglu et al., 2015), regulatory oversight (Hanson et al., 2011), and investor sentiment (Shleifer and Vishny, 1997). Volatile stock returns are used as input for some of the systemic risk measures employed in this paper, such as ΔCoVaR and MES, as they provide valuable insights into the interconnectedness and vulnerability of financial institutions. However, the relationship between volatile stock returns and systemic risk is not always straightforward, and other factors also play a crucial role in determining the extent to which shocks can propagate through the financial system.

This paper presents various systemic risk measures created using different frameworks. For example, Brownlees and Engle (2012) model time-varying linear dependencies using a multivariate Generalized Autoregressive Conditional Heteroscedasticity, Dynamic Conditional Correlation (GARCH-DCC) model to assess MES. Adrian and Brunnermeier (2016) allow for tail dependence using a quantile regression approach to determine ΔCoVaR. A direct comparison is not straightforward, as empirical differences could be caused by the estimation strategies. Therefore, we assume that all these risk measures are under a unified theoretical framework to supply a common platform. Following Brownlees and Engle (2012), we contemplate a bivariate GARCH process for the demeaned returns:

$$r_t = H_t^{1/2} v_t \tag{2}$$

where $r_t' = (r_{m,t} \quad r_{i,t})$ denotes the vector of market and financial institution returns, and the random vector $v_t' = (\varepsilon_{m,t} \quad \xi_{i,t})$ is serially independent and identically distributed (*i.i.d.*) over time with first moments: $\mathbb{E}(v_t) = 0$ and $\mathbb{E}\left(v_t v_t'\right) = I_2$, a two-by-two identity matrix. The H_t matrix denotes the conditional variance-covariance matrix:

$$H_t = \begin{pmatrix} \sigma_{m,t}^2 & \sigma_{i,t} \quad \sigma_{m,t} \quad \rho_{i,t} \\ \sigma_{i,t} \quad \sigma_{m,t} \quad \rho_{i,t} & \sigma_{i,t}^2 \end{pmatrix} \tag{3}$$

where $\sigma_{i,t}$ and $\sigma_{m,t}$ denote the conditional volatilities and $\rho_{i,t}$ the conditional correlation. No particular assumptions are made about the bivariate distribution of the standardized innovations v_t, which is assumed to be unknown. The time-varying conditional correlations $\rho_{i,t}$ are assumed to fully capture the dependence between the financial institution and market returns, implying that the standardized innovations $\varepsilon_{m,t}$ and $\xi_{i,t}$ are independently distributed at the time t[7]

Table 1 presents a comprehensive framework highlighting the similarities and differences between the ΔCoVaR, MES, SRISK, and Granger Causality Network measures. These systemic risk measures complement each other by capturing different aspects of systemic risk. While ΔCoVaR and MES focus on market-based measures of risk, SRISK incorporates balance sheet information. The Granger Causality Network provides a holistic view of the interconnectedness and causal relationships within the financial system. This framework allows researchers and practitioners to make more informed choices about which measures to use, depending on their research questions, data availability, and the specific aspects of systemic risk they wish to capture.

3.1. Granger causality network

Granger-causality tests and other techniques have been proposed to estimate the interconnectedness of financial institutions and the systemic risk of the entire financial system (Billio et al., 2012). These measures, derived from monthly return indices of hedge funds, brokers/dealers, insurance companies, and banks, reveal that Granger-causality networks are highly active and interconnected during times preceding systemic shocks. Granger-causality tests are customized to determine the direction and interconnectedness of financial institutions' bonds within the financial system. If past *X* values possess information useful for anticipating *Y* beyond the information inherent in the past *Y* values, then *Y* is Granger-caused by *X*. This Granger-causality equation is expressed as:

$$X_t = \sum_{j=1}^{m} a_j x_{t-j} + \sum_{j=1}^{m} b_j x_{t-j} + \epsilon_t \tag{4}$$

$$Y_t = \sum_{j=1}^{m} c_j x_{t-j} + \sum_{j=1}^{m} d_j x_{t-j} + \omega_t \tag{5}$$

where m is the max lag length, and ϵ_t and ω_t are two uncorrelated white noise processes. If b_j is not equal to zero, then *Y* affects *X*. Likewise, when c_j is different from zero, *X* causes *Y*, provided that the *p* -value is below 5 %. When both conditions hold true, the two time-series form a feedback connection.

The experiment is conducted on monthly return indices of banks, hedge funds, brokers/dealers, and insurance companies. The insight from this paper is based on the return indices of Eurozone financial institutions. Similarly, a collection of Eurozone financial sector indices (banking, diversified financials, insurance, and real estate) is estimated from the past 36 monthly returns on a quarterly basis from 2000 to 2015. The dynamic causality index (DCI) is calculated for each interval, where:

$$DCI_t = \frac{number\ of\ casual\ relationships\ in\ window}{total\ possible\ number\ of\ casual\ relatinships} \tag{6}$$

The DCI value precisely correlates with the financial system's level of interconnectedness, with a more interconnected system having a higher DCI value. Furthermore, connections of several financial institutions within each sector are estimated using a single institution Granger-causes at 5 %. A sample of 315 publicly listed financial institutions in the Eurozone is used.

Granger-causality tests are performed on a daily interval with the past returns of 36 months to determine the direction and interconnectedness of relationships among banks within the Eurozone financial system. The extent of the dynamic causality index reveals the financial system's interconnectedness, and the DCI can be calculated for each interval. Therefore, a higher DCI value indicates a more interconnected system.

3.2. Marginal expected shortfall (MES)

Various strategies can be employed to estimate MES. In this paper, we structure the multi-stage modeling approach to be comparable to Brownlees and Engle (2012). Inspired by the Dynamic Conditional Correlation (DCC) Framework by Engle (2002), (2009), this approach reveals how univariate GARCH models can be used to determine the volatilities and standardized residuals for each series. These standardized residuals are then used to determine the conditional correlations via the DCC framework. Nonparametric estimators are used to determine the MES's tail dependence, formulated from the standardized residuals

[7] See Benoit et al. (2017) for a detailed description of the unified framework for estimating MES, SRISK and ΔCoVaR.

Table 1
Comprehensive framework of various systemic risk measures.

Criteria	ΔCoVaR	MES	SRISK	Granger Causality
Conceptual foundations	Focuses on the conditional VaR (CoVaR), which measures the systemic risk contribution of an institution.	Measures the expected equity loss of a financial institution during a systemic crisis.	Estimates the capital shortfall of a financial institution during a crisis.	Analyzes the interconnectedness and causal relationships within the financial system.
Technical methodology	Uses quantile regression to estimate the CoVaR and its change (ΔCoVaR).	Calculates the expected shortfall of a financial institution's equity return during a crisis.	Employs contingent claim analysis and the Merton model to estimate the capital shortfall.	Applies network analysis and Granger causality tests to examine causal relationships between financial institutions.
Data requirements	Requires high-frequency equity data to estimate risk measures.	Require high-frequency equity data to estimate risk measures.	Can be computed using lower-frequency balance sheet data.	Utilizes high- or lower-frequency equity data or balance sheet data to construct the network.
Interpretation and implications	Measures an institution's contribution to systemic risk.	Captures an institution's vulnerability to systemic events.	Estimates the capital shortfall an institution may face during a crisis.	Provides insights into the interconnectedness and causal relationships within the financial system.

from the GARCH-DCC residuals.[8]

Considering the Cholesky decomposition of the variance-covariance matrix H_t:

$$H_t^{1/2} = \begin{pmatrix} \sigma_{m,t} & 0 \\ \sigma_{i,t} \quad \rho_{i,t} & \sigma_{i,t}\sqrt{1-\rho_{i,t}^2} \end{pmatrix} \tag{7}$$

Given Eq. (2), let $r_{i,t}$ and $r_{m,t}$ denote financial institution (sector or country) i's return and the market return on the day t, respectively. The following specification of the bivariate process of financial institution and market returns can be expressed as:

$$r_{m,t} = \sigma_{m,t} \quad \varepsilon_{m,t} \tag{8}$$

$$r_{i,t} = \sigma_{i,t} \quad \rho_{i,t} \quad \varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2} \quad \xi_{i,t} \tag{9}$$

$$(\varepsilon_{m,t} \quad , \quad \xi_{i,t}) \quad \sim \quad F$$

where σ and ρ depict the series' conditional volatility and correlation of the return, respectively. The shocks $\varepsilon_{m,t}$ and $\xi_{i,t}$ are assumed to be serially independent and identically distributed over time with zero mean, unit variance, and zero covariance, but they are not assumed to be independent random variables. These dependence assumptions are approved by Brownlees and Engle (2012) due to the extreme figures that show that these disruptions could happen simultaneously for SIFIs. With a potential threat of defaults, the financial institutions' disruptions may be further in the tail when the market is in the tail.

The stochastic setup can be described by the two conditional standard deviations and the conditional correlation. Asymmetric GARCH models determine the volatilities, while DCC models determine the correlations. The joint distribution F from which $\varepsilon_{m,t}$ and $\xi_{i,t}$ are derived remains unspecified, and straightforward nonparametric approaches are utilized for inference on tail dependence.

MES signifies the marginal contribution of the institution i to systemic risk, as determined by the system's ES. Initially suggested by Acharya et al. (2017), MES has been recently extended to a conditional version by Brownlees and Engle (2012). In theory, the q % level of the ES's expected returns in the worst q % of cases can be prolonged to the typical case where returns are greater than a certain threshold (C). Properly, the system's conditional ES is denoted as:

$$ES_{mt}(C) = \mathbb{E}_{t-1}(r_{mt}|r_{mt} < C) = \sum_{i=1}^{N} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \tag{10}$$

where C is some negative constant. A realization of the condition $r_{mt} < C$ is called a systemic event. Note that ES is defined as the negative tail expectation, with a higher ES value indicating a larger expected loss.

MES corresponds to the partial derivative of the system ES with respect to the weight of institution i in the economy (Scaillet, 2004, 2005):

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{\partial w_{it}} = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \tag{11}$$

MES can be seen as a natural enhancement to the marginal VaR concept suggested by Jorion (2007) to the ES, a coherent risk measure (Artzner et al., 1999). It determines the rise in system risk (calculated by ES) generated by a marginal increase in institution i's weight in the system. The greater the institution's MES, the greater its individual contribution to financial system risk. MES can be portrayed as a signal of how much a particular financial institution's share price will descend within a day when the market is undergoing a systemic event with an equity fall of at least the amount C. Therefore, MES can determine the expected capital loss a financial institution would experience in a systemic crisis. Financial institutions with high MES are typically sensitive to the aggregate market's performance and experience distress during systemic events, making them important candidates to be systemically risky.

For any conditioning event C, MES in Eq. (11) can be decomposed as a function of volatility, correlation, and tail expectations of the distribution of the standardized innovations:

$$MES_{i,t}(C) = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \tag{12}$$

$$MES_{i,t}(C) = \sigma_{i,t} \quad \rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2} \quad \mathbb{E}_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \tag{13}$$

A couple of notable features from the specification are worth mentioning, assuming a positive dependence between the financial institution and the market. Initially, more volatile financial institutions will cross-sectionally appear riskier, as MES is an increasing function of individual institutions. Unlike traditional risk measures, ES also relies on the correlation between the financial institution's return and the market. This focuses on the systemic nature of the risk measure, as SIFIs are seen as a combination of volatility, correlation, and tail dependence. The MES formula provides more substance to the tail expectation, either to the standardized market residual tail expectation or the standardized idiosyncratic financial institution residual tail expectation, based on being either a high or low correlation. The term $\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right)$ in Eq. (13) comes as the dependence assumption between $\varepsilon_{m,t}$ and $\xi_{i,t}$ would

[8] While simple and flexible, the modeling paradigm is appealing for a wide spectrum of univariate volatility models that exist, models for estimators of tail dependence as well as correlations.

become zero if dependence was determined completely by correlation.[9]

Assuming $\xi_{i,t}$ and $\varepsilon_{m,t}$ are independent, we have:

$$MES_{i,t}(C) = \sigma_{i,t} \quad \rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \tag{14}$$

or equivalently:

$$MES_{i,t}(C) = \sigma_{i,t} \quad \rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t}|r_{m,t} < C\right) \tag{15}$$

Let $\beta_{i,t} = \frac{\text{cov}(r_{i,t}, r_{m,t})}{\text{var}(r_{m,t})} = \frac{\sigma_{i,t} \quad \rho_{i,t}}{\sigma_{m,t}}$ denotes the time-varying beta of financial institution *i*. Combining $\beta_{i,t}$ with Eq. (15), we obtain:

$$MES_{i,t}(C) = \beta_{i,t} \quad \sigma_{m,t} \quad \mathbb{E}_{t-1}\left(\varepsilon_{m,t}|r_{m,t} < C\right) \tag{16}$$

$$MES_{i,t}(C) = \beta_{i,t} \quad \mathbb{E}_{t-1}\left(r_{m,t}|r_{m,t} < C\right) \tag{17}$$

The MES is portrayed as the product of the market return's truncated expectation for a certain threshold C and the time-varying beta. In theory, the market return's expected shortfall $ES_{m,t}(q)$ equates to the market return's truncated expectation for a given threshold equivalent to the conditional VaR (Jorion, 2007), $C = VaR_{m,t}(q)$:

$$ES_{m,t}(q) = \mathbb{E}_{t-1}\left(r_{m,t}|r_{m,t} < VaR_{m,t}(q)\right) \tag{18}$$

Then, the MES defined for the specific event $C = VaR_{m,t}$, denoted $MES_{i,t}(q)$, is simply expressed as the product of the time-varying financial institution beta and the expected shortfall of the market return:

$$MES_{i,t}(q) = \beta_{i,t} \quad ES_{m,t}(q) \tag{19}$$

3.3. Systemic risk index (SRISK)

As suggested by Acharya et al. (2012) and Brownlees and Engle (2012), the SRISK measure extends the MES to account for both the financial institution's liabilities and size. SRISK responds to a given financial institution's expected capital shortfall depending on whether a crisis affects the entire financial system. From this perspective, financial institutions with the largest capital shortfall are assumed to be the biggest contributors to the crisis and are considered the most systemically risky.

The function of SRISK is to determine a financial institution's expected capital shortfall when experiencing a crisis, estimated by a typical stock market collapse. SRISK endeavors to compute both balance sheets and equity markets and can be utilized as a market-based replacement for traditional regulatory stress tests.

SRISK for institution i at time t is defined by:

$$SRISK_{i,t} = E_t\left(CS_{i,t+h}|Crisis_{t:t+h}\right) \tag{20}$$

where CS abbreviates Capital Shortfall, and $t+h$ signifies the future point in time at which the crisis occurs. SRISK captures the financial institution's vulnerability in light of a system-wide shock. Following Brownlees and Engle (2012), the capital shortfall for an institution i at time t is signified by:

$$CS_{i,t} = \text{k}A_{i,t} - MV_{i,t} \tag{21}$$

$$CS_{i,t} = \text{k}\left(D_{i,t} + MV_{i,t}\right) - MV_{i,t} \tag{22}$$

where $MV_{i,t}$ denotes the market value of equity, $D_{i,t}$ represents the book value of debt, $A_{i,t} = D_{i,t} + MV_{i,t}$ is the quasi assets for an institution i at time t, and k is the efficient capital fraction, i.e., the minimum amount of quasi-assets institution i is meant to be funded via equity.[10] The quasi-assets can be seen as the market values of outstanding shares used instead of the book value of equity, as they are assessed on the institution's assets via the equity market (Brownlees and Engle, 2012).

In SRISK, a crisis is defined as a general stock market crash over the next h days of at least C percent:

$$Crisis_{t:t+h} = \left\{R_{M,t:t+h} \leq C\right\} \tag{23}$$

where $R_{M,t:t+h}$ is the cumulative market return over the next h days.

Using the definition of SRISK from Eq. (20) along with the definitions of capital shortfall and a crisis, the following expression for SRISK can be written:

$$SRISK_{i,t} = E_t\left(5.5\%.\left(D_{i,t+132} + MV_{i,t+132}\right) - MV_{i,t+132}|R_{M,t:t+132} \leq -40\%\right) \tag{24}$$

SRISK determines the capital shortfall in relation to a capital requirement of 5.5 percent of total assets in six months, provided that the stock market has fallen by 40 %. The remaining task is to depict the hypothetical share market crash into the asset values or, rather, how to model a hypothetical stock market crash that would influence the values of debt and the market value of the firm. With the simple assumption that the expected value of debt is unaffected by the crisis (Brownlees and Engle, 2012):

$$E_t\left(D_{i,t+132}|R_{M,t:t+132} \leq -40\%\right) = D_{i,t} \tag{25}$$

In practice, this assumption may not hold due to the use of hybrid debt, such as resolution regimes with bail-in. These features could suggest that the minimal value of debt will be reduced when a financial institution is in difficulty, resulting in a lower capital shortfall.

To ascertain an approximation of the expectation of the financial institution's market value conditional on a general stock market crash, it must be divided into two parts. One demonstrates what the market value is nowadays, and the second relates the expectation of the percentage the market value will fall based on a general stock market crash. Brownlees and Engle (2012) denote the latter as LRMES:

$$E_t\left(MV_{i,t+132}|R_{M,t:t+132} \leq -40\%\right) = MV_{i,t} \quad \left(1 + LRMES_{i,t}\right) \tag{26}$$

where

$$LRMES_{i,t} = E_t\left(MV_{i,t+132}|R_{M,t:t+132} \leq -40\%\right) \tag{27}$$

To compute the time-varying dependence between a particular financial institution and the stock market, Brownlees and Engle (2012) proposed the DCC. They suggested using GARCH models to model the univariate return series' time-varying variances. The joint model is identified as the GARCH-DCC model, and highlighting the use of dynamic models is fundamental when determining SRISK.[11] The variances are computed via univariate GARCH models, and a multivariate DCC model is used for the correlations.

The estimation of SRISK is based on the same framework as that of MES. According to Engle et al. (2015), the capital shortfall of a given

[9] If $\varepsilon_{m,t}$ and $\xi_{i,t}$ are independent, the conditioning event becomes irrelevant and by assumption $\mathbb{E}_{t-1} \quad \xi_{i,t} = 0$.

[10] While a leverage ratio of three percent ($k = 3$) is the current proposal from the Basel Committee of Banking Supervision, Brownlees and Engle (2012) use a slightly stricter percentage ($k = 5.5$) for European Financial Institutions and k=8 for American financial institutions. This paper utilizes a higher k of 5.5 percent for the Eurozone systemic risk analysis.

[11] While using various models for determining *LRMES*, Brownlees and Engle (2012) compared SRISK outcomes. They discovered that SRISK estimates gathered via the dynamic GARCH-DCC model Granger-causes SRISK estimates using both static and other dynamic models. In the end, the GARCH-DCC model is the most appropriate for LMRES and SRISK modeling as it ensures the most accurate signal.

financial institution i is defined as:

$$CS_{i,t} = kD_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right)W_{i,t} \quad (28)$$

where $D_{i,t}$ and $W_{i,t}$ denote the book value of total liabilities and equity of the institution i, k is a prudential capital ratio of equity to assets, and LRMES is given by the following equation:

$$LRMES_{i,t} = LRMES_{i,t:t+T} = -\mathbb{E}_{t-1}(R_{i,t:t+T} | R_{m,t:t+T} \leq -40\%) \quad (29)$$

where $R_{i,t:t+T}$ and $R_{m,t:t+T}$ are cumulative returns defined as:

$$R_{i,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{i,t+j}\right) - 1 \text{and} R_{m,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{m,t+j}\right) - 1 \quad (30)$$

LRMES is estimated at a time horizon of six months, and T is set at 126 trading days (6 months). Then, the LRMES is approximated without simulation by:

$$LRMES_{i,t} = -(\exp(18 * MES_{i,t}(q)) - 1) = 1 - \exp(18 * MES_{i,t}(q)) \quad (31)$$

Finally, the SRISK contribution of a given institution to the risk of the system, following Acharya et al. (2012), is given by:

$$SRISK_{i,t} = \max(0; CS_{i,t}) \quad (32)$$

$$SRISK_{i,t} = \max(0; \textit{required capital} - \textit{available capital}) \quad (33)$$

$$SRISK_{i,t} = \max\left(0; k\left(D_{i,t} + \left(1 - LRMES_{i,t}\right)W_{i,t}\right) - \left(1 - LRMES_{i,t}\right)W_{i,t}\right) \quad (34)$$

where k is the prudential capital ratio and $D_{i,t}$ is the book value of total liabilities. It is worth noting that if we define the leverage as $L_{i,t} = (D_{i,t} + W_{i,t})/W_{i,t}$, SRISK becomes:

$$SRISK_{i,t} = \max\left(0; (kL_{i,t} - 1 + (1-k)LRMES_{i,t})W_{i,t}\right) \quad (35)$$

We discovered that SRISK increases with leverage and also acknowledges the relationship of a financial institution with the system via LRMES. The latter coincides with the expected fall in a financial institution's equity value if the market falls more than a given threshold within the next six months. Acharya et al. (2012) suggest estimating it via the daily MES (determined by a threshold C equal to 2 %) as $LRMES_{i,t} \approx 1 - \exp(18 * \ MES_{it})$. This estimation equates to the institution's expected losses over a six-month period, obtained on the condition that the market drops more than 40 % over the next six months. Since SRISK is a function of MES, the potential nonlinear dependence in returns is considered in the calculation of nonlinear MES as given in Eq. (13). Therefore, the linear version of SRISK can be determined by MES, as shown in Eq. (19), in the definition of SRISK.

As a function of both the equity market expected shortfall, an institution's time-varying β (systematic risk), and the institution's joint tail risk with the market, LRMES tends to crash if the market crashes. Both effects can vary over time based on the use of dynamic econometric models.

The parameters can be approximated using two techniques: the time-consuming one-step approach, where the full likelihood is maximized, or the two-step approach, where the standardized residuals are calculated for estimating the DCC model's parameters. Engle (2009) sees the two-step approach as stable and, most of the time, close to the one-step approach. Since the two-step approach is less time-consuming, it is used in this paper.

Brownlees and Engle (2012) suggest calculating SRISK for the entire financial sector as follows:

$$SRISK_t = \sum_{i=1}^{N} \max(0; SRISK_{i,t}) \quad (36)$$

where N stands for the number of financial institutions within the financial sector under study. Eq. (36) revolves around the notion that financial institutions with capital surpluses do not take over institutions with capital shortfalls during a crisis, meaning capital surpluses cannot cover capital shortfalls. The purpose behind this is that possible capital shortfalls happen in a crisis, i.e. when the entire system is undercapitalized.

3.4. Delta conditional value-at-risk (ΔCoVaR)

There is a distinction between the conditioning event and the direction between MES and ΔCoVaR. MES investigates an institution's returns when the financial system is under distress and experiencing losses, whereas the original CoVaR (contribution $CoVaR_q^{sys|i}$) acts in reverse and investigates the financial system's returns when an institution is under financial distress. The difference is not due to the two measures' few intrinsic properties but is rather tied to the usage that has been done for each. In this paper, we use exposure CoVaR ($CoVaR_q^{i|sys}$) only, which is constructed with the same conditioning logic as MES.

CoVaR measures the degree to which a tail event in a financial institution spills over and causes or worsens a tail event in another institution (sector or country). $CoVaR_q^{i|sys}$ can be defined as a conditional VaR, that is, $VaR_{q,t}^i$ of the financial institution i, conditional on the event that the financial system, sys, is under stress ($r^{sys} = VaR_{q,t}^{sys}$). In other words, we can implicitly define $CoVaR_{q,t}^{i|sys}$ by the q -quantile of the conditional probability:

$$\Pr(r_t^i \quad \leq CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys}) = q \quad (37)$$

where r_t^i refers to the asset return of a financial institution, i. More simply, Eq. (37) avers that when the return of the financial system, sys, falls below a threshold value, the probability that losses of the financial institution i exceed CoVaR equals q.

VaR of each institution, i, is computed by estimating the following univariate model:

$$r_t^i = \mu_t^i + \varepsilon_{i,t} \quad (38)$$

where $\mu_t^i = q_0 + q_1 r_{t-1}^i; \varepsilon_{i,t} = z_{i,t} \quad \sigma_{i,t}$ and $z_{i,t}$ is $i.i.d.$ with zero mean and unit variance, and the conditional variance has the standard GARCH (1,1) specification:

$$\sigma_{i,t}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t-1}^2 + \beta_2^i \sigma_{i,t-1}^2 \quad (39)$$

Given a distributional assumption for z and, hence, the q-quantile of the estimated conditional distribution, we can compute the VaR of each institution i for each time period.[12]

Then, for each institution i, we estimate a bivariate GARCH model with Engle's (2002) DCC specification for returns of the institution and the financial system. Let $r_t = (r_t^{sys}, r_t^i)'$, whose joint dynamics are given by:

$$r_t = \mu_t + \varepsilon_t \quad (40)$$

$$\varepsilon_t = \sum_t^{1/2} z_t \quad (41)$$

where Σ_t is the (2×2) conditional covariance matrix of the error term ε_t and μ_t is the (2×1) vector of conditional means, and the standardized innovation vector $z_t = \sum_t^{-1/2}(r_t - \mu_t)$ is $i.i.d.$ with $E(z_t) = 0$ and $Var(z_t) = I_2$. We define D_t to be the (2x2) diagonal matrix with the conditional variances $\sigma_{x,t}^2$ and $\sigma_{y,t}^2$ along the diagonal, so that $\{D_{xx}\}_t = \{\Sigma_{xx}\}_t$, $\{D_{yy}\}_t = \{\Sigma_{yy}\}_t$ and $\{D_{xy}\}_t = 0$ for $x,y = s,i$. The conditional variances

[12] For VaR calculations via univariate GARCH models, refer to Duffie and Pan (1997) and Giot and Laurent (2003).

are modeled as $GARCH(1,1)$:

$$\sigma_{x,t}^2 = \theta_0^x + \theta_1^x \varepsilon_{x,t}^2 + \theta_2^x \sigma_{x,t-1}^2 \quad (42)$$

$$\sigma_{y,t}^2 = \theta_0^y + \theta_1^y \varepsilon_{y,t}^2 + \theta_2^y \sigma_{y,t-1}^2 \quad (43)$$

and the conditional covariance $\sigma_{xy,t}$ is:

$$\sigma_{xy,t} = \rho_{xy,t} \quad \sqrt{\sigma_{x,t}^2 \quad \sigma_{y,t}^2} \quad (44)$$

Let $C_t = \quad D_t^{-1/2} \Sigma_t D_t^{-1/2} = \{\rho_{xy}\}_t$ be the $(2x2)$ matrix of conditional correlations of ε_t. Following Engle (2002), we specify the conditional correlation matrix as follows:

$$C_t = diag(Q_t)^{-1/2} \quad x \quad Q_t \quad x diag(Q_t)^{-1/2} \quad (45)$$

$$Q_t = (1 - \delta_1 - \delta_2)\overline{Q} + \delta_1 (u_{t-1} u_{t-1}') + \delta_2 Q_{t-1} \quad (46)$$

where $\overline{Q}$ is the unconditional covariance matrix of $u_t = \{\varepsilon_{x,t}/\sigma_{x,t}\}_{x=s,i}$ and $diag(Q_t)$ is the $(2x2)$ matrix with the diagonal of Q_t on the diagonal and zeros off-diagonal.

Once we estimate the bivariate density $pdf_t(r_t^{sys}, r_t^i)$ for each $r_t = (r_t^{sys}, r_t^i)'$ pair in the above steps; we proceed to obtain our $CoVaR_{q,t}^{i|sys}$ measure for each financial institution i and time period t. Given the definition of $CoVaR$ in Eq. (37), it follows that:

$$\Pr(r_t^i \le CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys}) = q \quad (47)$$

$$\frac{\Pr(r_t^i \le CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys})}{\Pr(r_t^{sys} = VaR_{q,t}^{sys})} = q \quad (48)$$

By definition of $VaR_{q,t}^{sys}$, $\Pr\left(r_t^{sys} = VaR_{q,t}^{sys}\right) = q$ so:

$$\Pr(r_t^i \le CoVaR_{q,t}^{i|sys}, \quad r_t^{sys} = VaR_{q,t}^{sys}) = q^2 \quad (49)$$

If we let $x, y = i, sys$, given the $VaR_{q,t}^{sys}$ estimates, we can numerically solve the following double integral for $CoVaR_{q,t}^{i|sys}$

$$\int_{-\infty}^{CoVaR_{q,t}^{i|sys}} \int_{-\infty}^{VaR_{q,t}^{sys}} pdf_t(x,y) dy dx = q^2 \quad (50)$$

It is worth noting that the time-varying correlation between r_t^{sys} and r_t^i ensures that the $CoVaR_{q,t}^{i|sys}$ of a given financial institution has a time-varying exposure to its $VaR_{q,t}^i$.

4. Data

The sample employed in this paper comprises publicly listed financial institutions from the 17 Eurozone member states: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, and Spain. The initial sample comprises 639 European financial institutions, but 324 are excluded due to insufficient data coverage during the analysis period.[13] The resulting sample contains 315 European financial institutions representing four main sectors: banks, diversified financials, insurance, and real-estate.[14] Appendix A provides the number of financial institutions within each sector for all Eurozone member states.

The primary reason for limiting the sample to institutions with complete data is to ensure consistency and comparability across different systemic risk measures. Missing data could introduce biases and distortions, as some measures may be more sensitive to data gaps than others. While this approach may lead to survivorship bias, it is a necessary trade-off to maintain the integrity of the analysis. To mitigate the impact of survivorship bias, the excluded financial institutions did not fail or undergo acquisitions due to financial distress. Moreover, the analysis is extended to a broader set of institutions, not just banks. A comprehensive sensitivity analysis assesses the impact of including or excluding certain institutions on the overall results, revealing no significant deviations attributable to survivorship bias. Although some financial institutions may have discontinued operations or been acquired during the observation period, the remaining sample of 315 institutions represents a significant portion of the Eurozone financial system. These institutions, typically larger and more systemically important, likely provide a reasonable representation of overall systemic risk dynamics.

In contrast to previous research (see Beltratti and Stulz, 2012; Acharya et al., 2017; Brownlees and Engle, 2012), the sample is not restricted to financial institutions with total assets exceeding 10 billion; smaller financial institutions are included as well. Most systemic risk studies focus only on large financial institutions, the so-called “TBTF” (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Engle et al., 2015). However, Allen et al. (2012) note that smaller, more interconnected financial institutions could have significant systemic risk potential due to common risk factors. Kashyap and Stein (2000) point out that smaller financial institutions (those in the bottom ninety-fifth percentile by size) facing liquidity challenges are the main drivers of aggregate declines in loan supply. Consequently, focusing solely on the largest financial institutions may not capture the true nature of potential systemic risk. TITF and TMTF institutions could contribute to systemic risk even more than TBTF institutions.

The sample covers the period from January 3, 2000, to December 31, 2015. This timeframe provides a suitable platform to assess the systemic risk exposure of Eurozone financial institutions, as it includes several significant events (e.g., the U.S. subprime mortgage crisis, the Lehman Brothers collapse, and the European sovereign debt crisis). The pre-crisis period is defined as Q1 2000 - Q2 2007, the crisis period as Q3 2007 - Q4 2010 (when the majority of U.S. and Eurozone systemic events occurred), and the post-crisis period as Q1 2011 - Q4 2015.

Daily equity-adjusted prices (accounting for capital operations such as splits and dividends), value-weighted market index returns, number of shares outstanding, and book values of total liabilities are obtained from the Bloomberg database for the sample period. Most financial institutions in the sample have 4,173 daily return observations. Appendix B lists these institutions and their sector classification within each member state. For each financial institution, a weighted average of the returns of the remaining financial institutions in the sample serves as a proxy for the financial system (sector or member state). This approach ensures that the resulting system return portfolios are representative of the Eurozone financial system, allowing for the study of potential spillover effects between a stressed institution (sector or member state) and the financial system. Moreover, it rules out any spurious correlation that may arise due to sizeable disparities in the composition of the financial system proxy.

Table 2 presents the summary statistics of the Eurozone financial index returns and Eurozone member state financial sector returns for the entire period. The returns range from -76–45 %, with a daily average of

[13] Excluding financial institutions could result in selection bias in the outcome (Weiß et al., 2014). Vallascas and Keasey (2013) emphasized that financial institutions' transparency levels impact their systemic potential, with greater transparency associated with lower systemic risk potential. This statement encourages caution in omitting financial institutions with greater systemic risk, as doing so will bias the results. To reduce potential bias, we clarify that all excluded financial institutions have a minimum of one missing annual report for publicly accessible data.

[14] This broad classification by sector is categorized according to the Bloomberg GICS Industry Group Name.

Table 2
Summary statistics on returns.

	Mean	STD	Min.	Max.	Skewness	Kurtosis	JB	5%-VaR	5%-ES
Panel A: Eurozone Financial Sectors (2000–2015)									
Banks	-0.03	1.84	-10.31	17.23	0.09	6.63	7,670	2.72	4.33
DFinancials	-0.01	1.45	-9.46	10.20	-0.19	4.87	4,160	2.26	3.17
Insurance	-0.01	1.72	-12.49	10.92	-0.08	5.56	5,387	2.56	3.48
Real-estate	0.00	0.87	-6.05	6.62	-0.75	7.73	10,807	1.21	2.36
Panel B: Member States and Eurozone Financial Index (2000–2015)									
Austria	0.00	1.48	-11.29	12.53	-0.44	8.99	14,206	2.09	4.89
Belgium	0.00	1.63	-14.38	14.47	-0.38	9.75	16,648	2.29	3.80
Cyprus	-0.11	2.23	-12.69	16.09	0.02	4.51	3,545	3.19	9.46
Estonia	0.01	1.24	-34.46	13.49	-5.33	172.38	5,191,400	0.54	7.70
Finland	0.06	1.60	-16.00	11.01	-0.04	6.53	7,436	2.42	3.93
France	0.00	1.90	-11.14	15.71	0.13	6.59	7,571	2.76	4.30
Germany	-0.02	1.74	-13.08	14.39	-0.12	6.72	7,882	2.58	4.51
Greece	-0.15	3.35	-34.48	24.17	-0.68	12.39	27,045	4.48	13.43
Ireland	-0.12	3.94	-76.00	27.62	-1.96	42.91	323,140	4.74	14.35
Italy	-0.02	1.81	-9.99	14.94	-0.10	4.77	3,961	2.78	5.23
Luxembourg	0.00	1.06	-9.95	7.29	-0.32	6.79	8,090	1.72	13.69
Malta	0.02	1.10	-13.79	23.78	2.48	76.50	1,022,900	1.41	8.84
Netherlands	-0.02	2.37	-18.23	18.44	-0.07	8.85	13,637	3.20	14.16
Portugal	-0.07	1.87	-14.05	16.09	-0.06	6.84	8,142	2.68	7.44
Slovakia	0.08	2.50	-27.57	18.04	-0.79	15.13	39,733	3.65	15.82
Slovenia	-0.03	2.90	-47.61	44.93	-0.21	82.16	937,000	3.06	15.19
Spain	-0.01	1.87	-11.38	18.78	0.26	5.85	6,016	2.87	4.60
PIIGS	-0.04	1.68	-9.90	16.29	0.03	6.05	6,368	2.57	4.16
Eurozone	-0.02	1.62	-9.64	13.45	-0.01	5.92	6,105	2.39	3.67

Notes: The table displays the summary statistics for daily index returns of Eurozone financial sectors and each member state financial index from January 2000 to December 2015 (Overall Period). STD denotes the standard deviation. *JB* refers to the Jarque-Bera test for normality. The Jarque-Bera statistics are statistically significant at 1 %. ES and VaR are estimated under the assumption of $q = 5\%$ level.

-0.02 % across all member states. Four member states show average positive returns, while the remaining thirteen member states register average negative or zero returns. The evidence indicates that returns have been low for member states during the crisis period. Table 2 shows that the standard deviation ranges from 1.06 % to 3.94 %, with the average estimated at 1.99 %, higher than the average daily returns. As the standard deviation is a crude measure of risk, this finding suggests that investors are likely to face large losses at a given return. The evidence in Table 2 indicates that the return distributions are leptokurtic, with an average kurtosis of 25.77 and an average skewness of -0.40. Skewness and kurtosis have significant effects on asset allocation, option pricing, other financial market activities, and risk management. Investors typically seek stocks characterized by low negative skewness and low kurtosis (Kim and White, 2004). High negative skewness is generally caused by high turnover and infrequent high returns over prior periods. The Jarque-Bera statistic firmly rejects the null hypothesis of normality in the return distributions, proving the occurrence of massive losses during stress periods. The ranking of member states based on the highest ES is not exactly the same as the one produced by VaR, due to differences in their estimation procedures.

Although stock prices may exhibit under- and over-reaction during periods of market stress, they remain a valuable input for systemic risk analysis for several reasons: (1) The Efficient Market Hypothesis (EMH) posits that stock prices reflect all available information about an institution's value. While market efficiency may be reduced during turmoil, stock prices still incorporate important information about investor expectations and market sentiment. (2) Institutional investors and market makers, with significant resources and expertise, play a dominant role in financial markets. Their informed investment decisions help maintain a reasonable degree of market efficiency, even during periods of stress. (3) Financial turmoil is often characterized by a loss of investor confidence, which can lead to significant price movements. These price movements, while potentially over-reacting in the short-term, provide valuable signals about systemic risk dynamics. (4) While stock prices may not be perfectly efficient during times of turmoil, they are likely to be more efficient than other potential inputs for systemic risk analysis, such as credit default swap (CDS) spreads or bond yields, which can be subject to illiquidity and other distortions.

It is essential to note that systemic risk measures are not solely reliant on stock prices. They also incorporate information about interconnectedness and contagion within the financial system, which can be captured through network analysis and Granger causality tests. There are several reasons why stock returns remain a widely used and relevant measure in systemic risk analysis: (1) Stock returns are publicly available data, making them accessible to a wide range of researchers and practitioners. (2) Stock returns reflect the collective expectations and sentiment of market participants, which can provide valuable insights into the perceived riskiness of financial institutions (Baker and Wurgler, 2006). (3) Stock returns are available at high frequencies, such as daily or even intraday, allowing for more timely monitoring and analysis of systemic risk dynamics (Acharya et al., 2017). (4) There is a well-established body of literature and methodological approaches for analyzing systemic risk using stock returns (Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; Acharya et al., 2012). (5) The use of stock returns allows for easier comparison of systemic risk across different financial institutions, sectors, and regions, as many institutions are publicly-traded. While stock returns may have limitations, such as being subject to short-term volatility and not capturing all aspects of financial risk, they remain a valuable and widely used tool in systemic risk analysis.

5. Empirical analysis and results

5.1. Granger causality connections

This section uses the Granger causality test outlined in Eqs. 4 to 6 to analyze the interconnectedness of Eurozone financial institutions over the 2000–2015 period. The 36-month rolling window estimate of the dynamic causality index (DCI) ranges from 0.0522 to 0.2134 over the sample period, as shown in Fig. 1. The DCI provides valuable information on the time-varying interconnectedness of Eurozone financial institutions, demonstrating that the level of connectedness fluctuates

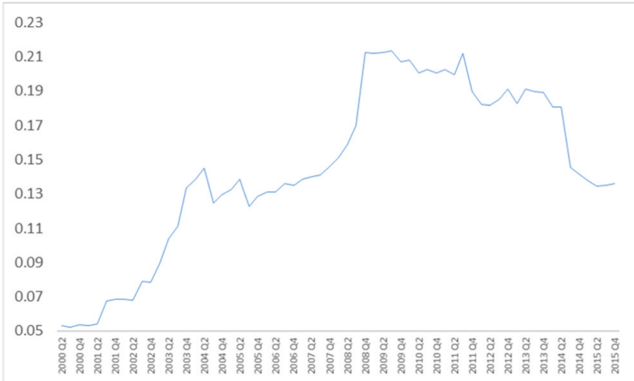

Fig. 1. Eurozone Financial Sector Dynamic Causality Index. Notes: The graph displays the DCI interconnectedness among the 315 financial institutions in the Eurozone on a quarterly basis from Q2 2000 to Q4 2015. We estimate DCI for sub-samples in an overlapping form by using returns from a widow of the previous 12 quarters. The level of interconnectedness in the financial system is measured by the magnitude of DCI, so a highly connected financial system is captured by a higher value of DCI and vice versa.

reasonably over time and spikes during periods of systemic shocks.

For example, the DCI exhibits a weak upward trend in the early sample period, reaching a minimum of 0.0522 in Q3 2000 before increasing to approximately 0.1448 in Q2 2004, when the Greek government declared its national statistics unreliable, and its budget deficit exceeded the 3 % Maastricht treaty limit (Cline and Wolff, 2012).[15] The DCI continued to fluctuate, spiking to 0.2124 in Q4 2008 following the collapse of Lehman Brothers and the onset of the subprime crisis, which disrupted the interbank payment system. It remained elevated in Q1 2009, reaching a higher peak of 0.2126 in Q2 2009 with the eruption of the Eurozone sovereign debt crisis and commands for France, Spain, Greece and Ireland to reduce their budget deficits. The DCI reached its highest level of 0.2134 in Q3 2009 as PIIGS countries implemented bailouts and austerity measures. Despite a downward trend post-crisis, the DCI continued to exhibit local peaks corresponding to key financial events (Weiß et al., 2014).

Figs. 2–4 display network diagrams of the statistically significant Granger causality relationships at the 5 % level among the daily returns of the 315 Eurozone financial institutions for three subsamples corresponding to tranquil and crisis periods. The curved lines connecting institutions indicate Granger causality relationships, where the returns of one institution at the date t Granger causes the returns of another at the date $t+1$. A GARCH process is used to adjust the relationships for autocorrelation and heteroskedasticity.

Figs. 2–4 show the Granger causality network within the Eurozone financial system's institutions. They can be seen as a proxy for how shocks could spillover within the system. It demonstrates the system's interconnections. The network diagrams show an increasing number of causal relations among the institutions since 2004. In the pre-crisis period (Q3 2004-Q2 2007), there were 13,836 significant links. This rose to 19,821 during the 2007 GFC and 2009 Eurozone crisis period before falling slightly to 18,905 post-crisis (Q3 2010-Q2 2013). This suggests that the Eurozone financial system becomes much more densely interconnected during crises compared to tranquil periods.

The figures also suggest that the Eurozone financial system becomes much more densely linked during financial crises when compared with

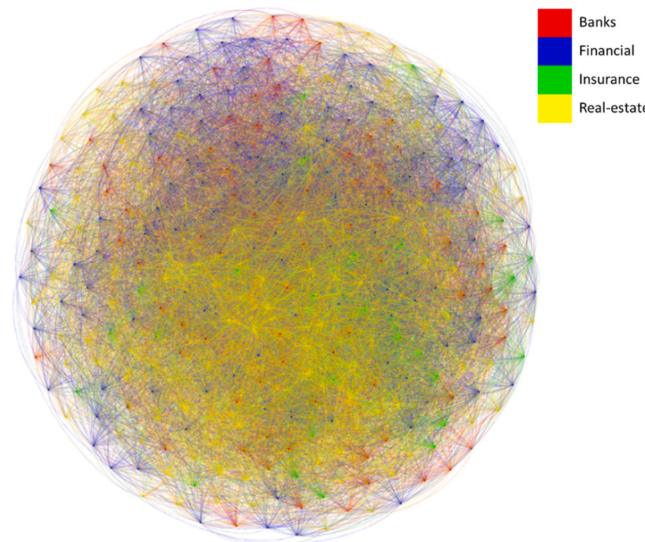

Fig. 2. Granger Causality Network for Eurozone Financial Sector (pre-crisis period). Notes: Linear Granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. The total number of 13,836 significant Granger causality relationships are present at a 5 % level within the pre-crisis sample (Q3 2004-Q2 2007). See Appendix (C) for the full list of financial institutions within each sector.

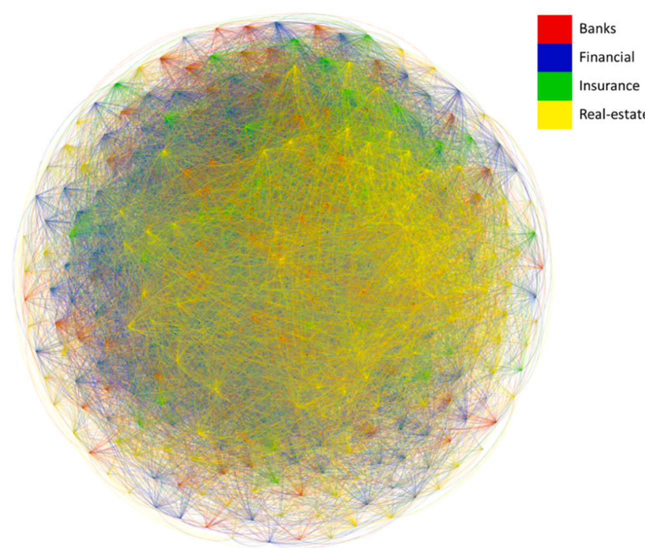

Fig. 3. Granger Causality Network for Eurozone Financial Sector (crisis period). Notes: Linear Granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. The total number of 19,821 significant Granger causality relationships are present at a 5 % level within the crisis sample (Q3 2007-Q2 2010). See Appendix (D) for the full list of financial institutions within each sector.

more periods of tranquility. For example, amongst the financial institutions in the pre-crisis period, the total number of causal relationships was 13,836, but these institutions became extremely interconnected during the crisis period, with 19,821 links, with an approximate increase of 43 %.

Table 3 presents the total number of significant Granger causal relations for each financial sector across the subperiods. The interconnectedness rankings changed over time. In the pre- and post-crisis periods, the real estate sector had the most connections, followed by diversified financials and banks, with insurance the least connected. However, during the crisis, the banking sector became the most

[15] Maastricht Treaty was signed in 1992 among 12 European Union members to attain the Economic and Monetary Union (EMU). The Stability and Growth Pact (SGP) was agreed upon in 1997 and went into force with the introduction of the Euro in 1999. It harmonizes the fiscal policy and unifies the monetary policy. All Eurozone members need to maintain low inflation, low-interest rates, a maximum of 60 % public debt and a maximum of 3 % budget deficit.

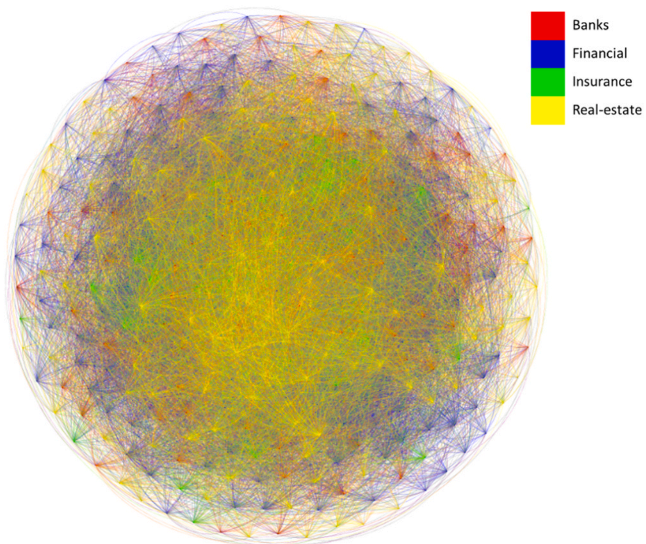

Fig. 4. Granger Causality Network for Eurozone Financial Sector (post-crisis period). Notes: Linear Granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. The total number of 18,905 significant Granger causality relationships are present at a 5 % level within the post-crisis sample (Q3 2010- Q2 2013). See Appendix (E) for the full list of financial institutions within each sector.

interconnected, followed by diversified financials, real estate, and insurance. Notably, insurance was consistently the least connected, while diversified financials ranked second across all periods.

Although the number of connections varied across samples, the proportion of connections within each sector was relatively stable. For example, the banking sector accounted for 27.52–32.09 % of total connections in each period. Banks ranked third pre- and post-crisis with 3,807 and 5,314 significant connections, respectively (27.52 % and 28.11 % of the total). However, they became the most connected sector during the crisis, with 6,361 significant relations (32.09 % of the total).

Overall, the Granger causality results indicate that Eurozone financial institutions became increasingly interconnected during the crisis period. While the number of causal relations decreased slightly post-crisis compared to pre-crisis levels, it remained elevated, suggesting the Eurozone financial system may be susceptible to systemic risk due to the high degree of interconnectedness among institutions.

5.2. Systemic risk measures

The high interconnectedness of Eurozone financial sectors demonstrated by the Granger-causality network raises the question of which sectors have the greatest exposure to systemic events in Europe. This is investigated using the ΔCoVaR, MES, and SRISK systemic risk measures discussed in Section 3.3.2–4, which enable the financial sectors to be ranked in order of systemic importance. Following Brownlees and Engle (2012), MES and SRISK are estimated using a GARCH-DCC model, with the threshold C set at a 2 % one-day market drop for short-run MES and a 40 % six-month drop for LRMES, assuming a 5 % coverage rate. ΔCoVaR is estimated using the same GARCH-DCC framework to allow comparison across the risk measures.

The main objectives of any systemic risk analysis are to rank financial institutions, sectors or member states according to their systemic risk exposure (or contribution) and thereby identify SIFIs. However, the results discussed in this section should be interpreted cautiously for two reasons: firstly, using period averages of the ΔCoVaR, MES and SRISK risk measures does not necessarily imply that one member state or sector was systemically riskier than another over the full sample period. Secondly, the analysis relies solely on daily estimated values of the risk measures. It is possible that constructing high confidence interval estimates for ΔCoVaR, MES and SRISK or setting high minimal prudential capital requirements for SRISK could lead to a member state or sector that appears less risky becoming a significant source of systemic risk exposure.

We measure systemic risk exposure at two levels within the 17 Eurozone member states: (i) Identifying which financial sector and member state has the highest exposure to overall Eurozone systemic risk at the union level. (ii) Identifying which member state is most exposed to systemic risk within each financial sector (banking, diversified financials, insurance and real estate). Table 4 provides descriptive statistics of the systemic risk measures for each Eurozone financial sector. MES and LRMES produce the same sector rankings within each period, while ΔCoVaR, MES and SRISK yield different rankings that also vary across periods. In absolute terms, the insurance sector has the highest average systemic risk exposure according to ΔCoVaR, MES and LRMES, while the banking sector is highest based on SRISK during the crisis period. Insurance ranked second most exposed for all risk measures in the crisis, while real estate was least exposed for all measures pre-crisis.

Table 5 shows that the member states most exposed to Eurozone stress events are the PIIGS (as a group of member states), Spain, Italy and France according to all systemic risk measures, though the specific ranking varies across measures, consistent with the TBTF paradigm. Table 6 demonstrates that each risk measure produces different rankings of the financial sectors within each member state. The divergence in rankings is not due to instability in a particular measure but rather reflects their fundamental differences. Therefore, the results from a single risk measure should not be generalized. Instead, integrating multiple systemic risk measures into a broader framework is necessary to capture the various dimensions of systemic risk.

The tail risk measure dynamics in Fig. 5 provide a relatively poor fit for the PIIGS countries during the crisis period, with several large ES and VaR exceptions in late 2009 and early 2011–2012. The market VaR reached extreme levels around October 2009 when Greece, Portugal and Spain launched austerity measures, and the overall financial market stumbled. However, the PIIGS experienced their most severe episodes in late 2008 and late 2012. Because the broader financial market was recovering slightly during these periods, the VaR estimates for PIIGS were less extreme at these points.

Table 3
Linear granger causality connections.

Financial Sector	Pre-crisis Period			Crisis Period			Post-crisis Period		
	Rank	links	% of Total	Rank	links	% of Total	Rank	links	% of Total
Banks	3	3,807	27.52 %	1	6,361	32.09 %	3	5,314	28.11 %
Financial	2	4,051	29.28 %	2	5,949	30.01 %	2	5,329	28.19 %
Insurance	4	1,511	10.92 %	4	2,261	11.41 %	4	2,418	12.79 %
Real-estate	1	4,467	32.29 %	3	5,250	26.49 %	1	5,844	30.91 %
Total		**13,836**			**19,821**			**18,905**	

Notes: This table reports the number of linear Granger causality connections among the daily returns of the four Eurozone financial sectors for three equal sub-periods of three years: pre-crisis period (Q3 2004-Q2 2007), crisis period (Q3 2007-Q2 2010) and post-crisis period (Q3 2010- Q2 2013). The linear Granger causal relationships are statistically significant at 5 %.

Table 4
Eurozone financial sectors average systemic risk measures.

Financial Sector		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (A): Overall Period									
Banks	Mean	3	1.94	3	2.12	3	30.18	1	290,107
	STD		1.16		1.27		12.99		183,698
DFinancials	Mean	1	2.21	1	2.42	1	33.35	2	46,715
	STD		1.34		1.48		14.47		41,679
Insurance	Mean	2	2.10	2	2.32	2	32.13	3	41,186
	STD		1.33		1.46		14.58		46,369
Real-estate	Mean	4	1.45	4	1.74	4	25.04	4	-22,804
	STD		1.09		1.32		14.63		14,513
Panel (B): Pre-crisis Period									
Banks	Mean	3	1.07	2	1.44	2	22.59	1	140,599
	STD		0.35		0.46		5.71		35,245
DFinancials	Mean	1	1.12	1	1.45	1	22.81	3	7,251
	STD		0.34		0.44		5.62		11,108
Insurance	Mean	2	1.09	3	1.39	3	21.82	2	34,846
	STD		0.37		0.46		5.92		18,093
Real-estate	Mean	4	0.56	4	0.93	4	15.17	4	-27,916
	STD		0.34		0.46		6.47		11,274
Panel (C): Crisis Period									
Banks	Mean	4	2.77	3	3.04	3	40.18	1	455,973
	STD		1.40		1.56		13.39		150,984
DFinancials	Mean	2	3.37	2	3.53	2	44.76	2	85,319
	STD		1.65		1.77		13.89		26,001
Insurance	Mean	1	3.72	1	3.60	1	45.45	3	77,729
	STD		1.77		1.75		13.47		27,769
Real-estate	Mean	3	2.81	4	2.98	4	39.48	4	-18,105
	STD		1.44		1.58		13.72		9,199
Panel (D): Post-crisis Period									
Banks	Mean	4	1.97	4	2.24	4	32.42	1	519,293
	STD		0.77		0.88		9.61		56,410
DFinancials	Mean	1	2.82	2	2.95	2	40.14	2	97,647
	STD		1.03		1.08		10.35		21,386
Insurance	Mean	2	2.68	1	3.01	1	40.72	3	76,117
	STD		1.01		1.15		10.92		22,252
Real-estate	Mean	3	2.25	3	2.50	3	35.27	4	-22,936
	STD		0.85		0.98		10.41		6,530

Notes: The table ranks the average exposure of systemic risk measures according to ΔCoVaR, MES, LRMES and SRISK of each Eurozone financial sector. Simple averages and standard deviations are computed within the four periods: overall period (2000–2015), pre-crisis period (Q3 2004 - Q2 2007), crisis period (Q3 2007 - Q2 2010) and post-crisis period (Q3 2010 - Q2 2013). Standard deviations and average MES, LRMES and ΔCoVaR figures are expressed as a percentage, while SRISK figures are expressed in terms of million Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

Fig. 6 plots the average daily conditional volatility series for the PIIGS member states and the Eurozone financial index over 2000–2015. Volatility was high in the early 2000s, likely associated with the 2001 dot-com recession, followed by an extended period of low volatility until spiking again in early 2008 as the economy experienced a significant pre-crash bubble. Volatility peaked in 2009, 2010, and 2011 during the European sovereign debt crisis and the implementation of various bailout plans. It then began slowly decaying but remained elevated compared to pre-crisis levels. The correlation between PIIGS and the overall market is relatively low but spikes during times of distress, as seen in 2002, 2003, 2009 and 2012.

Fig. 7 displays the evolution of the three main systemic risk measures (ΔCoVaR, MES, SRISK) for the PIIGS over 2000–2015. All measures rose around late 2008, with SRISK increasing much more in relative terms than the others. MES and ΔCoVaR follow a similar pattern as SRISK, peaking in October 2008 and spiking again in March 2009 and August 2011.

Fig. 8 shows a strong relationship between average ΔCoVaR and MES but a weak association of SRISK with both ΔCoVaR and MES. This could be explained by the TITF paradigm related to MES and ΔCoVaR, while SRISK captures both the TBTF effect through liabilities and the TITF effect through beta.

Fig. 9 plots the time-series average of PIIGS member states' standard financial risk measures (systematic risk, tail risk, correlation) and its exposure to systemic risk (ΔCoVaR, MES, and SRISK) over time. The time series analysis indicates that MES could be explained by VaR and ES, while beta exhibits similar spikes but a somewhat different overall pattern of MES over time. There is a strong relationship between ΔCoVaR and VaR, as also reported by Adrian and Brunnermeier (2016), Benoit et al. (2013), Andreev et al. (2005), and Boucher et al. (2014)[16]. Conditional volatility shows a similar pattern to ΔCoVaR, while conditional correlation poorly reflects the changes in ΔCoVaR over time. ES and LRMES display a trajectory similar to SRISK, while leverage matches it mainly during the crisis period. Market capitalization and beta move in the opposite direction of SRISK, with SRISK rising when the market value of equity (beta) falls and vice versa. Liability is only weakly related to SRISK.

Fig. 10 displays a cross-section plot of member state's average standard financial risk measures (systematic risk, tail risk, correlation) and its exposure to systemic risk (ΔCoVaR, MES, LRMES, and SRISK). The cross-sectional analysis shows a strong positive relationship between MES and beta ($R^2 = 0.8506$), implying that 5 % MES-based systemic risk rankings of member states largely mirror rankings based on sorting by time-varying beta. However, there are only weak associations

[16] An inferior relationship between ΔCoVaR and VaR was demonstrated in Girardi and Ergün's (2013) time series analysis due to the alternative meanings of ΔCoVaR used by Girardi and Ergün and not from the alternative CoVaR meanings.

Table 5
Eurozone member states average systemic risk measures.

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Austria	Mean	8	2.88	8	3.04	8	40.20	10	3,257
	STD		1.41		1.53		13.35		5,711
Belgium	Mean	6	3.14	9	2.93	9	39.19	7	29,295
	STD		1.52		1.48		13.17		16,210
Cyprus	Mean	13	1.99	12	2.49	12	34.51	15	-574
	STD		1.07		1.35		13.00		1,765
Estonia	Mean	16	0.13	15	0.43	15	7.36	17	-1,525
	STD		0.09		0.27		4.31		72
Finland	Mean	9	2.60	6	3.26	6	42.42	18	-3,187
	STD		1.26		1.59		13.35		1,519
France	Mean	4	3.24	4	3.50	4	44.54	1	254,553
	STD		1.60		1.75		13.59		49,190
Germany	Mean	5	3.16	5	3.38	5	43.46	2	160,127
	STD		1.51		1.66		13.53		29,816
Greece	Mean	10	2.32	10	2.81	10	38.01	14	-508
	STD		1.15		1.42		12.96		13,085
Ireland	Mean	12	2.07	13	2.00	13	28.90	8	12,117
	STD		1.11		1.16		12.67		6,679
Italy	Mean	3	3.41	2	3.63	3	45.61	4	64,306
	STD		1.67		1.82		13.79		36,683
Luxembourg	Mean	15	0.14	18	0.11	18	2.03	16	-1,024
	STD		0.07		0.06		0.98		64
Malta	Mean	17	0.08	17	0.14	17	2.50	13	-207
	STD		0.09		0.13		2.23		205
Netherlands	Mean	7	2.98	7	3.23	7	42.13	6	40,904
	STD		1.42		1.57		13.21		31,495
Portugal	Mean	11	2.28	11	2.63	11	35.62	9	5,361
	STD		1.35		1.54		14.13		3,791
Slovakia	Mean	18	0.05	16	0.26	16	4.62	11	277
	STD		0.03		0.13		2.17		76
Slovenia	Mean	14	0.38	14	0.48	14	7.65	12	-153
	STD		0.52		0.67		9.60		57
Spain	Mean	2	3.51	3	3.62	2	45.63	5	45,765
	STD		1.70		1.78		13.67		23,305
PIIGS	Mean	1	3.64	1	3.81	1	47.07	3	135,522
	STD		1.83		1.95		14.09		78,259

Notes: The table ranks the average exposure to systemic risk measures according to ΔCoVaR, MES, LRMES and SRISK of each member state in the Eurozone. Simple averages and standard deviations are computed within the crisis period (Q3 2007-Q2 2010). Standard deviations and average MES, LRMES and ΔCoVaR figures are expressed as a percentage, while SRISK figures are expressed in terms of million Euros. All risk measures are generated under the assumption of $q = 5\%$ level. See panels (A), (B) and (C) in Appendix (F) for systemic risk exposure values during the overall period (2000–2015), pre-crisis period (Q3 2004-Q2 2007) and the post-crisis period (Q3 2010- Q2 2013), respectively.

of MES with the tail risk measures ES and VaR, as well as between a state's VaR and its ΔCoVaR exposure to system-wide risk, consistent with findings by Adrian and Brunnermeier (2016), Girardi and Ergün (2013), Benoit et al. (2013), Andreev et al. (2005) and Boucher et al. (2014). Conditional volatility is also only weakly related to ΔCoVaR, though conditional correlation explains 99.6 % of the cross-sectional variance in state-level ΔCoVaR. The SRISK scatter plots show it is highly correlated with firm characteristics (liabilities and market capitalization) but not with the standard financial risk measures (systematic risk and tail risk). This suggests that regulating the risk of individual financial institutions, sectors or countries through tools like ES or VaR may not be optimal for protecting the overall financial system against systemic risk.

Table 7 presents the ranking of systemic risk measures, standard financial risk metrics and firm characteristics as of December 31, 2015. The MES ranking tends to identify the same SIFIs as rankings based on conditional correlation, beta and liabilities, with five, four and four out of eighteen member states (including PIIGS), respectively. Interestingly, the ΔCoVaR ranking is driven more by correlation than by the institution's individual VaR, with eight member states having matching ranks on ΔCoVaR and correlation. The SRISK ranking is highly sensitive to liabilities and market capitalization rather than leverage.

Fig. 11 shows that as of December 31, 2015, the Eurozone member states with the highest SRISK were France (€186.66 billion), the PIIGS (€82.68 billion), Germany (€56.28 billion) and Italy (€42.99 billion), while those with the lowest SRISK were Finland (€-19.46 billion), Ireland (€-15.90 billion) and Belgium (€-13.98 billion). This suggests that SRISK is influenced by economy size, with larger economies tending to have higher SRISK (relatively). To facilitate cross-country comparison, SRISK can be expressed as a percentage of GDP or stock market capitalization. On this basis, Greece had the highest SRISK to GDP at 8.63 %, followed by France (8.51 %) and Portugal (3.68 %), indicating less influence on the size of the economy. In terms of the stock market, Portugal's SRISK represented 140.44 % of its market cap, the highest proportion, followed by Greece (119.85 %), France (67.79 %) and Italy (29.20 %), highlighting the sensitivity of the PIIGS to systemic events.

Finally, Table 8 indicates that ΔCoVaR, MES and LRMES are typically associated with the number of institutions (capturing the TMTF paradigm) and the degree of connectedness via beta (reflecting the TITF paradigm), consistent with findings by Markose et al. (2010). Based on its definition, SRISK can be viewed as a compromise between the TBTF paradigm (through liabilities and market capitalization) and the TITF paradigm (through Granger causal connections), implying that large and highly interconnected institutions elevate systemic risk scores.

6. Robustness check

The dominance test aims to assess the significance of the rankings

Table 6
Average systemic risk measures of each financial sector within member states.

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (A): Banks									
Austria	Mean	5	3.84	5	4.28	4	51.75	9	6,549
	STD		1.52		1.72		12.09		2,720
Belgium	Mean	2	4.71	2	5.16	2	55.69	6	38,315
	STD		2.86		3.19		16.26		10,571
Cyprus	Mean	11	2.82	10	3.42	9	44.92	12	112
	STD		0.94		1.12		9.98		1,398
Finland	Mean	13	0.11	14	0.40	14	6.99	13	30
	STD		0.02		0.07		1.14		20
France	Mean	3	4.45	4	4.73	3	54.58	1	242,833
	STD		1.96		2.13		13.93		33,829
Germany	Mean	10	3.06	11	3.27	11	42.70	5	38,906
	STD		1.48		1.60		11.85		9,842
Greece	Mean	8	3.47	8	3.73	8	47.14	15	-1,010
	STD		1.38		1.51		12.53		11,787
Ireland	Mean	1	5.83	1	6.34	1	61.45	8	14,869
	STD		4.16		4.46		17.20		4,825
Italy	Mean	7	3.50	6	4.03	5	48.98	3	59,535
	STD		1.71		2.01		13.91		27,400
Malta	Mean	15	0.04	15	0.18	15	3.12	14	-189
	STD		0.05		0.11		1.77		199
Netherlands	Mean	4	4.05	3	4.98	7	48.19	7	36,787
	STD		3.89		4.68		27.20		29,796
Portugal	Mean	12	2.20	12	2.38	12	34.09	10	5,407
	STD		0.77		0.85		9.00		3,369
Slovakia	Mean	14	0.08	13	0.56	13	9.56	11	288
	STD		0.03		0.21		3.35		77
Spain	Mean	6	3.54	7	4.03	6	48.57	4	51,771
	STD		1.83		2.12		15.16		21,292
PIIGS	Mean	9	3.15	9	3.52	10	44.89	2	123,147
	STD		1.45		1.65		13.31		67,774
Panel (B): Diversified Financial									
Austria	Mean	12	0.26	12	0.53	12	9.06	5	-50
	STD		0.12		0.20		3.11		15
Belgium	Mean	4	2.17	4	2.27	4	31.84	14	-4,886
	STD		1.28		1.39		12.76		4,562
Cyprus	Mean	9	1.50	6	2.01	6	29.69	7	-107
	STD		0.64		0.80		8.70		67
Finland	Mean	11	0.96	11	1.21	11	19.36	8	-194
	STD		0.34		0.45		5.93		49
France	Mean	3	2.38	3	2.63	3	36.63	13	-3,578
	STD		0.97		1.09		10.39		2,380
Germany	Mean	1	3.38	1	3.62	1	45.51	1	92,880
	STD		1.68		1.86		13.56		16,656
Greece	Mean	8	1.69	9	1.83	9	27.53	2	2,887
	STD		0.63		0.69		7.47		1,390
Ireland	Mean	10	1.23	10	1.53	10	23.71	6	-56
	STD		0.46		0.53		6.94		26
Italy	Mean	6	1.97	7	2.00	7	29.67	11	-2,098
	STD		0.70		0.74		8.47		2,100
Luxembourg	Mean	13	0.09	13	0.23	13	4.11	9	-1,001
	STD		0.03		0.07		1.20		66
Netherlands	Mean	7	1.85	5	2.16	5	31.18	12	-2,160
	STD		0.84		1.01		10.43		824
Slovenia	Mean	14	0.00	14	0.00	14	0.03	4	-2
	STD		0.00		0.00		0.04		0
Spain	Mean	5	2.01	8	1.96	8	29.08	10	-1,456
	STD		0.76		0.77		8.94		361
PIIGS	Mean	2	2.99	2	3.16	2	41.54	3	554
	STD		1.40		1.52		13.16		3,864
Panel (C): Insurance									
Austria	Mean	8	2.18	8	2.32	8	33.00	10	-538
	STD		1.04		1.12		11.14		1,065
Cyprus	Mean	11	0.73	11	1.08	11	17.52	7	-33
	STD		0.28		0.30		4.26		7
Finland	Mean	5	2.78	6	2.66	6	36.86	12	-3,070
	STD		1.16		1.14		11.24		1,151
France	Mean	2	4.15	2	3.83	2	46.86	1	30,837
	STD		2.19		2.05		15.45		8,672
Germany	Mean	6	2.74	4	3.02	4	39.30	2	28,856
	STD		1.67		1.84		15.13		14,278
Greece	Mean	10	1.38	9	1.89	9	28.07	6	-12
	STD		0.71		0.81		9.67		16

(*continued on next page*)

Table 6 (*continued*)

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Ireland	Mean	9	1.54	10	1.70	10	25.65	9	-188
	STD		0.77		0.84		9.51		148
Italy	Mean	7	2.46	7	2.64	7	36.65	5	6,447
	STD		1.08		1.13		11.52		7,122
Netherlands	Mean	1	5.70	1	5.80	1	57.94	3	11,294
	STD		3.84		3.96		19.27		2,945
Slovenia	Mean	12	0.42	12	0.94	12	15.06	8	-137
	STD		0.46		0.63		8.41		51
Spain	Mean	4	2.96	5	2.87	5	39.18	11	-1,418
	STD		1.17		1.16		11.04		1,114
PIIGS	Mean	3	3.31	3	3.28	3	42.67	4	6,774
	STD		1.54		1.55		13.13		8,037
Panel (D): Real-estate									
Austria	Mean	2	3.20	1	3.93	2	46.49	6	-1,518
	STD		2.20		2.72		16.25		1,418
Belgium	Mean	8	1.41	8	1.65	8	24.84	8	-1,735
	STD		0.75		0.90		10.04		402
Cyprus	Mean	10	0.96	9	1.44	9	22.56	2	-177
	STD		0.43		0.50		6.41		107
Estonia	Mean	12	0.00	13	0.00	13	0.01	7	-1,646
	STD		0.00		0.00		0.02		5
Finland	Mean	1	3.22	2	3.86	1	48.85	3	-335
	STD		1.05		1.28		10.17		215
France	Mean	7	2.46	6	2.39	6	33.86	13	-6,871
	STD		1.06		1.07		11.28		2,934
Germany	Mean	3	3.16	10	1.26	10	19.92	10	-2,408
	STD		1.51		0.58		7.10		518
Greece	Mean	9	1.25	7	2.10	7	30.98	4	-342
	STD		0.46		0.74		7.34		153
Italy	Mean	6	2.62	3	2.96	4	39.44	5	-746
	STD		1.31		1.51		13.55		572
Malta	Mean	13	0.00	12	0.01	12	0.19	1	-12
	STD		0.00		0.00		0.00		1
Netherlands	Mean	5	2.67	5	2.89	3	39.44	9	-2,350
	STD		0.98		1.11		10.78		785
Spain	Mean	11	0.66	11	0.79	11	13.02	11	-2,977
	STD		0.42		0.44		6.93		2,477
PIIGS	Mean	4	2.67	4	2.95	5	39.29	12	-3,066
	STD		1.34		1.52		13.56		2,879

Notes: The table ranks the average exposure to systemic risk measures according to ΔCoVaR, MES, LRMES and SRISK of each member state in the Eurozone. Simple averages and standard deviations are computed within the crisis period (Q3 2007-Q2 2010). Standard deviations and average MES, LRMES and ΔCoVaR figures are expressed as a percentage, while SRISK figures are expressed in terms of million Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level. See Appendix (G), (H) and (I) for systemic risk exposure values during the overall period (2000–2015), pre-crisis period (Q3 2004-Q2 2007) and the post-crisis period (Q3 2010- Q2 2013), respectively.

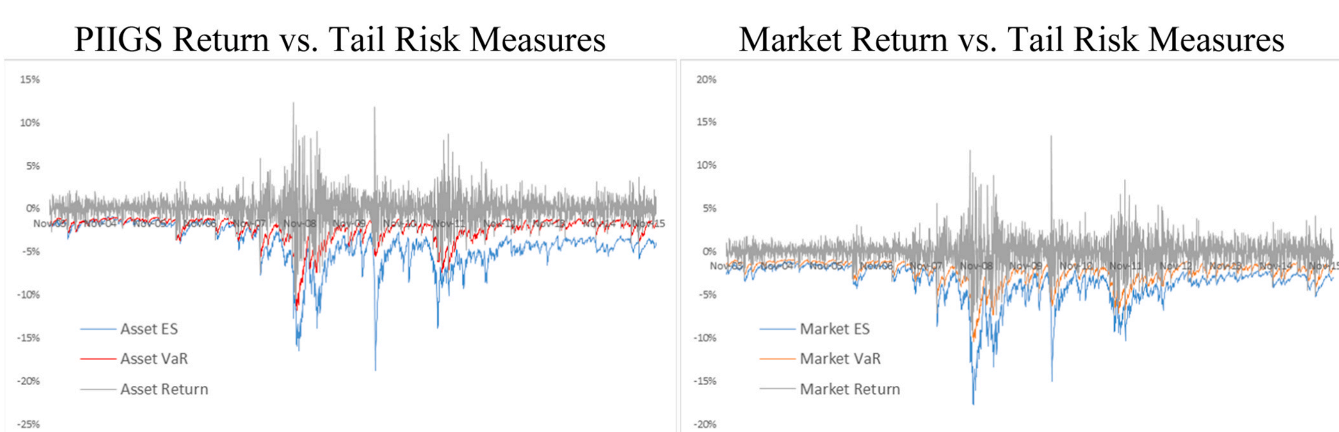

Fig. 5. Return vs Tail Risk Measures (VaR and ES). Notes: The left-side graph displays the asset return, VaR and ES of PIIGS countries, while the right-side graph displays the market return, VaR and ES. The analysis covers the overall period (2000–2015). Tail risk measures are generated under the assumption of $q = 5\%$ level. Return, VaR and ES figures are expressed as a percentage.

Fig. 6. Conditional Volatility and Correlation. Notes: The right-side graph displays the conditional volatility of the PIIGS returns, the middle graph displays the conditional volatility of the market returns, and the right-side graph displays the correlation between PIIGS returns and the market returns. The analysis covers the overall period (2000–2015). Conditional volatility and correlation are expressed as a percentage.

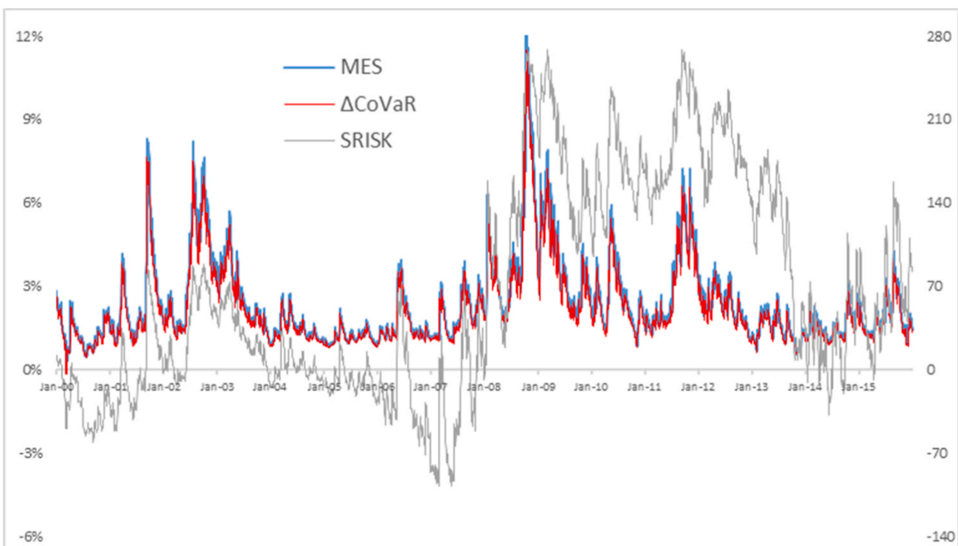

Fig. 7. Time Series Evolution of Systemic Risk Measures for PIIGS Member States. Notes: The graph displays the ΔCoVaR and MES (left axis) and the *SRISK* (right axis) of PIIGS countries within the overall period (2000–2015). Average ΔCoVaR and MES figures are expressed as a percentage while average SRISK is expressed in terms of Billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

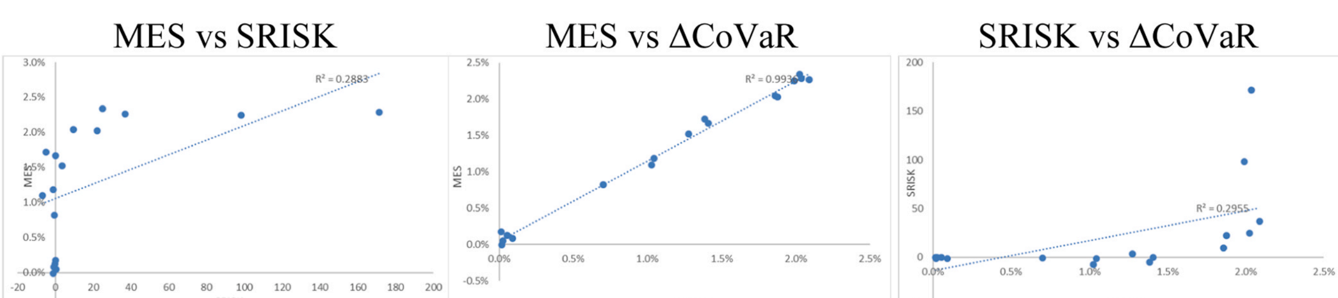

Fig. 8. Cross-Section Evolution of Systemic Risk Measures for Eurozone Member States. Notes: Each point represents a member state of the Eurozone. Averages are calculated for the overall period (2000–2015). The right-side graph displays the relationship between average MES (y-axis) and SRISK (x-axis), the middle graph displays the relationship between average MES (y-axis) and ΔCoVaR (x-axis), and the right-side graph displays the relationship between average SRISK (y-axis) and ΔCoVaR (x-axis). Average MES and ΔCoVaR figures are expressed as a percentage, while average SRISK figures are expressed in terms of Billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

obtained from different systemic risk measures (MES, SRISK, and ΔCoVaR) to determine whether a given financial sector (member state or institution) i contributes more to systemic risk than another financial sector (member state or institution) j. The standard KS test was not employed due to the estimation procedure providing "estimated" cumulative distribution functions (CDFs) for the systemic risk measures (ΔCoVaR, MES, and SRISK), which may introduce a nuisance parameter to the null hypothesis, known as the Durbin problem (Durbin, 1973). This issue can threaten the distribution-free nature of the standard KS test. To overcome the Durbin problem that arises when applying the KS test to two CDFs that are not distribution-free, Abadie's (2002) bootstrapping strategy was utilized.

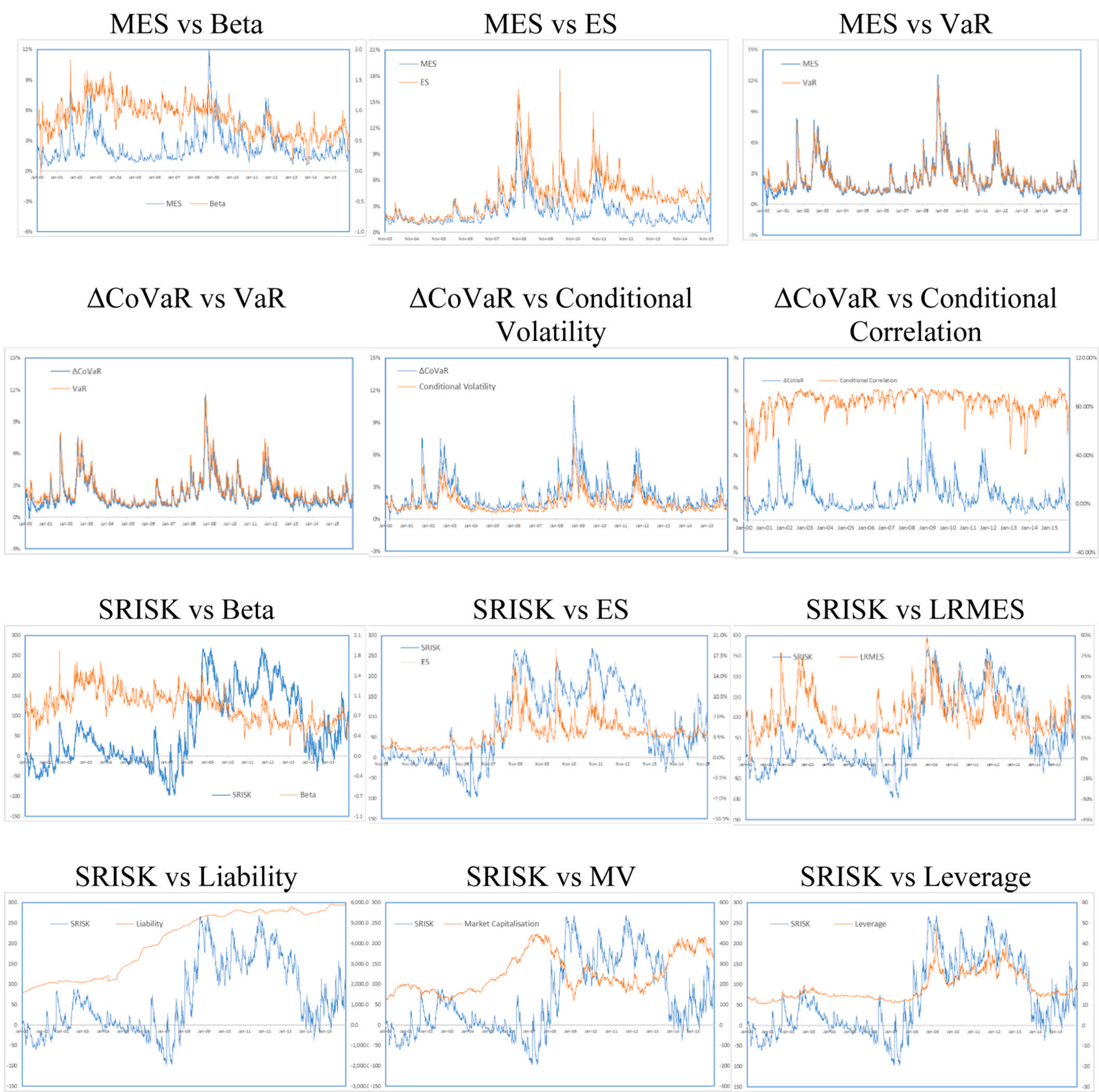

Fig. 9. Time-Series Analysis of Macro-prudential and Micro-prudential Measures. Notes: This figure shows the time-series average of daily systemic risk measures and standard financial risk measures. The estimation covers the period from January 3, 2000 to December 31, 2015. All risk measures are generated under the assumption of $q = 5\%$ level. MES, LRMES, ES, ΔCoVaR, VaR, conditional volatility and conditional correlation figures are expressed as a percentage, while SRISK, liability and market capitalization figures are expressed in terms of Billion Euros.

The bootstrap KS test is suitable for two primary reasons. First, the test compares the entire CDFs rather than focusing on mean values, which are sensitive to outliers and may lead to false conclusions from statistical tests based on these values. Second, the KS test is non-parametric and asymptotically distribution-free, eliminating the need for assumptions about the underlying distribution. This is in contrast to statistical tests based on mean values (e.g., Student-*t* tests or two-sample *z*-tests), which may have a higher risk of errors if the datasets are not normally distributed. The two-sample bootstrap KS test is applied to compare the CDFs of the MES (or SRISK or ΔCoVaR) for two financial sectors (or member states or institutions). The two-sample KS test statistic for the dominance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_x |A_m(x) - B_n(x)| \tag{51}$$

where $A_m(x)$ and $B_n(x)$ represent the CDFs of the MES (or SRISK or ΔCoVaR) related to two financial sectors (or member states or institutions), and m and n are the sizes of the two samples. For example, the null hypothesis for MES is defined as follows:

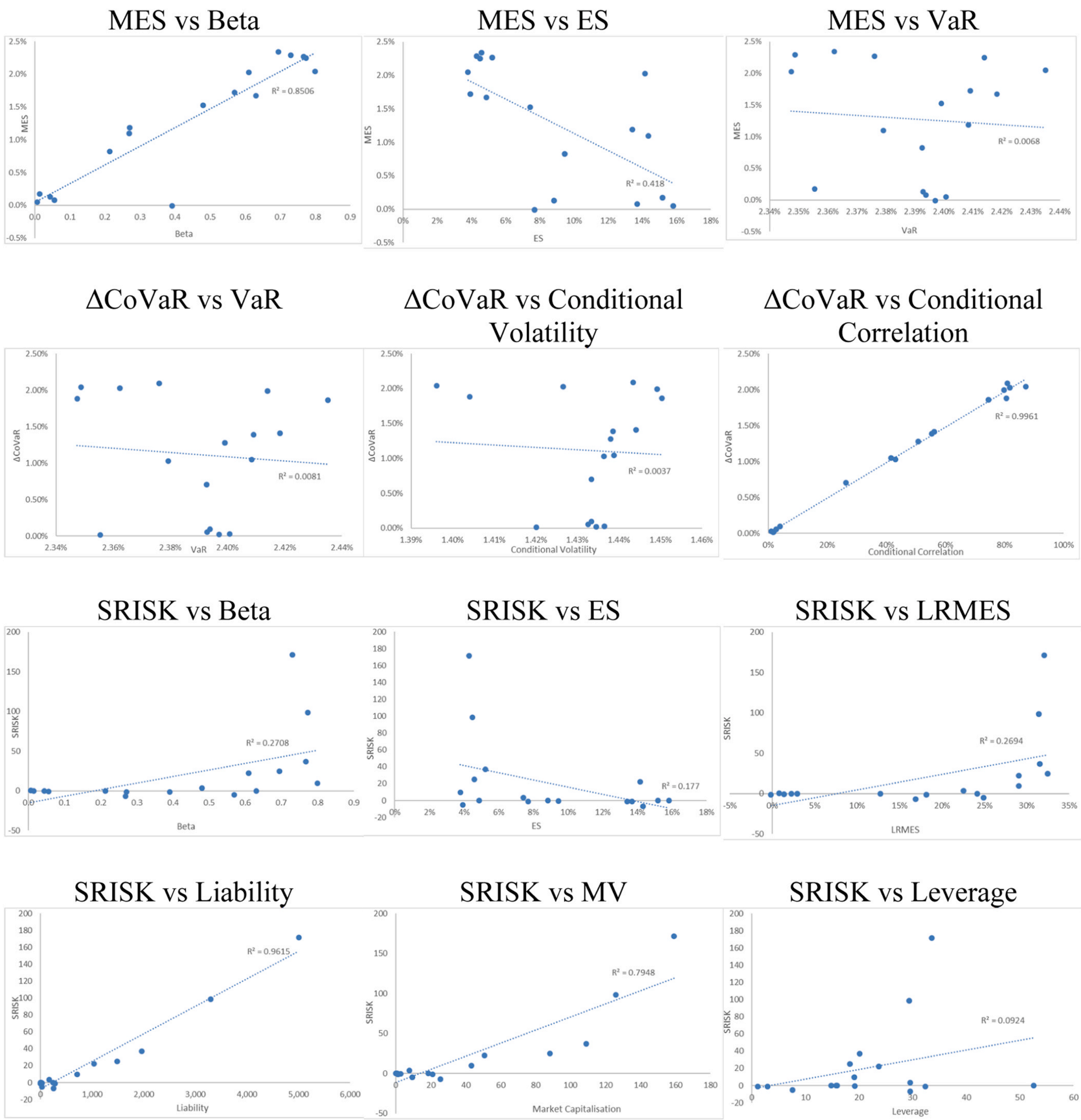

Fig. 10. Cross-Sectional Analysis of Macro-prudential and Micro-prudential Measures. Notes: The scatter plot shows the cross-sectional link between the time-series average of Eurozone member state's risk in isolation, measured by ES and VaR, firm characteristics, measured by leverage and market capitalization, and the time-series average exposure to systemic risk, measured by MES, SRISK and ΔCoVaR. All risk measures are generated under the assumption of $q = 5\%$ level. Each point represents a member state of the Eurozone. Averages are calculated for the overall period (2000–2015). Average MES, LRMES, ES, ΔCoVaR, VaR, conditional volatility and conditional correlation figures are expressed as a percentage, while average SRISK, liability and market capitalization figures are expressed in terms of Billion Euros.

$$H_0 : \left|MES^{Banks}\right| > \left|MES^{Insurance}\right| \tag{52}$$

The interpretation of the null hypothesis and the comparison of the results of the bootstrap KS stochastic dominance tests rely on the absolute values of MES and ΔCoVaR, while SRISK figures are already positive.

The bootstrap KS dominance test compares the CDFs of the systemic risk measures (MES, SRISK, and ΔCoVaR) related to two different financial sectors (banks, diversified financial, insurance, and real-estate). Results are presented in Table 9. We test whether the diversified financial sector is less or equally risky for the system compared to the real-estate sector. The p-value indicates that the null hypothesis is rejected at the 1 % significance level, implying that the diversified financial sector is systemically riskier than the real-estate sector within

Table 7
Systemic risk measures and firm characteristics values and ranking.

Member	MES	SRISK	ΔCoVaR	ES	VaR	β	MV	LTQ	LVG	ρ
Panel (A): Values										
Austria	1.40	-4.20	1.18	2.82	1.91	0.78	28.16	299.90	11.65	63.74
Belgium	1.64	-13.98	1.50	2.48	1.95	1.07	63.80	562.49	9.82	77.71
Cyprus	0.23	-0.15	0.21	11.15	1.88	0.07	1.90	28.46	16.01	11.68
Estonia	-0.01	-0.11	0.02	10.15	1.88	0.01	0.12	0.05	1.37	1.87
Finland	1.66	-19.46	1.35	2.90	1.90	0.75	30.42	33.96	2.12	73.66
France	1.91	186.66	1.70	2.97	1.92	0.89	275.34	6,749.93	25.51	90.55
Germany	1.66	56.28	1.45	2.97	1.97	0.77	202.08	3,599.23	18.81	73.12
Greece	0.55	15.16	0.45	29.05	1.89	0.05	12.65	472.43	38.35	25.30
Ireland	0.04	-15.90	0.08	11.66	1.80	0.01	29.48	213.78	8.25	5.68
Italy	1.78	42.99	1.65	3.89	1.87	0.74	147.21	2,616.31	18.77	83.72
Luxembourg	0.06	-1.47	0.07	6.78	1.88	0.05	1.85	4.63	3.50	3.91
Malta	0.09	-0.77	0.03	3.08	1.88	0.03	1.79	16.15	10.04	2.14
Netherlands	1.69	8.28	1.57	3.19	1.90	0.85	84.46	1,221.08	15.46	85.58
Portugal	1.07	6.61	0.90	9.60	1.88	0.27	4.71	186.83	40.71	48.41
Slovakia	0.04	0.03	0.02	12.77	1.89	0.00	0.56	10.18	19.08	1.09
Slovenia	0.15	-0.02	0.02	14.00	1.91	0.01	0.03	0.14	6.05	3.08
Spain	1.62	35.45	1.39	4.76	1.73	0.41	136.96	2,403.41	18.55	78.16
PIIGS	1.44	82.68	1.32	3.99	1.65	0.49	331.01	5,892.76	18.80	76.43
Panel (B): Rank										
Austria	9	15	9	17	4	4	10	9	11	9
Belgium	6	16	4	18	2	1	7	7	13	5
Cyprus	12	12	12	5	12	11	13	13	9	12
Estonia	18	11	18	6	13	17	17	18	18	17
Finland	4	18	7	16	7	6	8	12	17	7
France	1	1	1	14	3	2	2	1	3	1
Germany	5	3	5	15	1	5	3	3	5	8
Greece	11	6	11	1	8	13	11	8	2	11
Ireland	16	17	13	4	16	15	9	10	14	13
Italy	2	4	2	11	15	7	4	4	7	3
Luxembourg	15	14	14	8	11	12	14	16	16	14
Malta	14	13	15	13	10	14	15	14	12	16
Netherlands	3	7	3	12	6	3	6	6	10	2
Portugal	10	8	10	7	14	10	12	11	1	10
Slovakia	17	9	17	3	9	18	16	15	4	18
Slovenia	13	10	16	2	5	16	18	17	15	15
Spain	7	5	6	9	17	9	5	5	8	4
PIIGS	8	2	8	10	18	8	1	2	6	6
Panel (C): Concordant Pairs										
	MES	*SRISK*	*ΔCoVaR*	*ES*	*VaR*	β	MV	LTQ	LVG	ρ
MES										
SRISK	2									
ΔCoVaR	11	3								
ES	0	1	0							
VaR	2	2	2	0						
β	4	0	5	1	1					
MV	1	4	3	0	1	2				
LTQ	4	5	3	0	2	1	6			
LVG	2	0	2	0	1	2	0	2		
ρ	5	3	8	0	2	3	3	2	2	

Notes: In the upper panel, we report the values of systematic risk measures and firm characteristics for each member state in the Eurozone on December 31, 2015. Marginal expected shortfall (MES), delta conditional value at risk (ΔCoVaR), expected shortfall (ES), value at risk (VaR) and conditional correlation (ρ) are expressed as a percentage, while systemic risk index (SRISK), market capitalization (MV) and liabilities (LTQ) are expressed in billion Euros. Conditional beta (β) and leverage (LVG) are expressed in units. In the middle panel, we rank each Eurozone member state based on MES, SRISK, ΔCoVaR, ES, VaR, β, MV, LTQ, LVG, and ρ, respectively. In the lower panel, we report the number of concordant pairs between two macro-prudential risk measures or micro-prudential risk measures. MES, ΔCoVaR, ES, VaR and ρ figures are expressed as a percentage while SRISK, MV and LTQ figures are expressed in terms of billion Euros and β and LVG are times. All risk measures are generated under the assumption of $q = 5\%$ level.

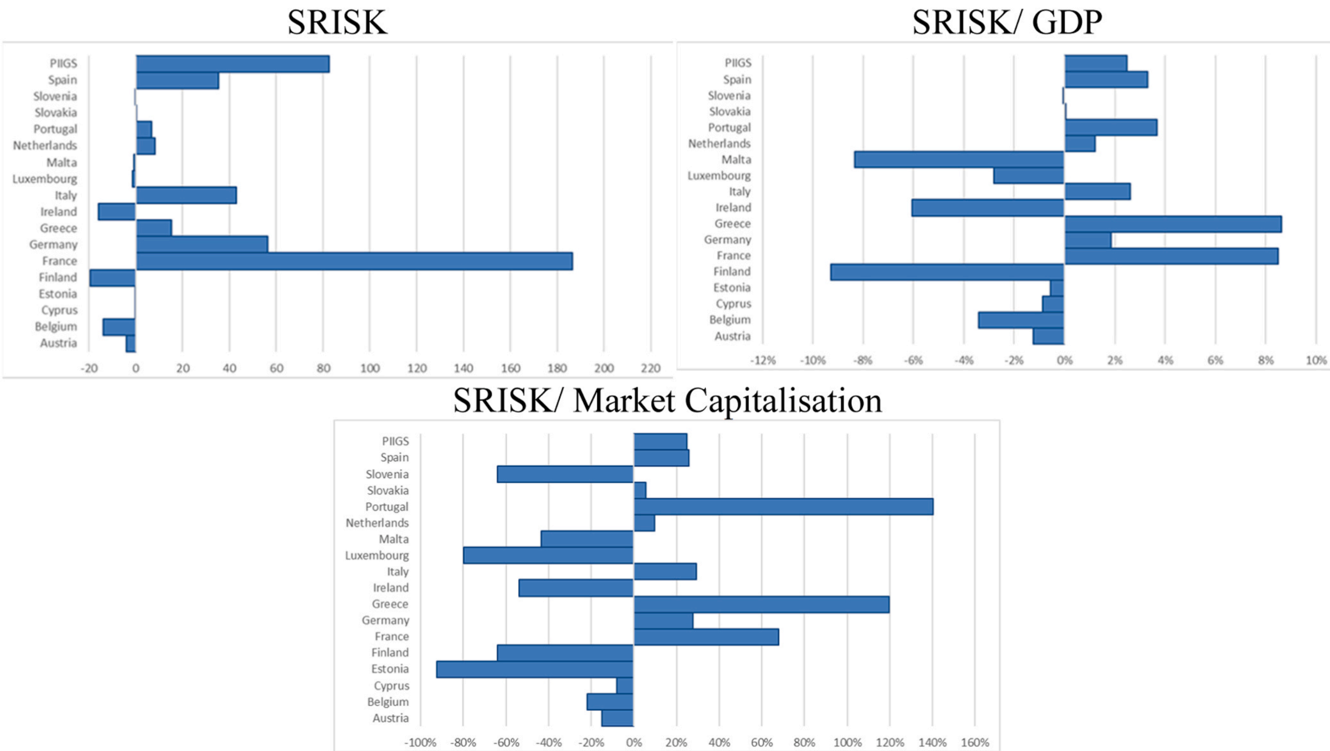

Fig. 11. SRISK of Eurozone Member States as of December 31, 2015. Notes: SRISK is expressed in terms of Billion Euros while SRISK/ nominal GDP and SRISK/ Market Capitalization are expressed as a percentage.

Table 8
Too-systemic-to-fail measures.

	MV	LTQ	GCC	# Institutions	β	ΔCoVaR	MES	LRMES	SRISK
Panel (A): Too-Systemic-To-Fail Measures Values									
Banks	410,825	12,650,023	6,361	75	0.68	2.77	3.04	40.18	455,973
DFinancials	86,708	2,405,030	5,949	105	1.03	3.37	3.53	44.76	85,319
Insurance	150,680	2,869,298	2,261	27	1.05	3.72	3.60	45.45	77,729
Real-estate	39,923	98,239	5,250	108	1.23	2.81	2.98	39.48	-18,105
Panel (B): Too-Systemic-To-Fail Measures Rank									
Banks	1	1	1	3	4	4	3	3	1
DFinancials	3	3	2	2	3	2	2	2	2
Insurance	2	2	4	4	2	1	1	1	3
Real-estate	4	4	3	1	1	3	4	4	4

Notes: In the upper panel, we report the values of too-systemic-to-fail and systematic risk measures for each Eurozone financial sector during the crisis period (Q3 2007-Q2 2010). MV and LTQ stand for market capitalization and liabilities (expressed in million Euros), which is a measure of too-big-to-fail, GCC and β stands for Granger-causality connections (expressed as a number of connections) and beta, which is a measure of too-interconnected-to-fail, # Institutions is the number of institutions within each sector, which is a measure of too-many-to-fail, ΔCoVaR, MES and LRMES are expressed as percentages while SRISKis expressed in million Euros. In the lower panel, we rank each Eurozone sector based on these measures. All risk measures are generated under the assumption of $q = 5\%$ level.

the Eurozone. Results concerning the following two comparisons, $Insurance \leq DFinancial$ and $Insurance \leq Realestate$, are more straightforward. The null hypothesis is rejected at the 1 % significance level in each case, confirming that the insurance sector is systemically riskier than the diversified financial sector and the real-estate sector, respectively.

Regarding the comparison between the banking sector and the other three sectors ($Banks \leq Insurance$, $Banks \leq Financial$ and $Banks \leq Realestate$), results indicate that the null hypothesis is rejected at the 1 % significance level in each scenario, emphasizing that the banking sector is systemically riskier than the insurance sector, the diversified financial sector, and the real-estate sector, respectively. The dominance test results also suggest that, for each comparison pair, the contributions of each financial sector to systemic risk are statistically different from each other.[17]

The bootstrap KS dominance test confirms the rankings generated by each systemic risk measure. Based on MES and ΔCoVaR, the diversified financial sector is systemically riskier than the insurance sector, which is

[17] Due to space constraints, KS dominance tests for Eurozone financial sectors (pre-crisis, crisis, and post-crisis), member states (overall, pre-crisis, crisis, and post-crisis), and member states within each financial sector (overall, pre-crisis, crisis, and post-crisis) are available upon request.

Table 9
KS dominance test for Eurozone financial sectors (Overall Period).

	ΔCoVaR		MES		LRMES	
	Stat	*p*-vlaue	Stat	*p*-vlaue	Stat	*p*-vlaue
H_0 : *Banks* ≤ *Realestate*	0.331	0.001	0.296	0.001	0.296	0.001
H_0 : *Insurance* ≤ *Banks*	0.090	0.001	0.098	0.001	0.098	0.001
H_0 : *Insurance* ≤ *Realestate*	0.289	0.001	0.260	0.001	0.260	0.001
H_0 : *DFinancial* ≤ *Insurance*	0.067	0.001	0.060	0.001	0.060	0.001
H_0 : *DFinancial* ≤ *Banks*	0.123	0.001	0.126	0.001	0.126	0.001
H_0 : *DFinancial* ≤ *Realestate*	0.332	0.001	0.301	0.001	0.301	0.001
	SRISK					
	Stat		*p*-vlaue			
H_0 : *Insurance* ≤ *Realestate*	0.856		0.001			
H_0 : *DFinancial* ≤ *Insurance*	0.111		0.001			
H_0 : *DFinancial* ≤ *Realestate*	0.920		0.001			
H_0 : *Banks* ≤ *DFinancial*	0.751		0.001			
H_0 : *Banks* ≤ *Insurance*	0.806		0.001			
H_0 : *Banks* ≤ *Realestate*	0.998		0.001			

Notes: The null hypothesis "*Banks* ≤ *Realestate*" means that the systemic risk measures (MES, SRISK and ΔCoVaR) related to the banking sector are lower (or equal to), in absolute value, than the systemic risk measures (MES, SRISK and ΔCoVaR) related to the real-estate sector. Therefore, the null hypothesis signifies that the banking sector is less or equally systemically risky than the real-estate sector.

riskier than banks, with the real-estate sector being the least SIFI. In contrast, based on SRISK, the banking sector has the highest systemic risk exposure, followed by diversified financials, insurance, and real-estate, respectively.

7. Limitations and future research

While stock returns provide valuable insights into systemic risk dynamics, relying solely on this measure has its limitations. To comprehensively assess systemic risk, it is crucial to consider additional factors that may be less sensitive to short-term fluctuations in stock prices. These factors include CDS spreads, bank-level stress tests, balance sheet data, interconnectedness metrics, and regulatory information (Cont et al., 2013). Incorporating these elements can provide a more robust understanding of the potential vulnerabilities within the financial system.

Deriving a bank's systemic risk indicator exclusively from equity prices may not capture the full extent of its financial health and potential impact on the broader financial system. Although equity prices offer valuable market-based signals, they should be complemented by other solvency-related information. To address this concern, certain systemic risk measures, such as SRISK, integrate additional data beyond equity prices. SRISK utilizes both the market value of equity and the book value of debt to estimate a bank's capital shortfall during a crisis, thus providing a more comprehensive assessment of systemic risk by combining market and balance sheet information. To ensure the relevance and timeliness of these systemic measures, future research should focus on incorporating more frequent data, enabling regulators and market participants to gain a real-time understanding of potential vulnerabilities.

While including data from both public and private financial institutions would undoubtedly enhance the analysis, practical constraints related to data availability pose a challenge. Access to confidential financial information of private financial institutions is limited. However, it is important to acknowledge that the publicly traded European financial institutions included in our analysis represent a significant portion of the overall financial sector, capturing a substantial part of the sector's systemic risk dynamics. Moreover, publicly traded financial institutions often serve as dominant players within the financial system, exhibiting high levels of interconnectedness with other institutions. Their activities and exposures can have significant spillover effects on both public and private financial institutions, making them crucial subjects for systemic risk analysis.

To facilitate a more comprehensive understanding of systemic risk, regulatory bodies and private financial institutions should strive to release more information. The exclusion of non-listed financial institutions has several implications. Firstly, it may fail to capture the full picture of systemic risk within the Eurozone financial system, as these institutions play a significant role in the broader financial ecosystem. Non-listed financial institutions may have different business models, risk profiles, and exposure patterns compared to their publicly traded counterparts, and their exclusion may result in missing important insights into the diversification of systemic risk. Additionally, non-listed financial institutions may be subject to different regulatory frameworks and oversight mechanisms, which could impact their risk management practices and overall contribution to systemic risk. The collective impact of non-listed financial institutions, particularly in terms of their interconnectedness with larger institutions, could be significant and should be taken into account for a comprehensive understanding of systemic risk.

To address the exclusion of non-listed financial institutions, future research could explore alternative data sources and methodologies. This could include using regulatory data, aggregated balance sheet information, or network-based approaches that incorporate information from other financial institutions and market participants. Regulatory bodies could play a role in facilitating a more comprehensive understanding of systemic risk by releasing more frequent and detailed financial information on non-listed financial institutions, albeit with appropriate safeguards for confidentiality. Non-listed financial institutions themselves could contribute to the understanding of systemic risk by voluntarily releasing more frequent and detailed financial information while maintaining appropriate levels of confidentiality. Furthermore, researchers could conduct sensitivity analyses to assess the impact of including or excluding certain non-listed institutions on the overall results, providing a deeper understanding of the potential biases associated with their exclusion. By addressing these implications and exploring potential avenues for incorporating information on non-listed financial institutions, future research can contribute to a more holistic understanding of systemic risk within the Eurozone financial system. Expanding the scope of analysis beyond publicly traded financial institutions and integrating a wider range of data sources will enable policymakers and market participants to make more informed decisions and effectively mitigate potential risks to financial stability.

8. Conclusion and policy recommendations

The lack of a universally accepted academic definition for systemic risk has led to a multitude of interpretations, with a typical definition describing it as a disruption in the functioning of financial services caused by the impairment of all or parts of the financial system, resulting in a negative impact on the real economy. Consequently, the numerous definitions have given rise to a correspondingly large number of systemic risk measures, each focusing on different aspects of the phenomenon. To effectively capture the various facets of systemic risk, it is crucial to apply multiple systemic risk measures simultaneously. As highlighted by Rodríguez-Moreno and Pena (2013), the duration of typical turmoil in the financial system can have multiple causes, making reliance on a single systemic risk measure potentially inappropriate or undesirable. Ellis et al. (2014) echoed this sentiment, arguing that the diversity of the financial system makes it unlikely for a single systemic risk measure or financial stability policy instrument to be universally applicable.

This paper evaluates interconnectedness and systemic risk exposure in the Eurozone financial sector by employing four prominent systemic risk measures: the Granger-causality Network by Billio et al. (2012), Marginal Expected Shortfall (MES) by Acharya et al. (2017), Systemic Risk Index (SRISK) by Acharya et al. (2012) and Brownlees and Engle (2012), and Delta Conditional Value-at-Risk (ΔCoVaR) by Adrian and Brunnermeier (2016). We assess systemic risk exposure at both the union level and the financial sector level (encompassing banking, diversified financials, insurance, and real estate). To facilitate comparisons, we unify the theoretical framework of the three measures. The sample period spans from 2000 to 2015 and is divided into three sub-periods: pre-crisis, crisis, and post-crisis.

By calculating Granger causality network connections for each financial institution within each financial sector in the Eurozone, we find that the Eurozone financial sectors have become increasingly interrelated over the past sixteen years, elevating the risk of systemic events. This finding aligns with the abundant evidence that correlation among financial markets has gained global significance, underscoring the need for mitigating controls. The SRISK definition, which considers market capitalization and liabilities, tends to assign higher systemic risk scores to large institutions, aligning with the "Too Big to Fail" (TBTF) paradigm. In contrast, MES and ΔCoVaR are more attracted to interconnected institutions via the beta and VaR, respectively, which is more closely associated with the "Too Interconnected to Fail" (TITF) paradigm (Markose et al., 2010). Thus, SRISK can be viewed as a compromise between the TBTF paradigm (via liabilities) and the TITF paradigm (via beta).

The empirical analysis, which applies the major systemic risk measures to Eurozone financial institutions, reveals that different systemic risk measures (MES, SRISK, and ΔCoVaR) produce different rankings of SIFIs at both the sector and country levels. This indicates that a single systemic risk measure is insufficient to capture the multidimensional nature of systemic risk. The divergence in systemic risk rankings is not attributable to the instability of a particular measure but rather to their fundamental differences. Consequently, the results of a single systemic risk measure cannot be generalized; instead, there is a need to integrate multiple systemic risk measures within a larger framework to capture the various aspects of systemic risk. The SIFIs rankings derived from macro-prudential measures (ΔCoVaR, MES, and SRISK) reflect similar rankings to those obtained from micro-prudential measures (ES and VaR) and market risk measures (beta, liability, and market capitalization). As a result, a one-factor linear model can explain the majority of the variability in systemic risk estimates, indicating that systemic risk measures fall short in determining the multiple facets of systemic risk.

In the time-series dimension, there is a strong relationship between MES with VaR and ES. The time-varying beta tends to increase during economic downturns, rendering MES procyclical. The empirical ΔCoVaR of a member state (sector) is strongly correlated with its VaR and conditional volatility. Consequently, if a certain member state (sector) aims to minimize its systemic risk score, given that the key driver of the country's MES or ΔCoVaR is the ES or VaR of its index return, the country must reduce the leptokurtosis and/or skewness of its index return distribution. SRISK is highly related to leverage, particularly during relatively distressed periods, and negatively related to market capitalization. The spikes in ES and LRMES are consistent with the spikes in SRISK. In the cross-sectional domain, a strong positive relationship exists between MES and institution beta, indicating that financial institutions' systemic risk rankings based on MES mirror rankings obtained by assigning institutions based on betas. A similar result was discovered for SRISK with liabilities and market capitalization, as well as for ΔCoVaR and conditional correlation.

We develop a dominance test for the empirical results using the bootstrap Kolmogorov-Smirnov test proposed by Abadie (2002). The bootstrap KS stochastic dominance test provides evidence that the ranking of systemic risk exposure is significant, confirming that a certain sector (member state) has a higher systemic risk exposure compared to another sector (member state). The results are consistent for the three systemic risk measures (MES, SRISK, and ΔCoVaR) at the three levels (union, sector, and member state) for all sub-periods (overall, pre-crisis, crisis, and post-crisis).

CRediT authorship contribution statement

Amir Armanious: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization.

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Appendix A. Financial institutions within each financial sector in Eurozone members

Country	Code	Banks	DFinancials	Insurance	Real-estate	Total
Austria	AT	5	2	2	7	**16**
Belgium	BE	2	11	0	15	**28**
Cyprus	CY	3	6	3	4	**16**
Estonia	EE	0	0	0	2	**2**
Finland	FI	1	4	1	4	**10**

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Country	Code	Banks	DFinancials	Insurance	Real-estate	Total
France	FR	20	19	5	24	**68**
Germany	DE	9	40	6	24	**79**
Greece	EL	5	2	1	4	**12**
Ireland	IE	2	1	1	0	**4**
Italy	IT	13	6	4	6	**29**
Luxembourg	LU	0	4	0	0	**4**
Malta	MT	4	0	0	1	**5**
Netherlands	NL	2	5	1	7	**15**
Portugal	PT	3	0	0	0	**3**
Slovakia	SK	1	0	0	0	**1**
Slovenia	SI	0	1	1	0	**2**
Spain	ES	5	4	2	10	**21**
Total		**75**	**105**	**27**	**108**	**315**

Notes: Data is extracted from Bloomberg. This broad classification by sector is categorised according to the Bloomberg GICS Industry Group Name.

Appendix B. Dataset tickers and company names of Eurozone member states

#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
1	Austria	ATRS AV Equity	ATRIUM EUROPEAN	Real Estate Operating Companies	Real Estate
2	Austria	BKUS AV Equity	BKS BANK AG	Diversified Banks	Banks
3	Austria	BTUV AV Equity	BANK FUER TIROL	Diversified Banks	Banks
4	Austria	CAI AV Equity	CA IMMOBILIEN AN	Real Estate Operating Companies	Real Estate
5	Austria	CWI AV Equity	CONWERT IMMOBILI	Real Estate Development	Real Estate
6	Austria	EBS AV Equity	ERSTE GROUP BANK	Diversified Banks	Banks
7	Austria	IIA AV Equity	IMMOFINANZ AG	Real Estate Operating Companies	Real Estate
8	Austria	OBS AV Equity	OBERBANK AG	Diversified Banks	Banks
9	Austria	SPI AV Equity	S IMMO AG	Real Estate Operating Companies	Real Estate
10	Austria	STM AV Equity	STADLAUER MALZFA	Real Estate Operating Companies	Real Estate
11	Austria	UBS AV Equity	UBM REALITAETEN	Diversified Real Estate Activities	Real Estate
12	Austria	UIV AV Equity	UNTERNEHMENS INV	Asset Management & Custody Banks	Diversified Financials
13	Austria	UQA AV Equity	UNIQA INSURANCE	Multi-line Insurance	Insurance
14	Austria	VIG AV Equity	VIENNA INSURANCE	Multi-line Insurance	Insurance
15	Austria	VVPS AV Equity	VOLKSBANK VORARL	Diversified Banks	Banks
16	Austria	WPB AV Equity	WIENER PRIVATBAN	Investment Banking & Brokerage	Diversified Financials
17	Belgium	ACKB BB Equity	ACKERMANS & VAN	Multi-Sector Holdings	Diversified Financials
18	Belgium	ATEB BB Equity	ATENOR GROUP	Real Estate Operating Companies	Real Estate
19	Belgium	BEFB BB Equity	BEFIMMO	Office REITs	Real Estate
20	Belgium	BELR BB Equity	BELRECA	Diversified Real Estate Activities	Real Estate
21	Belgium	BELU BB Equity	BELUGA	Asset Management & Custody Banks	Diversified Financials
22	Belgium	BNB BB Equity	BANQ NATL BELGIQ	Specialized Finance	Diversified Financials
23	Belgium	BREB BB Equity	BREDERODE	Asset Management & Custody Banks	Diversified Financials
24	Belgium	COFB BB Equity	COFINIMMO	Diversified REITs	Real Estate
25	Belgium	COMB BB Equity	CIE BOIS SAUVAGE	Multi-Sector Holdings	Diversified Financials
26	Belgium	CPINV BB Equity	CARE PROPERTY IN	Residential REITs	Real Estate
27	Belgium	DEXB BB Equity	DEXIA SA	Diversified Banks	Banks
28	Belgium	GBLB BB Equity	GROUPE BRUX LAMB	Multi-Sector Holdings	Diversified Financials
29	Belgium	GIMB BB Equity	GIMV NV	Asset Management & Custody Banks	Diversified Financials
30	Belgium	HOMI BB Equity	HOME INVEST BELG	Residential REITs	Real Estate
31	Belgium	IMMO BB Equity	IMMOBEL	Real Estate Development	Real Estate
32	Belgium	INTO BB Equity	INTERVEST OFFICE	Office REITs	Real Estate
33	Belgium	KBC BB Equity	KBC GROEP	Diversified Banks	Banks
34	Belgium	KBCA BB Equity	KBC ANCORA	Other Diversified Financial Services	Diversified Financials
35	Belgium	LEAS BB Equity	LEASINVEST	Office REITs	Real Estate
36	Belgium	QFG BB Equity	QUESTFOR GR-PRIC	Asset Management & Custody Banks	Diversified Financials
37	Belgium	RET BB Equity	RETAIL ESTATES	Retail REITs	Real Estate
38	Belgium	SOF BB Equity	SOFINA	Multi-Sector Holdings	Diversified Financials
39	Belgium	SOFT BB Equity	SOFTIMAT	Real Estate Operating Companies	Real Estate
40	Belgium	TUB BB Equity	FINANCIERE DE TU	Asset Management & Custody Banks	Diversified Financials
41	Belgium	VASTB BB Equity	VASTNED RETAIL B	Retail REITs	Real Estate
42	Belgium	WDP BB Equity	WAREHOUSES DE PA	Industrial REITs	Real Estate
43	Belgium	WEB BB Equity	WEB SCA	Diversified REITs	Real Estate
44	Belgium	WEHB BB Equity	WERELDHAVE BELGM	Retail REITs	Real Estate
45	Cyprus	AIAS CY Equity	AIANTAS INVESTME	Asset Management & Custody Banks	Diversified Financials
46	Cyprus	ATL CY Equity	ATLANTIC INSURAN	Multi-line Insurance	Insurance
47	Cyprus	BOCY CY Equity	BANK OF CYPRUS	Diversified Banks	Banks
48	Cyprus	DEM CY Equity	DEMETRA INVESTME	Asset Management & Custody Banks	Diversified Financials
49	Cyprus	ELF CY Equity	ELLINAS FINANCE	Specialized Finance	Diversified Financials
50	Cyprus	EXE CY Equity	CYVENTURE CAPITA	Asset Management & Custody Banks	Diversified Financials
51	Cyprus	FWW CY Equity	WOOLWORTH CYPRUS	Diversified Real Estate Activities	Real Estate
52	Cyprus	HB CY Equity	HELLENIC BANK PU	Diversified Banks	Banks
53	Cyprus	KG CY Equity	K+G COMPLEX PCL	Diversified Real Estate Activities	Real Estate
54	Cyprus	LI CY Equity	LAIKI CAPITAL PC	Investment Banking & Brokerage	Diversified Financials
55	Cyprus	LIB CY Equity	LIBERTY LIFE INS	Multi-line Insurance	Insurance

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#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
56	Cyprus	MINE CY Equity	MINERVA INSURANC	Multi-line Insurance	Insurance
57	Cyprus	PES CY Equity	PHILOKTIMATIKI	Diversified Real Estate Activities	Real Estate
58	Cyprus	PND CY Equity	PANDORA INVE LTD	Real Estate Development	Real Estate
59	Cyprus	SFS CY Equity	SFS GROUP	Investment Banking & Brokerage	Diversified Financials
60	Cyprus	USB CY Equity	USB BANK PLC	Regional Banks	Banks
61	Estonia	PKG1T ET Equity	PRO KAPITAL GRUP	Real Estate Development	Real Estate
62	Estonia	TPD1T ET Equity	AS TRIGON PROPER	Real Estate Operating Companies	Real Estate
63	Finland	ALBAV FH Equity	ALANDSBANKEN-A	Diversified Banks	Banks
64	Finland	CPMBV FH Equity	CAPMAN OYJ-B SHS	Asset Management & Custody Banks	Diversified Financials
65	Finland	CTY1S FH Equity	CITYCON OYJ	Real Estate Operating Companies	Real Estate
66	Finland	EQV1V FH Equity	EQ OYJ	Asset Management & Custody Banks	Diversified Financials
67	Finland	NORVE FH Equity	NORVESTIA OYJ-B	Asset Management & Custody Banks	Diversified Financials
68	Finland	SAMAS FH Equity	SAMPO OYJ-A SHS	Multi-line Insurance	Insurance
69	Finland	SCI1V FH Equity	SIEVI CAPITAL PL	Asset Management & Custody Banks	Diversified Financials
70	Finland	SDA1V FH Equity	SPONDA OYJ	Real Estate Operating Companies	Real Estate
71	Finland	INVEST FH Equity	SUOMEN SAASTAJIE	Real Estate Operating Companies	Real Estate
72	Finland	TPS1V FH Equity	TECHNOPOLIS OYJ	Real Estate Operating Companies	Real Estate
73	France	ABCA FP Equity	ABC ARBITRAGE	Specialized Finance	Diversified Financials
74	France	ACA FP Equity	CREDIT AGRICOLE	Diversified Banks	Banks
75	France	ALGIS FP Equity	GLOBAL INVESTMEN	Asset Management & Custody Banks	Diversified Financials
76	France	ALIDS FP Equity	IDSUD	Asset Management & Custody Banks	Diversified Financials
77	France	ALSAS FP Equity	STRADIM ESPACE	Real Estate Development	Real Estate
78	France	ALSIP FP Equity	SI PARTICIPATION	Asset Management & Custody Banks	Diversified Financials
79	France	ALTA FP Equity	ALTAREA	Retail REITs	Real Estate
80	France	APR FP Equity	APRIL	Insurance Brokers	Insurance
81	France	AREIT FP Equity	ALTAREIT	Diversified Real Estate Activities	Real Estate
82	France	ARTO FP Equity	ARTOIS (IND FIN)	Multi-Sector Holdings	Diversified Financials
83	France	BERR FP Equity	FIN ETANG BERRE	Diversified Real Estate Activities	Real Estate
84	France	BNP FP Equity	BNP PARIBAS	Diversified Banks	Banks
85	France	BQRE FP Equity	BANQUE REUNION	Regional Banks	Banks
86	France	CAF FP Equity	CR DE CA IDF	Regional Banks	Banks
87	France	CAT31 FP Equity	CREDIT AGRICOLE	Regional Banks	Banks
88	France	CC FP Equity	CIC	Diversified Banks	Banks
89	France	CCN FP Equity	CA NORMANDIE SEI	Regional Banks	Banks
90	France	CIV FP Equity	CA ILLE ET VILAI	Regional Banks	Banks
91	France	CMO FP Equity	CREDIT AGR MORBI	Regional Banks	Banks
92	France	CNF FP Equity	CA NORD DE FRANC	Regional Banks	Banks
93	France	CNP FP Equity	CNP ASSURANCES	Life & Health Insurance	Insurance
94	France	COUR FP Equity	COURTOIS-R	Real Estate Development	Real Estate
95	France	CRAP FP Equity	CA ALPES PROVENC	Regional Banks	Banks
96	France	CRAV FP Equity	CA ATLANTIQUE VE	Regional Banks	Banks
97	France	CRLO FP Equity	CA LOIRE-HAUTE-L	Regional Banks	Banks
98	France	CRSU FP Equity	CA SUD RHONE ALP	Regional Banks	Banks
99	France	CRTO FP Equity	CA TOURAINE POIT	Regional Banks	Banks
100	France	CS FP Equity	AXA	Multi-line Insurance	Insurance
101	France	DP FP Equity	IRD NORD CALAIS	Diversified Real Estate Activities	Real Estate
102	France	EEM FP Equity	ELEC & EAUX MADA	Real Estate Operating Companies	Real Estate
103	France	EIFF FP Equity	TOUR EIFFEL	Office REITs	Real Estate
104	France	ELE FP Equity	EULER HERMES GRO	Property & Casualty Insurance	Insurance
105	France	FDL FP Equity	FDL	Residential REITs	Real Estate
106	France	FDPA FP Equity	FONCIERE DE PARI	Real Estate Operating Companies	Real Estate
107	France	FDR FP Equity	FONCIERE DES REG	Diversified REITs	Real Estate
108	France	FFP FP Equity	FFP	Multi-Sector Holdings	Diversified Financials
109	France	FLY FP Equity	FONCIERE LYONN	Office REITs	Real Estate
110	France	FMU FP Equity	FONCIERE DES MUR	Hotel & Resort REITs	Real Estate
111	France	GFC FP Equity	GECINA SA	Diversified REITs	Real Estate
112	France	GLE FP Equity	SOC GENERALE SA	Diversified Banks	Banks
113	France	ICAD FP Equity	ICADE	Diversified REITs	Real Estate
114	France	IDIP FP Equity	IDI	Asset Management & Custody Banks	Diversified Financials
115	France	IMDA FP Equity	IMMOBIL DASSAULT	Diversified REITs	Real Estate
116	France	IML FP Equity	AFFINE	Diversified REITs	Real Estate
117	France	KN FP Equity	NATIXIS	Diversified Banks	Banks
118	France	LBON FP Equity	LEBON	Asset Management & Custody Banks	Diversified Financials
119	France	LD FP Equity	LOCINDUS	Thrifts & Mortgage Finance	Banks
120	France	LI FP Equity	KLEPIERRE	Retail REITs	Real Estate
121	France	LTA FP Equity	ALTAMIR	Asset Management & Custody Banks	Diversified Financials
122	France	MF FP Equity	WENDEL	Multi-Sector Holdings	Diversified Financials
123	France	MLCFM FP Equity	CFM	Diversified Banks	Banks
124	France	MLCVG FP Equity	TRAMWAYS VAR GAR	Asset Management & Custody Banks	Diversified Financials
125	France	MLFMM FP Equity	MARTIN MAUREL SA	Diversified Banks	Banks
126	France	MLMAB FP Equity	BAUD (ANTOINE)	Real Estate Operating Companies	Real Estate
127	France	MONC FP Equity	MONCEY FINANCIER	Multi-Sector Holdings	Diversified Financials
128	France	MRM FP Equity	M.R.M.	Diversified REITs	Real Estate
129	France	ORC FP Equity	ORCO PROPERTY GR	Diversified Real Estate Activities	Real Estate
130	France	ORIA FP Equity	FIDUCIAL REAL ES	Real Estate Operating Companies	Real Estate
131	France	PAOR FP Equity	PARIS ORLEANS	Diversified Capital Markets	Diversified Financials

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#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
132	France	RF FP Equity	EURAZEO	Multi-Sector Holdings	Diversified Financials
133	France	SCDU FP Equity	SCHAEFFER-DUFOUR	Asset Management & Custody Banks	Diversified Financials
134	France	SCR FP Equity	SCOR SE	Reinsurance	Insurance
135	France	SFBS FP Equity	SOFIBUS PATRIMOI	Real Estate Operating Companies	Real Estate
136	France	SOFR FP Equity	SOFRAGI	Asset Management & Custody Banks	Diversified Financials
137	France	SPEL FP Equity	FONCIERE VOLTA	Real Estate Operating Companies	Real Estate
138	France	SY FP Equity	SALVEPAR	Multi-Sector Holdings	Diversified Financials
139	France	UFF FP Equity	UNION FIN FRANCE	Asset Management & Custody Banks	Diversified Financials
140	France	VIL FP Equity	VIEL ET COMPAGNI	Investment Banking & Brokerage	Diversified Financials
141	Germany	AAA GR Equity	AAA-AG ALLGEM AN	Real Estate Operating Companies	Real Estate
142	Germany	ABHA GR Equity	HASEN-BRAEU AG	Real Estate Operating Companies	Real Estate
143	Germany	ADC GR Equity	ADCAPITAL AG	Asset Management & Custody Banks	Diversified Financials
144	Germany	ADL GR Equity	ADLER REAL EST	Real Estate Development	Real Estate
145	Germany	AGR GR Equity	AGROB IMMOBILIEN	Real Estate Operating Companies	Real Estate
146	Germany	ALG GR Equity	ALBIS LEAS. AG G	Specialized Finance	Diversified Financials
147	Germany	ALV GR Equity	ALLIANZ SE-VINK	Multi-line Insurance	Insurance
148	Germany	ARL GR Equity	AAREAL BANK AG	Thrifts & Mortgage Finance	Banks
149	Germany	ATW GR Equity	ALLERTHAL-WERKE	Asset Management & Custody Banks	Diversified Financials
150	Germany	BBH GR Equity	DEUTSCHE BALATON	Asset Management & Custody Banks	Diversified Financials
151	Germany	BBI GR Equity	BBI BUERGERLICHE	Real Estate Operating Companies	Real Estate
152	Germany	BBR GR Equity	BUERGER RAVENSB	Real Estate Operating Companies	Real Estate
153	Germany	BFK GR Equity	BASTFASERKONTOR	Real Estate Operating Companies	Real Estate
154	Germany	BFV GR Equity	BERLINER EFFEKTE	Investment Banking & Brokerage	Diversified Financials
155	Germany	BTBA GR Equity	BMP MEDIA INVEST	Asset Management & Custody Banks	Diversified Financials
156	Germany	BWB GR Equity	BAADER BANK	Investment Banking & Brokerage	Diversified Financials
157	Germany	CBK GR Equity	COMMERZBANK	Diversified Banks	Banks
158	Germany	CCB GR Equity	TIBERIUS HOLDING	Asset Management & Custody Banks	Diversified Financials
159	Germany	CMBT GR Equity	ATEVIA AG	Asset Management & Custody Banks	Diversified Financials
160	Germany	COM GR Equity	COMDIRECT BANK	Diversified Banks	Banks
161	Germany	DAL GR Equity	DAHLBUSCH AG	Real Estate Operating Companies	Real Estate
162	Germany	DB1 GR Equity	DEUTSCHE BOERSE	Specialized Finance	Diversified Financials
163	Germany	DBAN GR Equity	DEUTSCHE BETEILI	Asset Management & Custody Banks	Diversified Financials
164	Germany	DBK GR Equity	DEUTSCHE BANK-RG	Diversified Capital Markets	Diversified Financials
165	Germany	DEQ GR Equity	DEUTSCHE EUROSHO	Real Estate Operating Companies	Real Estate
166	Germany	DGR GR Equity	DEUTSCHE GRUNDST	Real Estate Services	Real Estate
167	Germany	DIC GR Equity	DIC ASSET AG	Diversified Real Estate Activities	Real Estate
168	Germany	DLB GR Equity	DLB ANLAGESERVIC	Asset Management & Custody Banks	Diversified Financials
169	Germany	DRN GR Equity	DAB BANK AG	Investment Banking & Brokerage	Diversified Financials
170	Germany	DVB GR Equity	DVB BANK SE	Diversified Banks	Banks
171	Germany	EFF GR Equity	DEUTSCHE EFFECTE	Asset Management & Custody Banks	Diversified Financials
172	Germany	EFS GR Equity	EFFECTEN-SPIEGEL	Asset Management & Custody Banks	Diversified Financials
173	Germany	EUX GR Equity	EUWAX AG	Investment Banking & Brokerage	Diversified Financials
174	Germany	FAK GR Equity	FALKENSTEIN	Asset Management & Custody Banks	Diversified Financials
175	Germany	FRS GR Equity	FORIS AG	Specialized Finance	Diversified Financials
176	Germany	GBQ GR Equity	GBK BETEILIGUNGE	Asset Management & Custody Banks	Diversified Financials
177	Germany	GLJ GR Equity	GRENKELEASING AG	Specialized Finance	Diversified Financials
178	Germany	GWK3 GR Equity	GAG IMMOBILIEN A	Real Estate Operating Companies	Real Estate
179	Germany	HAB GR Equity	HAMBORNER REIT	Diversified REITs	Real Estate
180	Germany	HGL GR Equity	HAMBURG GETREIDE	Asset Management & Custody Banks	Diversified Financials
181	Germany	HNR1 GR Equity	HANNOVER RUECK S	Reinsurance	Insurance
182	Germany	HRU GR Equity	HORUS AG	Asset Management & Custody Banks	Diversified Financials
183	Germany	IKB GR Equity	IKB DEUT INDBANK	Diversified Banks	Banks
184	Germany	IPO GR Equity	HEIDELBERGER BET	Specialized Finance	Diversified Financials
185	Germany	KBU GR Equity	COLONIA REAL EST	Real Estate Operating Companies	Real Estate
186	Germany	KSW GR Equity	KST BETEILIGUNGS	Asset Management & Custody Banks	Diversified Financials
187	Germany	LBN GR Equity	NYMPHENBURG IMM	Real Estate Operating Companies	Real Estate
188	Germany	LBR GR Equity	CUSTODIA HLDG	Real Estate Operating Companies	Real Estate
189	Germany	MBK GR Equity	MERKUR BANK KGAA	Diversified Banks	Banks
190	Germany	MLP GR Equity	MLP AG	Asset Management & Custody Banks	Diversified Financials
191	Germany	MPCK GR Equity	MPC CAPITAL AG	Asset Management & Custody Banks	Diversified Financials
192	Germany	MUK GR Equity	BAYERISCHE GEWER	Real Estate Operating Companies	Real Estate
193	Germany	MUV2 GR Equity	MUENCHENER RUE-R	Reinsurance	Insurance
194	Germany	MWB GR Equity	MWB FAIRTRADE	Investment Banking & Brokerage	Diversified Financials
195	Germany	NBG6 GR Equity	NUERNB BETEI 'B'	Multi-line Insurance	Insurance
196	Germany	OLB GR Equity	OLDENBURG LANDES	Regional Banks	Banks
197	Germany	ICP GR Equity	PANAMAX AG	Asset Management & Custody Banks	Diversified Financials
198	Germany	PEH GR Equity	PEH WERTPAPIER	Asset Management & Custody Banks	Diversified Financials
199	Germany	PPZ GR Equity	POMMER PROV ZUCK	Asset Management & Custody Banks	Diversified Financials
200	Germany	RLV GR Equity	RHEINLAND HLDG	Multi-line Insurance	Insurance
201	Germany	RMO GR Equity	RM RHEINER MANAG	Asset Management & Custody Banks	Diversified Financials
202	Germany	SGB GR Equity	SCHLOSSGARTENBAU	Real Estate Operating Companies	Real Estate
203	Germany	SIN GR Equity	SINNER AG	Real Estate Operating Companies	Real Estate
204	Germany	SMWN GR Equity	SM WIRTSCHAFTSBE	Real Estate Operating Companies	Real Estate
205	Germany	SPB GR Equity	SEDLMAYR GRUND	Real Estate Operating Companies	Real Estate
206	Germany	SPT6 GR Equity	SPARTA AG	Asset Management & Custody Banks	Diversified Financials
207	Germany	SPZI GR Equity	MISTRAL MEDI-REG	Asset Management & Custody Banks	Diversified Financials

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#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
208	Germany	STG GR Equity	STINAG STUTTGART	Real Estate Operating Companies	Real Estate
209	Germany	SVE GR Equity	SHAREHOLDER VALU	Asset Management & Custody Banks	Diversified Financials
210	Germany	TEG GR Equity	TAG IMMOBILIEN	Real Estate Development	Real Estate
211	Germany	TUB GR Equity	HSBC TRINKAUS &	Diversified Banks	Banks
212	Germany	UBK GR Equity	UMWELTBANK AG	Diversified Banks	Banks
213	Germany	UCA1 GR Equity	U.C.A. AG	Asset Management & Custody Banks	Diversified Financials
214	Germany	VEH GR Equity	VALORA EFFEKTEN	Investment Banking & Brokerage	Diversified Financials
215	Germany	VHO GR Equity	VALUE HOLDINGS	Asset Management & Custody Banks	Diversified Financials
216	Germany	VVV3 GR Equity	OKOWORLD AG	Other Diversified Financial Services	Diversified Financials
217	Germany	WEG1 GR Equity	WESTGRUND AG	Diversified Real Estate Activities	Real Estate
218	Germany	WLV GR Equity	WUERTTEMBERG LEB	Life & Health Insurance	Insurance
219	Germany	WUW GR Equity	WUESTENROT & WUE	Other Diversified Financial Services	Diversified Financials
220	Greece	ALPHA GA Equity	ALPHA BANK A.E.	Diversified Banks	Banks
221	Greece	ASTAK GA Equity	ALPHA ASTIKA AKI	Real Estate Services	Real Estate
222	Greece	ETE GA Equity	NATL BANK GREECE	Diversified Banks	Banks
223	Greece	EUPIC GA Equity	EUROPEAN RELIANC	Life & Health Insurance	Insurance
224	Greece	EUROB GA Equity	EUROBANK ERGASIA	Diversified Banks	Banks
225	Greece	EXAE GA Equity	HELLENIC EXCHANG	Specialized Finance	Diversified Financials
226	Greece	KAMP GA Equity	REDS SA	Diversified Real Estate Activities	Real Estate
227	Greece	KEKR GA Equity	KEKROPS	Real Estate Development	Real Estate
228	Greece	LAMDA GA Equity	LAMDA DEVELOPMEN	Diversified Real Estate Activities	Real Estate
229	Greece	TATT GA Equity	ATTICA BANK SA	Diversified Banks	Banks
230	Greece	TELL GA Equity	BANK GREECE	Specialized Finance	Diversified Financials
231	Greece	TPEIR GA Equity	PIRAEUS BANK	Diversified Banks	Banks
232	Ireland	ALBK ID Equity	ALLIED IRISH BK	Diversified Banks	Banks
233	Ireland	BKIR ID Equity	BANK IRELAND	Diversified Banks	Banks
234	Ireland	FBD ID Equity	FBD HOLDINGS PLC	Multi-line Insurance	Insurance
235	Ireland	IFP ID Equity	IFG GROUP PLC	Other Diversified Financial Services	Diversified Financials
236	Italy	AE IM Equity	AEDES SPA	Diversified Real Estate Activities	Real Estate
237	Italy	BDB IM Equity	BANCO DESIO	Diversified Banks	Banks
238	Italy	BIM IM Equity	BANCA INTERMOBIL	Investment Banking & Brokerage	Diversified Financials
239	Italy	BMPS IM Equity	BANCA MONTE DEI	Diversified Banks	Banks
240	Italy	BNS IM Equity	BENI STABILI SPA	Office REITs	Real Estate
241	Italy	BPE IM Equity	BANCA POP EMILIA	Diversified Banks	Banks
242	Italy	BPSO IM Equity	BANCA POP SONDRI	Diversified Banks	Banks
243	Italy	BRI IM Equity	BRIOSCHI	Diversified Real Estate Activities	Real Estate
244	Italy	BSRP IM Equity	BANCO SARDEG-RSP	Regional Banks	Banks
245	Italy	CASS IM Equity	CATTOLICA ASSIC	Life & Health Insurance	Insurance
246	Italy	CE IM Equity	CREDITO EMILIANO	Diversified Banks	Banks
247	Italy	CRG IM Equity	BANCA CARIGE	Diversified Banks	Banks
248	Italy	CVAL IM Equity	CREDITO VALTELLI	Regional Banks	Banks
249	Italy	DEA IM Equity	DEA CAPITAL SPA	Asset Management & Custody Banks	Diversified Financials
250	Italy	G IM Equity	GENERALI ASSIC	Multi-line Insurance	Insurance
251	Italy	GAB IM Equity	GABETTI PROPERTY	Diversified Real Estate Activities	Real Estate
252	Italy	IF IM Equity	BANCA IFIS SPA	Specialized Finance	Diversified Financials
253	Italy	ISP IM Equity	INTESA SANPAOLO	Diversified Banks	Banks
254	Italy	LVEN IM Equity	LVENTURE GROUP	Asset Management & Custody Banks	Diversified Financials
255	Italy	MB IM Equity	MEDIOBANCA	Investment Banking & Brokerage	Diversified Financials
256	Italy	NR IM Equity	NOVA RE	Diversified Real Estate Activities	Real Estate
257	Italy	PEL IM Equity	BANCA POP ETRURI	Regional Banks	Banks
258	Italy	PMI IM Equity	BANCA POP MILANO	Diversified Banks	Banks
259	Italy	PRO IM Equity	BANCA PROFILO	Investment Banking & Brokerage	Diversified Financials
260	Italy	RN IM Equity	RISANAMENTO SPA	Diversified Real Estate Activities	Real Estate
261	Italy	UBI IM Equity	UBI BANCA SCPA	Diversified Banks	Banks
262	Italy	UCG IM Equity	UNICREDIT SPA	Diversified Banks	Banks
263	Italy	UNI IM Equity	UNIPOL GRUPPO FI	Multi-line Insurance	Insurance
264	Italy	VAS IM Equity	VITTORIA ASSIC	Multi-line Insurance	Insurance
265	Luxembourg	COFI LX Equity	COFI	Asset Management & Custody Banks	Diversified Financials
266	Luxembourg	INSIN LX Equity	IDB HOLDINGS S.A	Investment Banking & Brokerage	Diversified Financials
267	Luxembourg	LXMP LX Equity	LUXEMPART SA	Asset Management & Custody Banks	Diversified Financials
268	Luxembourg	QUIL LX Equity	QUILVEST SA	Asset Management & Custody Banks	Diversified Financials
269	Malta	BOV MV Equity	BANK VALLETTA	Diversified Banks	Banks
270	Malta	FIM MV Equity	FIMBANK PLC	Diversified Banks	Banks
271	Malta	HSB MV Equity	HSBC BANK MALTA	Diversified Banks	Banks
272	Malta	LOM MV Equity	LOMBARD BANK MAL	Regional Banks	Banks
273	Malta	PZC MV Equity	PLAZA CENTERS	Real Estate Operating Companies	Real Estate
274	Netherlands	AGN NA Equity	AEGON NV	Life & Health Insurance	Insurance
275	Netherlands	BEVER NA Equity	BEVER HOLDING	Diversified Real Estate Activities	Real Estate
276	Netherlands	BINCK NA Equity	BINCKBANK NV	Investment Banking & Brokerage	Diversified Financials
277	Netherlands	CORA NA Equity	CORIO NV	Retail REITs	Real Estate
278	Netherlands	ECMPA NA Equity	EUROCOMMERCI-CVA	Retail REITs	Real Estate
279	Netherlands	GROHA NA Equity	GROOTHANDELS	Real Estate Operating Companies	Real Estate
280	Netherlands	HAL NA Equity	HAL TRUST	Multi-Sector Holdings	Diversified Financials
281	Netherlands	INGA NA Equity	ING GROEP NV	Diversified Banks	Banks
282	Netherlands	KA NA Equity	KAS BANK NV-CVA	Asset Management & Custody Banks	Diversified Financials
283	Netherlands	KARD NA Equity	KARDAN NV	Multi-Sector Holdings	Diversified Financials

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#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
284	Netherlands	LANS NA Equity	VAN LANSCHOT-CVA	Diversified Banks	Banks
285	Netherlands	NSI NA Equity	NSI NV	Diversified REITs	Real Estate
286	Netherlands	VALUE NA Equity	VALUE8 NV	Asset Management & Custody Banks	Diversified Financials
287	Netherlands	VASTN NA Equity	VASTNED RETAIL N	Retail REITs	Real Estate
288	Netherlands	WHA NA Equity	WERELDHAVE NV	Diversified REITs	Real Estate
289	Portugal	BCP PL Equity	BANCO COM PORT-R	Diversified Banks	Banks
290	Portugal	BPI PL Equity	BANCO BPI SA-REG	Diversified Banks	Banks
291	Portugal	ESF PL Equity	ESPIRITO SANTO	Diversified Banks	Banks
292	Slovakia	VUB SK Equity	VUB AS	Diversified Banks	Banks
293	Slovenia	KDHR SV Equity	KMECKA DRUZBA	Property & Casualty Insurance	Insurance
294	Slovenia	NIKN SV Equity	NIKA INVESTIRANJ	Other Diversified Financial Services	Diversified Financials
295	Spain	ALB SM Equity	ALBA	Multi-Sector Holdings	Diversified Financials
296	Spain	BBVA SM Equity	BBVA	Diversified Banks	Banks
297	Spain	BKT SM Equity	BANKINTER	Diversified Banks	Banks
298	Spain	CEV SM Equity	CEVASA SA-	Real Estate Operating Companies	Real Estate
299	Spain	CGI SM Equity	GEN DE INVERSION	Asset Management & Custody Banks	Diversified Financials
300	Spain	COL SM Equity	INMOBILIARIA COL	Real Estate Operating Companies	Real Estate
301	Spain	FICIS SM Equity	FINANZAS E INVER	Real Estate Operating Companies	Real Estate
302	Spain	GCO SM Equity	CATALANA OCC	Multi-line Insurance	Insurance
303	Spain	ILV SM Equity	INMOLEVANTE SA	Real Estate Development	Real Estate
304	Spain	LIB SM Equity	LIBERTAS SIETE	Real Estate Operating Companies	Real Estate
305	Spain	MAP SM Equity	MAPFRE SA	Multi-line Insurance	Insurance
306	Spain	MTB SM Equity	MONTEBALITO SA	Diversified Real Estate Activities	Real Estate
307	Spain	POP SM Equity	BANCO POPULAR	Diversified Banks	Banks
308	Spain	QBT SM Equity	QUABIT INMOBILIA	Diversified Real Estate Activities	Real Estate
309	Spain	REA SM Equity	CARTERA INDUSTRI	Asset Management & Custody Banks	Diversified Financials
310	Spain	SAB SM Equity	BANCO SABADELL	Diversified Banks	Banks
311	Spain	SAN SM Equity	BANCO SANTANDER	Diversified Banks	Banks
312	Spain	STG SM Equity	SOTOGRANDE	Diversified Real Estate Activities	Real Estate
313	Spain	TST SM Equity	TESTA INMUEBLES	Real Estate Operating Companies	Real Estate
314	Spain	UBS SM Equity	URBAS GRUPO FINA	Real Estate Development	Real Estate
315	Spain	UEI SM Equity	UNION EUROPEA IN	Asset Management & Custody Banks	Diversified Financials

Appendix C. Number of granger causality connections of each Eurozone financial institution (Pre-Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	63
2	BTUV AV Equity	Banks	Austria	24
3	EBS AV Equity	Banks	Austria	42
4	OBS AV Equity	Banks	Austria	39
5	VVPS AV Equity	Banks	Austria	56
6	DEXB BB Equity	Banks	Belgium	55
7	KBC BB Equity	Banks	Belgium	73
8	BOCY CY Equity	Banks	Cyprus	114
9	HB CY Equity	Banks	Cyprus	92
10	USB CY Equity	Banks	Cyprus	16
11	ALBAV FH Equity	Banks	Finland	14
12	ACA FP Equity	Banks	France	66
13	BNP FP Equity	Banks	France	73
14	BQRE FP Equity	Banks	France	18
15	CAF FP Equity	Banks	France	16
16	CAT31 FP Equity	Banks	France	18
17	CC FP Equity	Banks	France	38
18	CCN FP Equity	Banks	France	26
19	CIV FP Equity	Banks	France	27
20	CMO FP Equity	Banks	France	22
21	CNF FP Equity	Banks	France	46
22	CRAP FP Equity	Banks	France	22
23	CRAV FP Equity	Banks	France	19
24	CRLO FP Equity	Banks	France	24
25	CRSU FP Equity	Banks	France	17
26	CRTO FP Equity	Banks	France	32
27	GLE FP Equity	Banks	France	87
28	KN FP Equity	Banks	France	78
29	LD FP Equity	Banks	France	29
30	MLCFM FP Equity	Banks	France	15
31	MLFMM FP Equity	Banks	France	23
32	ARL GR Equity	Banks	Germany	39
33	CBK GR Equity	Banks	Germany	116
34	COM GR Equity	Banks	Germany	77
35	DVB GR Equity	Banks	Germany	35
36	IKB GR Equity	Banks	Germany	72

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#	Ticker	Sector	Country	# of Connections
37	MBK GR Equity	Banks	Germany	39
38	OLB GR Equity	Banks	Germany	66
39	TUB GR Equity	Banks	Germany	23
40	UBK GR Equity	Banks	Germany	39
41	ALPHA GA Equity	Banks	Greece	37
42	ETE GA Equity	Banks	Greece	51
43	EUROB GA Equity	Banks	Greece	50
44	TATT GA Equity	Banks	Greece	37
45	TPEIR GA Equity	Banks	Greece	60
46	ALBK ID Equity	Banks	Ireland	65
47	BKIR ID Equity	Banks	Ireland	68
48	BDB IM Equity	Banks	Italy	71
49	BMPS IM Equity	Banks	Italy	79
50	BPE IM Equity	Banks	Italy	36
51	BPSO IM Equity	Banks	Italy	40
52	BSRP IM Equity	Banks	Italy	53
53	CE IM Equity	Banks	Italy	58
54	CRG IM Equity	Banks	Italy	50
55	CVAL IM Equity	Banks	Italy	54
56	ISP IM Equity	Banks	Italy	65
57	PEL IM Equity	Banks	Italy	90
58	PMI IM Equity	Banks	Italy	37
59	UBI IM Equity	Banks	Italy	76
60	UCG IM Equity	Banks	Italy	49
61	BOV MV Equity	Banks	Malta	25
62	FIM MV Equity	Banks	Malta	35
63	HSB MV Equity	Banks	Malta	30
64	LOM MV Equity	Banks	Malta	37
65	INGA NA Equity	Banks	Netherlands	85
66	LANS NA Equity	Banks	Netherlands	44
67	BCP PL Equity	Banks	Portugal	57
68	BPI PL Equity	Banks	Portugal	58
69	ESF PL Equity	Banks	Portugal	37
70	VUB SK Equity	Banks	Slovakia	14
71	BBVA SM Equity	Banks	Spain	97
72	BKT SM Equity	Banks	Spain	80
73	POP SM Equity	Banks	Spain	125
74	SAB SM Equity	Banks	Spain	86
75	SAN SM Equity	Banks	Spain	81
76	UIV AV Equity	Financial	Austria	24
77	WPB AV Equity	Financial	Austria	39
78	ACKB BB Equity	Financial	Belgium	31
79	BELU BB Equity	Financial	Belgium	30
80	BNB BB Equity	Financial	Belgium	25
81	BREB BB Equity	Financial	Belgium	31
82	COMB BB Equity	Financial	Belgium	26
83	GBLB BB Equity	Financial	Belgium	99
84	GIMB BB Equity	Financial	Belgium	38
85	KBCA BB Equity	Financial	Belgium	50
86	QFG BB Equity	Financial	Belgium	26
87	SOF BB Equity	Financial	Belgium	52
88	TUB BB Equity	Financial	Belgium	29
89	AIAS CY Equity	Financial	Cyprus	30
90	DEM CY Equity	Financial	Cyprus	50
91	ELF CY Equity	Financial	Cyprus	24
92	EXE CY Equity	Financial	Cyprus	36
93	LI CY Equity	Financial	Cyprus	48
94	SFS CY Equity	Financial	Cyprus	58
95	CPMBV FH Equity	Financial	Finland	42
96	EQV1V FH Equity	Financial	Finland	41
97	NORVE FH Equity	Financial	Finland	34
98	SCI1V FH Equity	Financial	Finland	21
99	ABCA FP Equity	Financial	France	27
100	ALGIS FP Equity	Financial	France	22
101	ALIDS FP Equity	Financial	France	26
102	ALSIP FP Equity	Financial	France	50
103	ARTO FP Equity	Financial	France	27
104	FFP FP Equity	Financial	France	57
105	IDIP FP Equity	Financial	France	44
106	LBON FP Equity	Financial	France	18
107	LTA FP Equity	Financial	France	30
108	MF FP Equity	Financial	France	76
109	MLCVG FP Equity	Financial	France	21
110	MONC FP Equity	Financial	France	23
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	58

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#	Ticker	Sector	Country	# of Connections
113	SCDU FP Equity	Financial	France	45
114	SOFR FP Equity	Financial	France	23
115	SY FP Equity	Financial	France	33
116	UFF FP Equity	Financial	France	42
117	VIL FP Equity	Financial	France	42
118	ADC GR Equity	Financial	Germany	17
119	ALG GR Equity	Financial	Germany	18
120	ATW GR Equity	Financial	Germany	20
121	BBH GR Equity	Financial	Germany	28
122	BFV GR Equity	Financial	Germany	16
123	BTBA GR Equity	Financial	Germany	26
124	BWB GR Equity	Financial	Germany	55
125	CCB GR Equity	Financial	Germany	41
126	CMBT GR Equity	Financial	Germany	39
127	DB1 GR Equity	Financial	Germany	84
128	DBAN GR Equity	Financial	Germany	51
129	DBK GR Equity	Financial	Germany	131
130	DLB GR Equity	Financial	Germany	62
131	DRN GR Equity	Financial	Germany	74
132	EFF GR Equity	Financial	Germany	26
133	EFS GR Equity	Financial	Germany	15
134	EUX GR Equity	Financial	Germany	39
135	FAK GR Equity	Financial	Germany	54
136	FRS GR Equity	Financial	Germany	31
137	GBQ GR Equity	Financial	Germany	17
138	GLJ GR Equity	Financial	Germany	16
139	HGL GR Equity	Financial	Germany	16
140	HRU GR Equity	Financial	Germany	15
141	IPO GR Equity	Financial	Germany	17
142	KSW GR Equity	Financial	Germany	49
143	MLP GR Equity	Financial	Germany	39
144	MPCK GR Equity	Financial	Germany	41
145	MWB GR Equity	Financial	Germany	49
146	ICP GR Equity	Financial	Germany	26
147	PEH GR Equity	Financial	Germany	49
148	PPZ GR Equity	Financial	Germany	27
149	RMO GR Equity	Financial	Germany	49
150	SPT6 GR Equity	Financial	Germany	43
151	SPZI GR Equity	Financial	Germany	18
152	SVE GR Equity	Financial	Germany	32
153	UCA1 GR Equity	Financial	Germany	36
154	VEH GR Equity	Financial	Germany	26
155	VHO GR Equity	Financial	Germany	22
156	VVV3 GR Equity	Financial	Germany	25
157	WUW GR Equity	Financial	Germany	31
158	EXAE GA Equity	Financial	Greece	65
159	TELL GA Equity	Financial	Greece	33
160	IFP ID Equity	Financial	Ireland	22
161	BIM IM Equity	Financial	Italy	45
162	DEA IM Equity	Financial	Italy	37
163	IF IM Equity	Financial	Italy	41
164	LVEN IM Equity	Financial	Italy	22
165	MB IM Equity	Financial	Italy	67
166	PRO IM Equity	Financial	Italy	41
167	COFI LX Equity	Financial	Luxembourg	78
168	INSIN LX Equity	Financial	Luxembourg	30
169	LXMP LX Equity	Financial	Luxembourg	18
170	QUIL LX Equity	Financial	Luxembourg	29
171	BINCK NA Equity	Financial	Netherlands	57
172	HAL NA Equity	Financial	Netherlands	52
173	KA NA Equity	Financial	Netherlands	73
174	KARD NA Equity	Financial	Netherlands	37
175	VALUE NA Equity	Financial	Netherlands	22
176	NIKN SV Equity	Financial	Slovenia	25
177	ALB SM Equity	Financial	Spain	69
178	CGI SM Equity	Financial	Spain	48
179	REA SM Equity	Financial	Spain	81
180	UEI SM Equity	Financial	Spain	41
181	UQA AV Equity	Insurance	Austria	68
182	VIG AV Equity	Insurance	Austria	48
183	ATL CY Equity	Insurance	Cyprus	40
184	LIB CY Equity	Insurance	Cyprus	19
185	MINE CY Equity	Insurance	Cyprus	45
186	SAMAS FH Equity	Insurance	Finland	76
187	APR FP Equity	Insurance	France	36
188	CNP FP Equity	Insurance	France	70

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#	Ticker	Sector	Country	# of Connections
189	CS FP Equity	Insurance	France	69
190	ELE FP Equity	Insurance	France	41
191	SCR FP Equity	Insurance	France	62
192	ALV GR Equity	Insurance	Germany	90
193	HNR1 GR Equity	Insurance	Germany	72
194	MUV2 GR Equity	Insurance	Germany	103
195	NBG6 GR Equity	Insurance	Germany	16
196	RLV GR Equity	Insurance	Germany	63
197	WLV GR Equity	Insurance	Germany	21
198	EUPIC GA Equity	Insurance	Greece	44
199	FBD ID Equity	Insurance	Ireland	34
200	CASS IM Equity	Insurance	Italy	66
201	G IM Equity	Insurance	Italy	46
202	UNI IM Equity	Insurance	Italy	61
203	VAS IM Equity	Insurance	Italy	54
204	AGN NA Equity	Insurance	Netherlands	71
205	KDHR SV Equity	Insurance	Slovenia	24
206	GCO SM Equity	Insurance	Spain	95
207	MAP SM Equity	Insurance	Spain	77
208	ATRS AV Equity	Real	Austria	48
209	CAI AV Equity	Real	Austria	49
210	CWI AV Equity	Real	Austria	49
211	IIA AV Equity	Real	Austria	62
212	SPI AV Equity	Real	Austria	85
213	STM AV Equity	Real	Austria	23
214	UBS AV Equity	Real	Austria	33
215	ATEB BB Equity	Real	Belgium	46
216	BEFB BB Equity	Real	Belgium	89
217	BELR BB Equity	Real	Belgium	34
218	COFB BB Equity	Real	Belgium	49
219	CPINV BB Equity	Real	Belgium	32
220	HOMI BB Equity	Real	Belgium	34
221	IMMO BB Equity	Real	Belgium	20
222	INTO BB Equity	Real	Belgium	43
223	LEAS BB Equity	Real	Belgium	21
224	RET BB Equity	Real	Belgium	30
225	SOFT BB Equity	Real	Belgium	15
226	VASTB BB Equity	Real	Belgium	23
227	WDP BB Equity	Real	Belgium	38
228	WEB BB Equity	Real	Belgium	48
229	WEHB BB Equity	Real	Belgium	57
230	FWW CY Equity	Real	Cyprus	38
231	KG CY Equity	Real	Cyprus	77
232	PES CY Equity	Real	Cyprus	16
233	PND CY Equity	Real	Cyprus	27
234	PKG1T ET Equity	Real	Estonia	0
235	TPD1T ET Equity	Real	Estonia	24
236	CTY1S FH Equity	Real	Finland	46
237	SDA1V FH Equity	Real	Finland	50
238	INVEST FH Equity	Real	Finland	19
239	TPS1V FH Equity	Real	Finland	37
240	ALSAS FP Equity	Real	France	41
241	ALTA FP Equity	Real	France	43
242	AREIT FP Equity	Real	France	64
243	BERR FP Equity	Real	France	20
244	COUR FP Equity	Real	France	17
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	74
248	FDL FP Equity	Real	France	35
249	FDPA FP Equity	Real	France	18
250	FDR FP Equity	Real	France	35
251	FLY FP Equity	Real	France	23
252	FMU FP Equity	Real	France	39
253	GFC FP Equity	Real	France	95
254	ICAD FP Equity	Real	France	17
255	IMDA FP Equity	Real	France	36
256	IML FP Equity	Real	France	30
257	LI FP Equity	Real	France	78
258	MLMAB FP Equity	Real	France	93
259	MRM FP Equity	Real	France	16
260	ORC FP Equity	Real	France	89
261	ORIA FP Equity	Real	France	20
262	SFBS FP Equity	Real	France	36
263	SPEL FP Equity	Real	France	11
264	AAA GR Equity	Real	Germany	30

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#	Ticker	Sector	Country	# of Connections
265	ABHA GR Equity	Real	Germany	18
266	ADL GR Equity	Real	Germany	20
267	AGR GR Equity	Real	Germany	47
268	BBI GR Equity	Real	Germany	28
269	BBR GR Equity	Real	Germany	33
270	BFK GR Equity	Real	Germany	41
271	DAL GR Equity	Real	Germany	28
272	DEQ GR Equity	Real	Germany	67
273	DGR GR Equity	Real	Germany	30
274	DIC GR Equity	Real	Germany	49
275	GWK3 GR Equity	Real	Germany	37
276	HAB GR Equity	Real	Germany	57
277	KBU GR Equity	Real	Germany	44
278	LBN GR Equity	Real	Germany	27
279	LBR GR Equity	Real	Germany	41
280	MUK GR Equity	Real	Germany	49
281	SGB GR Equity	Real	Germany	48
282	SIN GR Equity	Real	Germany	21
283	SMWN GR Equity	Real	Germany	38
284	SPB GR Equity	Real	Germany	33
285	STG GR Equity	Real	Germany	42
286	TEG GR Equity	Real	Germany	50
287	WEG1 GR Equity	Real	Germany	17
288	ASTAK GA Equity	Real	Greece	43
289	KAMP GA Equity	Real	Greece	29
290	KEKR GA Equity	Real	Greece	38
291	LAMDA GA Equity	Real	Greece	40
292	AE IM Equity	Real	Italy	48
293	BNS IM Equity	Real	Italy	77
294	BRI IM Equity	Real	Italy	44
295	GAB IM Equity	Real	Italy	24
296	NR IM Equity	Real	Italy	15
297	RN IM Equity	Real	Italy	66
298	PZC MV Equity	Real	Malta	33
299	BEVER NA Equity	Real	Netherlands	10
300	CORA NA Equity	Real	Netherlands	57
301	ECMPA NA Equity	Real	Netherlands	75
302	GROHA NA Equity	Real	Netherlands	31
303	NSI NA Equity	Real	Netherlands	62
304	VASTN NA Equity	Real	Netherlands	34
305	WHA NA Equity	Real	Netherlands	93
306	CEV SM Equity	Real	Spain	114
307	COL SM Equity	Real	Spain	34
308	FICIS SM Equity	Real	Spain	82
309	ILV SM Equity	Real	Spain	44
310	LIB SM Equity	Real	Spain	17
311	MTB SM Equity	Real	Spain	54
312	QBT SM Equity	Real	Spain	125
313	STG SM Equity	Real	Spain	43
314	TST SM Equity	Real	Spain	27
315	UBS SM Equity	Real	Spain	21
Total				**13,836**

Appendix D. Number of granger causality connections of each Eurozone financial institution (Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	41
2	BTUV AV Equity	Banks	Austria	12
3	EBS AV Equity	Banks	Austria	124
4	OBS AV Equity	Banks	Austria	81
5	VVPS AV Equity	Banks	Austria	44
6	DEXB BB Equity	Banks	Belgium	155
7	KBC BB Equity	Banks	Belgium	139
8	BOCY CY Equity	Banks	Cyprus	123
9	HB CY Equity	Banks	Cyprus	88
10	USB CY Equity	Banks	Cyprus	89
11	ALBAV FH Equity	Banks	Finland	27
12	ACA FP Equity	Banks	France	90
13	BNP FP Equity	Banks	France	74
14	BQRE FP Equity	Banks	France	50
15	CAF FP Equity	Banks	France	65
16	CAT31 FP Equity	Banks	France	58

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#	Ticker	Sector	Country	# of Connections
17	CC FP Equity	Banks	France	73
18	CCN FP Equity	Banks	France	79
19	CIV FP Equity	Banks	France	82
20	CMO FP Equity	Banks	France	36
21	CNF FP Equity	Banks	France	43
22	CRAP FP Equity	Banks	France	53
23	CRAV FP Equity	Banks	France	53
24	CRLO FP Equity	Banks	France	44
25	CRSU FP Equity	Banks	France	69
26	CRTO FP Equity	Banks	France	40
27	GLE FP Equity	Banks	France	67
28	KN FP Equity	Banks	France	122
29	LD FP Equity	Banks	France	31
30	MLCFM FP Equity	Banks	France	13
31	MLFMM FP Equity	Banks	France	38
32	ARL GR Equity	Banks	Germany	143
33	CBK GR Equity	Banks	Germany	147
34	COM GR Equity	Banks	Germany	122
35	DVB GR Equity	Banks	Germany	36
36	IKB GR Equity	Banks	Germany	38
37	MBK GR Equity	Banks	Germany	15
38	OLB GR Equity	Banks	Germany	126
39	TUB GR Equity	Banks	Germany	66
40	UBK GR Equity	Banks	Germany	29
41	ALPHA GA Equity	Banks	Greece	102
42	ETE GA Equity	Banks	Greece	121
43	EUROB GA Equity	Banks	Greece	106
44	TATT GA Equity	Banks	Greece	93
45	TPEIR GA Equity	Banks	Greece	115
46	ALBK ID Equity	Banks	Ireland	126
47	BKIR ID Equity	Banks	Ireland	172
48	BDB IM Equity	Banks	Italy	68
49	BMPS IM Equity	Banks	Italy	136
50	BPE IM Equity	Banks	Italy	110
51	BPSO IM Equity	Banks	Italy	99
52	BSRP IM Equity	Banks	Italy	81
53	CE IM Equity	Banks	Italy	142
54	CRG IM Equity	Banks	Italy	104
55	CVAL IM Equity	Banks	Italy	105
56	ISP IM Equity	Banks	Italy	170
57	PEL IM Equity	Banks	Italy	147
58	PMI IM Equity	Banks	Italy	132
59	UBI IM Equity	Banks	Italy	104
60	UCG IM Equity	Banks	Italy	98
61	BOV MV Equity	Banks	Malta	18
62	FIM MV Equity	Banks	Malta	14
63	HSB MV Equity	Banks	Malta	15
64	LOM MV Equity	Banks	Malta	31
65	INGA NA Equity	Banks	Netherlands	141
66	LANS NA Equity	Banks	Netherlands	39
67	BCP PL Equity	Banks	Portugal	101
68	BPI PL Equity	Banks	Portugal	99
69	ESF PL Equity	Banks	Portugal	74
70	VUB SK Equity	Banks	Slovakia	7
71	BBVA SM Equity	Banks	Spain	132
72	BKT SM Equity	Banks	Spain	121
73	POP SM Equity	Banks	Spain	130
74	SAB SM Equity	Banks	Spain	149
75	SAN SM Equity	Banks	Spain	134
76	UIV AV Equity	Financial	Austria	25
77	WPB AV Equity	Financial	Austria	45
78	ACKB BB Equity	Financial	Belgium	126
79	BELU BB Equity	Financial	Belgium	26
80	BNB BB Equity	Financial	Belgium	59
81	BREB BB Equity	Financial	Belgium	122
82	COMB BB Equity	Financial	Belgium	59
83	GBLB BB Equity	Financial	Belgium	134
84	GIMB BB Equity	Financial	Belgium	69
85	KBCA BB Equity	Financial	Belgium	106
86	QFG BB Equity	Financial	Belgium	39
87	SOF BB Equity	Financial	Belgium	111
88	TUB BB Equity	Financial	Belgium	94
89	AIAS CY Equity	Financial	Cyprus	29
90	DEM CY Equity	Financial	Cyprus	39
91	ELF CY Equity	Financial	Cyprus	17
92	EXE CY Equity	Financial	Cyprus	30

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#	Ticker	Sector	Country	# of Connections
93	LI CY Equity	Financial	Cyprus	30
94	SFS CY Equity	Financial	Cyprus	66
95	CPMBV FH Equity	Financial	Finland	28
96	EQV1V FH Equity	Financial	Finland	27
97	NORVE FH Equity	Financial	Finland	86
98	SCI1V FH Equity	Financial	Finland	48
99	ABCA FP Equity	Financial	France	68
100	ALGIS FP Equity	Financial	France	53
101	ALIDS FP Equity	Financial	France	17
102	ALSIP FP Equity	Financial	France	45
103	ARTO FP Equity	Financial	France	22
104	FFP FP Equity	Financial	France	161
105	IDIP FP Equity	Financial	France	93
106	LBON FP Equity	Financial	France	92
107	LTA FP Equity	Financial	France	44
108	MF FP Equity	Financial	France	85
109	MLCVG FP Equity	Financial	France	16
110	MONC FP Equity	Financial	France	50
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	112
113	SCDU FP Equity	Financial	France	13
114	SOFR FP Equity	Financial	France	51
115	SY FP Equity	Financial	France	60
116	UFF FP Equity	Financial	France	51
117	VIL FP Equity	Financial	France	37
118	ADC GR Equity	Financial	Germany	45
119	ALG GR Equity	Financial	Germany	23
120	ATW GR Equity	Financial	Germany	58
121	BBH GR Equity	Financial	Germany	30
122	BFV GR Equity	Financial	Germany	30
123	BTBA GR Equity	Financial	Germany	29
124	BWB GR Equity	Financial	Germany	59
125	CCB GR Equity	Financial	Germany	23
126	CMBT GR Equity	Financial	Germany	65
127	DB1 GR Equity	Financial	Germany	121
128	DBAN GR Equity	Financial	Germany	133
129	DBK GR Equity	Financial	Germany	169
130	DLB GR Equity	Financial	Germany	72
131	DRN GR Equity	Financial	Germany	74
132	EFF GR Equity	Financial	Germany	29
133	EFS GR Equity	Financial	Germany	52
134	EUX GR Equity	Financial	Germany	18
135	FAK GR Equity	Financial	Germany	31
136	FRS GR Equity	Financial	Germany	25
137	GBQ GR Equity	Financial	Germany	30
138	GLJ GR Equity	Financial	Germany	92
139	HGL GR Equity	Financial	Germany	16
140	HRU GR Equity	Financial	Germany	25
141	IPO GR Equity	Financial	Germany	21
142	KSW GR Equity	Financial	Germany	58
143	MLP GR Equity	Financial	Germany	88
144	MPCK GR Equity	Financial	Germany	101
145	MWB GR Equity	Financial	Germany	19
146	ICP GR Equity	Financial	Germany	28
147	PEH GR Equity	Financial	Germany	52
148	PPZ GR Equity	Financial	Germany	12
149	RMO GR Equity	Financial	Germany	15
150	SPT6 GR Equity	Financial	Germany	58
151	SPZI GR Equity	Financial	Germany	7
152	SVE GR Equity	Financial	Germany	37
153	UCA1 GR Equity	Financial	Germany	47
154	VEH GR Equity	Financial	Germany	61
155	VHO GR Equity	Financial	Germany	43
156	VVV3 GR Equity	Financial	Germany	27
157	WUW GR Equity	Financial	Germany	54
158	EXAE GA Equity	Financial	Greece	107
159	TELL GA Equity	Financial	Greece	127
160	IFP ID Equity	Financial	Ireland	133
161	BIM IM Equity	Financial	Italy	70
162	DEA IM Equity	Financial	Italy	50
163	IF IM Equity	Financial	Italy	90
164	LVEN IM Equity	Financial	Italy	53
165	MB IM Equity	Financial	Italy	81
166	PRO IM Equity	Financial	Italy	97
167	COFI LX Equity	Financial	Luxembourg	43
168	INSIN LX Equity	Financial	Luxembourg	37

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#	Ticker	Sector	Country	# of Connections
169	LXMP LX Equity	Financial	Luxembourg	21
170	QUIL LX Equity	Financial	Luxembourg	18
171	BINCK NA Equity	Financial	Netherlands	108
172	HAL NA Equity	Financial	Netherlands	98
173	KA NA Equity	Financial	Netherlands	113
174	KARD NA Equity	Financial	Netherlands	46
175	VALUE NA Equity	Financial	Netherlands	14
176	NIKN SV Equity	Financial	Slovenia	19
177	ALB SM Equity	Financial	Spain	82
178	CGI SM Equity	Financial	Spain	25
179	REA SM Equity	Financial	Spain	28
180	UEI SM Equity	Financial	Spain	27
181	UQA AV Equity	Insurance	Austria	32
182	VIG AV Equity	Insurance	Austria	118
183	ATL CY Equity	Insurance	Cyprus	47
184	LIB CY Equity	Insurance	Cyprus	52
185	MINE CY Equity	Insurance	Cyprus	21
186	SAMAS FH Equity	Insurance	Finland	157
187	APR FP Equity	Insurance	France	100
188	CNP FP Equity	Insurance	France	66
189	CS FP Equity	Insurance	France	103
190	ELE FP Equity	Insurance	France	58
191	SCR FP Equity	Insurance	France	112
192	ALV GR Equity	Insurance	Germany	144
193	HNR1 GR Equity	Insurance	Germany	125
194	MUV2 GR Equity	Insurance	Germany	130
195	NBG6 GR Equity	Insurance	Germany	41
196	RLV GR Equity	Insurance	Germany	56
197	WLV GR Equity	Insurance	Germany	11
198	EUPIC GA Equity	Insurance	Greece	45
199	FBD ID Equity	Insurance	Ireland	46
200	CASS IM Equity	Insurance	Italy	115
201	G IM Equity	Insurance	Italy	112
202	UNI IM Equity	Insurance	Italy	133
203	VAS IM Equity	Insurance	Italy	65
204	AGN NA Equity	Insurance	Netherlands	101
205	KDHR SV Equity	Insurance	Slovenia	42
206	GCO SM Equity	Insurance	Spain	98
207	MAP SM Equity	Insurance	Spain	131
208	ATRS AV Equity	Real	Austria	49
209	CAI AV Equity	Real	Austria	68
210	CWI AV Equity	Real	Austria	131
211	IIA AV Equity	Real	Austria	116
212	SPI AV Equity	Real	Austria	79
213	STM AV Equity	Real	Austria	12
214	UBS AV Equity	Real	Austria	21
215	ATEB BB Equity	Real	Belgium	34
216	BEFB BB Equity	Real	Belgium	36
217	BELR BB Equity	Real	Belgium	29
218	COFB BB Equity	Real	Belgium	118
219	CPINV BB Equity	Real	Belgium	19
220	HOMI BB Equity	Real	Belgium	20
221	IMMO BB Equity	Real	Belgium	35
222	INTO BB Equity	Real	Belgium	78
223	LEAS BB Equity	Real	Belgium	74
224	RET BB Equity	Real	Belgium	33
225	SOFT BB Equity	Real	Belgium	40
226	VASTB BB Equity	Real	Belgium	76
227	WDP BB Equity	Real	Belgium	60
228	WEB BB Equity	Real	Belgium	16
229	WEHB BB Equity	Real	Belgium	44
230	FWW CY Equity	Real	Cyprus	56
231	KG CY Equity	Real	Cyprus	24
232	PES CY Equity	Real	Cyprus	12
233	PND CY Equity	Real	Cyprus	41
234	PKG1T ET Equity	Real	Estonia	0
235	TPD1T ET Equity	Real	Estonia	50
236	CTY1S FH Equity	Real	Finland	94
237	SDA1V FH Equity	Real	Finland	66
238	INVEST FH Equity	Real	Finland	31
239	TPS1V FH Equity	Real	Finland	63
240	ALSAS FP Equity	Real	France	32
241	ALTA FP Equity	Real	France	49
242	AREIT FP Equity	Real	France	13
243	BERR FP Equity	Real	France	20
244	COUR FP Equity	Real	France	27

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#	Ticker	Sector	Country	# of Connections
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	72
248	FDL FP Equity	Real	France	22
249	FDPA FP Equity	Real	France	24
250	FDR FP Equity	Real	France	84
251	FLY FP Equity	Real	France	40
252	FMU FP Equity	Real	France	49
253	GFC FP Equity	Real	France	100
254	ICAD FP Equity	Real	France	107
255	IMDA FP Equity	Real	France	17
256	IML FP Equity	Real	France	39
257	LI FP Equity	Real	France	104
258	MLMAB FP Equity	Real	France	7
259	MRM FP Equity	Real	France	17
260	ORC FP Equity	Real	France	106
261	ORIA FP Equity	Real	France	40
262	SFBS FP Equity	Real	France	39
263	SPEL FP Equity	Real	France	17
264	AAA GR Equity	Real	Germany	43
265	ABHA GR Equity	Real	Germany	49
266	ADL GR Equity	Real	Germany	35
267	AGR GR Equity	Real	Germany	23
268	BBI GR Equity	Real	Germany	32
269	BBR GR Equity	Real	Germany	23
270	BFK GR Equity	Real	Germany	7
271	DAL GR Equity	Real	Germany	30
272	DEQ GR Equity	Real	Germany	117
273	DGR GR Equity	Real	Germany	33
274	DIC GR Equity	Real	Germany	98
275	GWK3 GR Equity	Real	Germany	25
276	HAB GR Equity	Real	Germany	164
277	KBU GR Equity	Real	Germany	116
278	LBN GR Equity	Real	Germany	32
279	LBR GR Equity	Real	Germany	30
280	MUK GR Equity	Real	Germany	17
281	SGB GR Equity	Real	Germany	24
282	SIN GR Equity	Real	Germany	1
283	SMWN GR Equity	Real	Germany	35
284	SPB GR Equity	Real	Germany	62
285	STG GR Equity	Real	Germany	22
286	TEG GR Equity	Real	Germany	50
287	WEG1 GR Equity	Real	Germany	37
288	ASTAK GA Equity	Real	Greece	64
289	KAMP GA Equity	Real	Greece	79
290	KEKR GA Equity	Real	Greece	30
291	LAMDA GA Equity	Real	Greece	43
292	AE IM Equity	Real	Italy	86
293	BNS IM Equity	Real	Italy	93
294	BRI IM Equity	Real	Italy	73
295	GAB IM Equity	Real	Italy	51
296	NR IM Equity	Real	Italy	13
297	RN IM Equity	Real	Italy	84
298	PZC MV Equity	Real	Malta	34
299	BEVER NA Equity	Real	Netherlands	18
300	CORA NA Equity	Real	Netherlands	121
301	ECMPA NA Equity	Real	Netherlands	93
302	GROHA NA Equity	Real	Netherlands	14
303	NSI NA Equity	Real	Netherlands	59
304	VASTN NA Equity	Real	Netherlands	102
305	WHA NA Equity	Real	Netherlands	130
306	CEV SM Equity	Real	Spain	30
307	COL SM Equity	Real	Spain	61
308	FICIS SM Equity	Real	Spain	14
309	ILV SM Equity	Real	Spain	20
310	LIB SM Equity	Real	Spain	24
311	MTB SM Equity	Real	Spain	26
312	QBT SM Equity	Real	Spain	36
313	STG SM Equity	Real	Spain	29
314	TST SM Equity	Real	Spain	11
315	UBS SM Equity	Real	Spain	57
Total				**1,981**

Appendix E. Number of granger causality connections of each Eurozone financial institution (Post-Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	26
2	BTUV AV Equity	Banks	Austria	37
3	EBS AV Equity	Banks	Austria	168
4	OBS AV Equity	Banks	Austria	14
5	VVPS AV Equity	Banks	Austria	24
6	DEXB BB Equity	Banks	Belgium	60
7	KBC BB Equity	Banks	Belgium	143
8	BOCY CY Equity	Banks	Cyprus	63
9	HB CY Equity	Banks	Cyprus	38
10	USB CY Equity	Banks	Cyprus	17
11	ALBAV FH Equity	Banks	Finland	21
12	ACA FP Equity	Banks	France	134
13	BNP FP Equity	Banks	France	144
14	BQRE FP Equity	Banks	France	27
15	CAF FP Equity	Banks	France	59
16	CAT31 FP Equity	Banks	France	43
17	CC FP Equity	Banks	France	83
18	CCN FP Equity	Banks	France	70
19	CIV FP Equity	Banks	France	45
20	CMO FP Equity	Banks	France	35
21	CNF FP Equity	Banks	France	52
22	CRAP FP Equity	Banks	France	38
23	CRAV FP Equity	Banks	France	28
24	CRLO FP Equity	Banks	France	22
25	CRSU FP Equity	Banks	France	34
26	CRTO FP Equity	Banks	France	30
27	GLE FP Equity	Banks	France	144
28	KN FP Equity	Banks	France	108
29	LD FP Equity	Banks	France	28
30	MLCFM FP Equity	Banks	France	21
31	MLFMM FP Equity	Banks	France	0
32	ARL GR Equity	Banks	Germany	122
33	CBK GR Equity	Banks	Germany	128
34	COM GR Equity	Banks	Germany	78
35	DVB GR Equity	Banks	Germany	13
36	IKB GR Equity	Banks	Germany	14
37	MBK GR Equity	Banks	Germany	23
38	OLB GR Equity	Banks	Germany	43
39	TUB GR Equity	Banks	Germany	31
40	UBK GR Equity	Banks	Germany	74
41	ALPHA GA Equity	Banks	Greece	83
42	ETE GA Equity	Banks	Greece	77
43	EUROB GA Equity	Banks	Greece	52
44	TATT GA Equity	Banks	Greece	36
45	TPEIR GA Equity	Banks	Greece	90
46	ALBK ID Equity	Banks	Ireland	86
47	BKIR ID Equity	Banks	Ireland	121
48	BDB IM Equity	Banks	Italy	65
49	BMPS IM Equity	Banks	Italy	107
50	BPE IM Equity	Banks	Italy	83
51	BPSO IM Equity	Banks	Italy	71
52	BSRP IM Equity	Banks	Italy	109
53	CE IM Equity	Banks	Italy	86
54	CRG IM Equity	Banks	Italy	107
55	CVAL IM Equity	Banks	Italy	74
56	ISP IM Equity	Banks	Italy	135
57	PEL IM Equity	Banks	Italy	95
58	PMI IM Equity	Banks	Italy	102
59	UBI IM Equity	Banks	Italy	100
60	UCG IM Equity	Banks	Italy	164
61	BOV MV Equity	Banks	Malta	22
62	FIM MV Equity	Banks	Malta	11
63	HSB MV Equity	Banks	Malta	53
64	LOM MV Equity	Banks	Malta	38
65	INGA NA Equity	Banks	Netherlands	140
66	LANS NA Equity	Banks	Netherlands	50
67	BCP PL Equity	Banks	Portugal	68
68	BPI PL Equity	Banks	Portugal	89
69	ESF PL Equity	Banks	Portugal	43
70	VUB SK Equity	Banks	Slovakia	15
71	BBVA SM Equity	Banks	Spain	151
72	BKT SM Equity	Banks	Spain	126
73	POP SM Equity	Banks	Spain	115
74	SAB SM Equity	Banks	Spain	120

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#	Ticker	Sector	Country	# of Connections
75	SAN SM Equity	Banks	Spain	148
76	UIV AV Equity	Financial	Austria	46
77	WPB AV Equity	Financial	Austria	25
78	ACKB BB Equity	Financial	Belgium	116
79	BELU BB Equity	Financial	Belgium	30
80	BNB BB Equity	Financial	Belgium	119
81	BREB BB Equity	Financial	Belgium	103
82	COMB BB Equity	Financial	Belgium	35
83	GBLB BB Equity	Financial	Belgium	133
84	GIMB BB Equity	Financial	Belgium	69
85	KBCA BB Equity	Financial	Belgium	127
86	QFG BB Equity	Financial	Belgium	44
87	SOF BB Equity	Financial	Belgium	127
88	TUB BB Equity	Financial	Belgium	65
89	AIAS CY Equity	Financial	Cyprus	7
90	DEM CY Equity	Financial	Cyprus	21
91	ELF CY Equity	Financial	Cyprus	23
92	EXE CY Equity	Financial	Cyprus	55
93	LI CY Equity	Financial	Cyprus	87
94	SFS CY Equity	Financial	Cyprus	26
95	CPMBV FH Equity	Financial	Finland	60
96	EQV1V FH Equity	Financial	Finland	60
97	NORVE FH Equity	Financial	Finland	59
98	SCI1V FH Equity	Financial	Finland	28
99	ABCA FP Equity	Financial	France	133
100	ALGIS FP Equity	Financial	France	32
101	ALIDS FP Equity	Financial	France	60
102	ALSIP FP Equity	Financial	France	47
103	ARTO FP Equity	Financial	France	14
104	FFP FP Equity	Financial	France	120
105	IDIP FP Equity	Financial	France	26
106	LBON FP Equity	Financial	France	46
107	LTA FP Equity	Financial	France	44
108	MF FP Equity	Financial	France	161
109	MLCVG FP Equity	Financial	France	12
110	MONC FP Equity	Financial	France	24
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	103
113	SCDU FP Equity	Financial	France	21
114	SOFR FP Equity	Financial	France	58
115	SY FP Equity	Financial	France	26
116	UFF FP Equity	Financial	France	46
117	VIL FP Equity	Financial	France	54
118	ADC GR Equity	Financial	Germany	22
119	ALG GR Equity	Financial	Germany	18
120	ATW GR Equity	Financial	Germany	31
121	BBH GR Equity	Financial	Germany	71
122	BFV GR Equity	Financial	Germany	27
123	BTBA GR Equity	Financial	Germany	15
124	BWB GR Equity	Financial	Germany	29
125	CCB GR Equity	Financial	Germany	30
126	CMBT GR Equity	Financial	Germany	38
127	DB1 GR Equity	Financial	Germany	94
128	DBAN GR Equity	Financial	Germany	37
129	DBK GR Equity	Financial	Germany	161
130	DLB GR Equity	Financial	Germany	44
131	DRN GR Equity	Financial	Germany	54
132	EFF GR Equity	Financial	Germany	53
133	EFS GR Equity	Financial	Germany	24
134	EUX GR Equity	Financial	Germany	31
135	FAK GR Equity	Financial	Germany	38
136	FRS GR Equity	Financial	Germany	29
137	GBQ GR Equity	Financial	Germany	25
138	GLJ GR Equity	Financial	Germany	64
139	HGL GR Equity	Financial	Germany	17
140	HRU GR Equity	Financial	Germany	21
141	IPO GR Equity	Financial	Germany	58
142	KSW GR Equity	Financial	Germany	13
143	MLP GR Equity	Financial	Germany	43
144	MPCK GR Equity	Financial	Germany	44
145	MWB GR Equity	Financial	Germany	28
146	ICP GR Equity	Financial	Germany	27
147	PEH GR Equity	Financial	Germany	66
148	PPZ GR Equity	Financial	Germany	87
149	RMO GR Equity	Financial	Germany	11
150	SPT6 GR Equity	Financial	Germany	31

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#	Ticker	Sector	Country	# of Connections
151	SPZI GR Equity	Financial	Germany	39
152	SVE GR Equity	Financial	Germany	20
153	UCA1 GR Equity	Financial	Germany	34
154	VEH GR Equity	Financial	Germany	28
155	VHO GR Equity	Financial	Germany	19
156	VVV3 GR Equity	Financial	Germany	41
157	WUW GR Equity	Financial	Germany	51
158	EXAE GA Equity	Financial	Greece	53
159	TELL GA Equity	Financial	Greece	66
160	IFP ID Equity	Financial	Ireland	28
161	BIM IM Equity	Financial	Italy	45
162	DEA IM Equity	Financial	Italy	66
163	IF IM Equity	Financial	Italy	47
164	LVEN IM Equity	Financial	Italy	46
165	MB IM Equity	Financial	Italy	106
166	PRO IM Equity	Financial	Italy	134
167	COFI LX Equity	Financial	Luxembourg	43
168	INSIN LX Equity	Financial	Luxembourg	16
169	LXMP LX Equity	Financial	Luxembourg	17
170	QUIL LX Equity	Financial	Luxembourg	23
171	BINCK NA Equity	Financial	Netherlands	89
172	HAL NA Equity	Financial	Netherlands	107
173	KA NA Equity	Financial	Netherlands	64
174	KARD NA Equity	Financial	Netherlands	68
175	VALUE NA Equity	Financial	Netherlands	21
176	NIKN SV Equity	Financial	Slovenia	46
177	ALB SM Equity	Financial	Spain	82
178	CGI SM Equity	Financial	Spain	21
179	REA SM Equity	Financial	Spain	16
180	UEI SM Equity	Financial	Spain	20
181	UQA AV Equity	Insurance	Austria	88
182	VIG AV Equity	Insurance	Austria	136
183	ATL CY Equity	Insurance	Cyprus	17
184	LIB CY Equity	Insurance	Cyprus	14
185	MINE CY Equity	Insurance	Cyprus	32
186	SAMAS FH Equity	Insurance	Finland	146
187	APR FP Equity	Insurance	France	104
188	CNP FP Equity	Insurance	France	124
189	CS FP Equity	Insurance	France	157
190	ELE FP Equity	Insurance	France	98
191	SCR FP Equity	Insurance	France	126
192	ALV GR Equity	Insurance	Germany	171
193	HNR1 GR Equity	Insurance	Germany	151
194	MUV2 GR Equity	Insurance	Germany	141
195	NBG6 GR Equity	Insurance	Germany	30
196	RLV GR Equity	Insurance	Germany	19
197	WLV GR Equity	Insurance	Germany	41
198	EUPIC GA Equity	Insurance	Greece	20
199	FBD ID Equity	Insurance	Ireland	40
200	CASS IM Equity	Insurance	Italy	73
201	G IM Equity	Insurance	Italy	132
202	UNI IM Equity	Insurance	Italy	55
203	VAS IM Equity	Insurance	Italy	95
204	AGN NA Equity	Insurance	Netherlands	138
205	KDHR SV Equity	Insurance	Slovenia	61
206	GCO SM Equity	Insurance	Spain	122
207	MAP SM Equity	Insurance	Spain	87
208	ATRS AV Equity	Real	Austria	67
209	CAI AV Equity	Real	Austria	81
210	CWI AV Equity	Real	Austria	112
211	IIA AV Equity	Real	Austria	138
212	SPI AV Equity	Real	Austria	58
213	STM AV Equity	Real	Austria	23
214	UBS AV Equity	Real	Austria	18
215	ATEB BB Equity	Real	Belgium	85
216	BEFB BB Equity	Real	Belgium	75
217	BELR BB Equity	Real	Belgium	67
218	COFB BB Equity	Real	Belgium	111
219	CPINV BB Equity	Real	Belgium	42
220	HOMI BB Equity	Real	Belgium	27
221	IMMO BB Equity	Real	Belgium	49
222	INTO BB Equity	Real	Belgium	36
223	LEAS BB Equity	Real	Belgium	36
224	RET BB Equity	Real	Belgium	30
225	SOFT BB Equity	Real	Belgium	21
226	VASTB BB Equity	Real	Belgium	34

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#	Ticker	Sector	Country	# of Connections
227	WDP BB Equity	Real	Belgium	69
228	WEB BB Equity	Real	Belgium	35
229	WEHB BB Equity	Real	Belgium	22
230	FWW CY Equity	Real	Cyprus	16
231	KG CY Equity	Real	Cyprus	22
232	PES CY Equity	Real	Cyprus	8
233	PND CY Equity	Real	Cyprus	39
234	PKG1T ET Equity	Real	Estonia	57
235	TPD1T ET Equity	Real	Estonia	81
236	CTY1S FH Equity	Real	Finland	106
237	SDA1V FH Equity	Real	Finland	138
238	INVEST FH Equity	Real	Finland	39
239	TPS1V FH Equity	Real	Finland	78
240	ALSAS FP Equity	Real	France	35
241	ALTA FP Equity	Real	France	60
242	AREIT FP Equity	Real	France	45
243	BERR FP Equity	Real	France	24
244	COUR FP Equity	Real	France	38
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	139
248	FDL FP Equity	Real	France	23
249	FDPA FP Equity	Real	France	20
250	FDR FP Equity	Real	France	108
251	FLY FP Equity	Real	France	49
252	FMU FP Equity	Real	France	60
253	GFC FP Equity	Real	France	122
254	ICAD FP Equity	Real	France	115
255	IMDA FP Equity	Real	France	28
256	IML FP Equity	Real	France	94
257	LI FP Equity	Real	France	129
258	MLMAB FP Equity	Real	France	73
259	MRM FP Equity	Real	France	40
260	ORC FP Equity	Real	France	61
261	ORIA FP Equity	Real	France	44
262	SFBS FP Equity	Real	France	12
263	SPEL FP Equity	Real	France	18
264	AAA GR Equity	Real	Germany	22
265	ABHA GR Equity	Real	Germany	33
266	ADL GR Equity	Real	Germany	49
267	AGR GR Equity	Real	Germany	26
268	BBI GR Equity	Real	Germany	44
269	BBR GR Equity	Real	Germany	22
270	BFK GR Equity	Real	Germany	30
271	DAL GR Equity	Real	Germany	66
272	DEQ GR Equity	Real	Germany	117
273	DGR GR Equity	Real	Germany	48
274	DIC GR Equity	Real	Germany	111
275	GWK3 GR Equity	Real	Germany	24
276	HAB GR Equity	Real	Germany	95
277	KBU GR Equity	Real	Germany	42
278	LBN GR Equity	Real	Germany	11
279	LBR GR Equity	Real	Germany	24
280	MUK GR Equity	Real	Germany	31
281	SGB GR Equity	Real	Germany	25
282	SIN GR Equity	Real	Germany	18
283	SMWN GR Equity	Real	Germany	18
284	SPB GR Equity	Real	Germany	17
285	STG GR Equity	Real	Germany	15
286	TEG GR Equity	Real	Germany	57
287	WEG1 GR Equity	Real	Germany	64
288	ASTAK GA Equity	Real	Greece	33
289	KAMP GA Equity	Real	Greece	44
290	KEKR GA Equity	Real	Greece	49
291	LAMDA GA Equity	Real	Greece	38
292	AE IM Equity	Real	Italy	36
293	BNS IM Equity	Real	Italy	133
294	BRI IM Equity	Real	Italy	98
295	GAB IM Equity	Real	Italy	72
296	NR IM Equity	Real	Italy	54
297	RN IM Equity	Real	Italy	116
298	PZC MV Equity	Real	Malta	59
299	BEVER NA Equity	Real	Netherlands	31
300	CORA NA Equity	Real	Netherlands	136
301	ECMPA NA Equity	Real	Netherlands	127
302	GROHA NA Equity	Real	Netherlands	8

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#	Ticker	Sector	Country	# of Connections
303	NSI NA Equity	Real	Netherlands	77
304	VASTN NA Equity	Real	Netherlands	128
305	WHA NA Equity	Real	Netherlands	118
306	CEV SM Equity	Real	Spain	22
307	COL SM Equity	Real	Spain	98
308	FICIS SM Equity	Real	Spain	15
309	ILV SM Equity	Real	Spain	19
310	LIB SM Equity	Real	Spain	15
311	MTB SM Equity	Real	Spain	28
312	QBT SM Equity	Real	Spain	47
313	STG SM Equity	Real	Spain	12
314	TST SM Equity	Real	Spain	38
315	UBS SM Equity	Real	Spain	27
Total				**18,905**

Appendix F. Eurozone Member States Average Systemic Risk Measures

Member State		*ΔCoVaR*		*MES*		*LRMES*		*SRISK*	
		Rank	%	Rank	%	Rank	Value	Rank	%
Panel (A): Overall Period									
Austria	Mean	8	1.41	9	1.67	9	24.15	11	5
	STD		1.14		1.32		14.87		5,461
Belgium	Mean	7	1.86	6	2.04	7	29.03	7	9,497
	STD		1.20		1.33		14.22		16,562
Cyprus	Mean	13	0.70	13	0.82	13	12.76	13	-451
	STD		0.75		0.90		11.72		1,642
Estonia	Mean	18	0.02	18	-0.01	18	-0.14	16	-1,309
	STD		0.01		0.00		0.08		619
Finland	Mean	9	1.39	8	1.72	8	24.92	17	-4,904
	STD		1.06		1.28		14.67		5,422
France	Mean	3	2.04	3	2.29	3	32.03	1	171,479
	STD		1.21		1.35		13.68		89,636
Germany	Mean	5	1.99	5	2.25	5	31.44	2	98,425
	STD		1.24		1.39		14.21		57,032
Greece	Mean	11	1.04	11	1.19	11	18.14	15	-1,177
	STD		0.86		0.97		11.72		13,249
Ireland	Mean	12	1.03	12	1.10	12	16.90	18	-7,043
	STD		0.82		0.94		11.61		17,651
Italy	Mean	2	2.09	4	2.27	4	31.52	4	36,888
	STD		1.33		1.45		14.53		44,566
Luxembourg	Mean	14	0.09	16	0.08	16	1.43	14	-962
	STD		0.05		0.04		0.79		238
Malta	Mean	15	0.05	15	0.13	15	2.25	12	-251
	STD		0.06		0.10		1.72		272
Netherlands	Mean	6	1.88	7	2.03	6	29.05	6	22,245
	STD		1.15		1.23		13.32		29,117
Portugal	Mean	10	1.28	10	1.52	10	22.57	8	3,361
	STD		0.94		1.14		13.03		4,532
Slovakia	Mean	16	0.04	17	0.06	17	1.07	9	318
	STD		0.10		0.12		1.98		734
Slovenia	Mean	17	0.03	14	0.16	14	2.74	10	93
	STD		0.14		0.24		3.79		771
Spain	Mean	4	2.03	2	2.34	2	32.45	5	24,790
	STD		1.26		1.44		14.17		28,774
PIIGS	Mean	1	2.21	1	2.39	1	32.80	3	64,887
	STD		1.43		1.56		14.87		88,757

Member State		*ΔCoVaR*		*MES*		*LRMES*		*SRISK*	
		Rank	%	Rank	%	Rank	Value	Rank	%
Panel (B): Pre-crisis Period									
Austria	Mean	10	0.57	10	1.65	10	23.91	15	-1,647
	STD		0.25		1.30		14.48		6,251
Belgium	Mean	7	0.87	7	1.73	7	25.16	11	-650
	STD		0.34		1.26		13.82		5,934
Cyprus	Mean	13	0.22	13	1.59	13	22.96	10	-627
	STD		0.13		1.34		15.24		5,403
Estonia	Mean	14	0.09	14	1.56	14	22.56	12	-661
	STD		0.03		1.36		15.60		5,368
Finland	Mean	9	0.60	8	1.69	8	24.51	13	-903
	STD		0.27		1.28		14.12		5,490

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Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	Value	Rank	%
France	Mean	4	1.00	4	1.75	4	25.41	1	19,054
	STD		0.34		1.26		13.71		41,635
Germany	Mean	2	1.10	5	1.75	5	25.41	2	13,333
	STD		0.35		1.26		13.70		30,202
Greece	Mean	11	0.55	12	1.64	12	23.78	17	-3,466
	STD		0.26		1.31		14.58		8,717
Ireland	Mean	8	0.72	9	1.67	9	24.31	14	-1,468
	STD		0.25		1.29		14.18		5,819
Italy	Mean	3	1.06	1	1.78	1	25.77	16	-1,727
	STD		0.38		1.25		13.67		8,118
Luxembourg	Mean	15	0.05	18	1.51	18	21.56	9	-522
	STD		0.08		1.42		16.79		5,353
Malta	Mean	17	0.02	17	1.52	17	21.75	7	-392
	STD		0.01		1.41		16.53		5,353
Netherlands	Mean	6	0.94	6	1.74	6	25.21	3	778
	STD		0.36		1.26		13.80		7,280
Portugal	Mean	12	0.41	11	1.65	11	23.86	8	-512
	STD		0.19		1.30		14.49		5,413
Slovakia	Mean	16	0.02	15	1.53	15	21.91	5	-347
	STD		0.03		1.40		16.34		5,356
Slovenia	Mean	18	-0.05	16	1.52	16	21.81	6	-362
	STD		0.03		1.40		16.46		5,355
Spain	Mean	5	0.98	3	1.75	3	25.44	4	201
	STD		0.34		1.26		13.73		7,394
PIIGS	Mean	1	1.19	2	1.78	2	25.76	18	-4,091
	STD		0.38		1.25		13.65		16,432

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	Value	Rank	%
Panel (C): Post-crisis Period									
Austria	Mean	7	2.27	9	2.31	9	33.31	10	2,615
	STD		0.83		0.86		9.44		4,009
Belgium	Mean	1	2.56	3	2.75	3	38.07	7	17,088
	STD		0.96		1.04		10.33		14,741
Cyprus	Mean	12	0.87	13	0.73	13	12.06	11	1,130
	STD		0.40		0.38		5.71		731
Estonia	Mean	16	0.00	17	-0.21	17	-3.81	16	-1,392
	STD		0.00		0.08		1.42		638
Finland	Mean	9	2.13	8	2.42	8	34.01	18	-6,312
	STD		1.02		1.15		12.30		2,671
France	Mean	3	2.54	7	2.60	7	36.58	1	273,207
	STD		0.88		0.90		9.34		30,666
Germany	Mean	2	2.56	2	2.79	2	38.52	3	151,181
	STD		0.94		1.03		10.17		24,947
Greece	Mean	13	0.85	12	0.79	12	12.98	8	14,243
	STD		0.39		0.42		6.27		4,285
Ireland	Mean	11	0.90	11	1.14	11	18.24	17	-4,432
	STD		0.34		0.44		6.05		15,185
Italy	Mean	4	2.52	5	2.69	5	37.42	4	94,313
	STD		0.95		1.03		10.27		16,654
Luxembourg	Mean	17	-0.04	18	-0.25	18	-4.52	15	-1,182
	STD		0.02		0.09		1.69		46
Malta	Mean	18	-0.15	16	0.10	16	1.74	14	-496
	STD		0.09		0.12		2.05		88
Netherlands	Mean	6	2.38	6	2.63	6	36.78	6	57,516
	STD		0.91		1.01		10.39		8,583
Portugal	Mean	10	1.67	10	1.92	10	28.53	9	8,860
	STD		0.68		0.79		9.03		1,049
Slovakia	Mean	15	0.03	14	0.31	14	5.40	12	339
	STD		0.14		0.23		3.89		26
Slovenia	Mean	14	0.08	15	0.27	15	4.63	13	-80
	STD		0.12		0.17		2.90		18
Spain	Mean	5	2.44	1	2.90	1	39.53	5	64,698
	STD		0.98		1.16		10.97		15,089
PIIGS	Mean	8	2.25	4	2.71	4	37.42	2	182,575
	STD		0.95		1.15		11.18		32,550

Notes: The table ranks the average exposure to systemic risk measures according to *MES*, *LRMES*, *SRISK and*Δ*CoVaR* of each member state in the Eurozone. Simple averages and standard deviations are computed within the overall period (2000–2015) in panel (A), pre-crisis period (Q3 2004-Q2 2007) in panel (B), and post-crisis period (Q3 2010- Q2 2013) in panel (C). Standard deviations and average *MES*, *LRMES and*Δ*CoVaR* figures are expressed as a percentage while *SRISK* figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

Appendix G. Average systemic risk measures of each financial sector within member states (Overall Period)

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (A): Banks									
Austria	Mean	10	1.78	9	2.20	9	30.51	8	3,829
	STD		1.32		1.51		15.46		2,909
Belgium	Mean	3	2.70	2	3.11	3	38.65	7	19,689
	STD		2.10		2.40		19.14		13,389
Cyprus	Mean	12	1.07	12	1.32	12	19.65	12	-25
	STD		0.99		1.12		14.02		1,399
Finland	Mean	13	0.09	13	0.30	13	5.26	11	60
	STD		0.02		0.07		1.12		50
France	Mean	2	2.76	3	2.97	2	38.84	1	169,334
	STD		1.64		1.78		15.50		84,593
Germany	Mean	9	1.95	10	2.18	8	31.22	5	26,358
	STD		1.01		1.12		11.29		10,656
Greece	Mean	7	2.12	8	2.21	10	30.27	14	-2,557
	STD		1.51		1.60		17.01		10,981
Ireland	Mean	6	2.34	6	2.63	6	32.70	15	-3,178
	STD		2.47		2.74		19.55		14,225
Italy	Mean	5	2.45	4	2.70	5	35.76	3	38,474
	STD		1.59		1.75		16.75		35,993
Malta	Mean	15	0.04	14	0.11	14	1.93	13	-246
	STD		0.11		0.14		1.88		270
Netherlands	Mean	1	2.92	1	3.25	1	39.12	6	24,129
	STD		2.46		2.70		20.61		23,933
Portugal	Mean	11	1.53	11	1.92	11	27.64	9	3,717
	STD		1.00		1.20		13.76		4,526
Slovakia	Mean	14	0.05	15	0.07	15	1.02	10	332
	STD		0.28		0.36		4.80		861
Spain	Mean	4	2.46	5	2.67	4	36.41	4	32,074
	STD		1.30		1.42		13.72		27,830
PIIGS	Mean	8	2.09	7	2.27	7	31.75	2	64,485
	STD		1.23		1.33		14.17		78,881
Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.18	12	0.40	12	6.94	5	-58
	STD		0.11		0.19		2.94		24
Belgium	Mean	6	1.20	6	1.44	6	21.72	14	-7,757
	STD		0.89		1.03		11.58		4,704
Cyprus	Mean	9	0.73	11	0.90	11	14.45	7	-131
	STD		0.55		0.59		8.61		110
Finland	Mean	10	0.71	10	0.92	10	15.08	8	-187
	STD		0.36		0.44		6.35		81
France	Mean	5	1.31	4	1.59	4	23.74	13	-5,546
	STD		0.92		1.05		12.25		2,924
Germany	Mean	1	2.06	1	2.49	1	34.34	1	60,577
	STD		1.20		1.44		13.35		33,946
Greece	Mean	7	1.10	8	1.26	8	19.85	2	3,451
	STD		0.56		0.60		7.96		2,889
Ireland	Mean	11	0.59	9	1.15	9	18.10	6	-77
	STD		0.43		0.67		8.52		45
Italy	Mean	3	1.68	3	1.98	3	29.20	11	-2,202
	STD		0.77		0.88		10.22		2,600
Luxembourg	Mean	13	0.08	13	0.32	13	5.54	9	-917
	STD		0.02		0.08		1.37		227
Netherlands	Mean	8	0.90	7	1.36	7	20.96	12	-2,553
	STD		0.63		0.80		9.58		2,316
Slovenia	Mean	14	0.00	14	0.00	14	0.05	4	-4
	STD		0.00		0.00		0.05		2
Spain	Mean	4	1.34	5	1.51	5	23.28	10	-1,452
	STD		0.64		0.71		9.05		463
PIIGS	Mean	2	1.95	2	2.20	2	30.95	3	72
	STD		1.19		1.33		14.20		5,592
Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	8	0.92	9	1.14	9	17.45	10	-879
	STD		0.84		0.97		12.40		1,078

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Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Cyprus	Mean	12	0.34	11	0.73	11	12.19	7	-33
	STD		0.18		0.26		3.95		40
Finland	Mean	7	1.46	7	1.63	7	24.26	12	-4,250
	STD		0.92		1.01		12.40		4,855
France	Mean	2	2.65	2	2.98	2	39.13	1	22,918
	STD		1.51		1.70		14.66		11,003
Germany	Mean	3	2.08	3	2.47	3	33.68	2	15,673
	STD		1.37		1.61		14.63		24,558
Greece	Mean	9	0.88	8	1.50	8	23.25	9	-332
	STD		0.49		0.58		7.53		2,610
Ireland	Mean	10	0.53	10	0.93	10	14.88	8	-228
	STD		0.48		0.65		8.59		192
Italy	Mean	5	1.84	5	2.02	5	29.31	4	3,685
	STD		0.97		1.06		12.12		9,561
Netherlands	Mean	1	3.11	1	3.58	1	43.01	3	7,890
	STD		2.32		2.64		17.95		7,018
Slovenia	Mean	11	0.44	12	0.64	12	9.37	5	2,529
	STD		0.93		1.03		16.73		5,210
Spain	Mean	6	1.61	6	1.83	6	26.74	11	-1,447
	STD		1.00		1.09		13.02		1,608
PIIGS	Mean	4	1.94	4	2.09	4	29.58	6	2,141
	STD		1.23		1.32		14.23		9,969

Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (D): Real-estate									
Austria	Mean	6	0.93	5	1.28	6	17.46	9	-2,732
	STD		1.30		1.78		18.20		1,989
Belgium	Mean	8	0.58	10	0.73	10	11.77	8	-2,273
	STD		0.53		0.66		9.34		1,472
Cyprus	Mean	12	0.44	9	0.85	9	14.01	1	-93
	STD		0.20		0.31		4.52		80
Estonia	Mean	13	0.01	13	0.13	13	2.24	6	-1,288
	STD		0.01		0.19		3.27		615
Finland	Mean	1	1.37	2	1.74	2	25.08	4	-645
	STD		1.07		1.33		15.22		554
France	Mean	5	1.02	6	1.27	5	19.19	13	-8,724
	STD		0.85		1.05		13.22		6,707
Germany	Mean	11	0.46	11	0.67	11	11.11	10	-2,962
	STD		0.34		0.44		6.45		1,603
Greece	Mean	7	0.66	7	1.06	7	17.06	3	-338
	STD		0.34		0.46		6.32		168
Italy	Mean	3	1.30	1	1.83	1	26.36	5	-963
	STD		1.00		1.29		14.32		717
Malta	Mean	10	0.46	12	0.61	12	8.82	2	-178
	STD		0.81		1.12		15.41		340
Netherlands	Mean	4	1.14	4	1.40	4	20.76	11	-2,988
	STD		0.92		1.14		14.26		1,678
Spain	Mean	9	0.50	8	0.87	8	14.19	7	-2,099
	STD		0.33		0.48		6.94		2,429
PIIGS	Mean	2	1.31	3	1.69	3	24.42	12	-3,213
	STD		1.05		1.32		15.13		3,341

Notes: The table ranks the average exposure to systemic risk measures according to *MES*, *SRISK and*Δ*CoVaR* of each member state in the Eurozone. Simple averages and standard deviations are computed within the overall period (2000–2015). Standard deviations and average *MES and*Δ*CoVaR* figures are expressed as a percentage while *SRISK* figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

Appendix H. Average systemic risk measures of each financial sector within member states (Pre-crisis Period)

Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (A): Banks									
Austria	Mean	9	0.87	9	1.33	7	21.22	7	358
	STD		0.23		0.29		4.00		1,664
Belgium	Mean	4	1.06	5	1.46	5	22.70	4	11,688
	STD		0.42		0.55		6.78		3,752
Cyprus	Mean	11	0.52	11	0.92	11	15.10	12	-884
	STD		0.28		0.42		6.04		1,232
Finland	Mean	13	0.05	13	0.48	13	8.24	9	22
	STD		0.01		0.05		0.87		8

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Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
France	Mean	1	1.34	2	1.73	2	26.54	1	112,008
	STD		0.31		0.39		4.88		19,421
Germany	Mean	3	1.15	1	1.79	1	27.31	2	18,988
	STD		0.31		0.43		5.13		3,154
Greece	Mean	10	0.85	8	1.33	9	21.12	15	-14,218
	STD		0.31		0.42		5.52		5,618
Ireland	Mean	7	0.92	4	1.48	4	23.09	13	-3,305
	STD		0.30		0.44		5.68		1,878
Italy	Mean	5	0.94	7	1.33	8	21.17	6	1,431
	STD		0.28		0.38		5.10		7,602
Malta	Mean	15	0.03	14	0.23	14	4.08	10	-92
	STD		0.02		0.14		2.25		138
Netherlands	Mean	8	0.92	6	1.45	6	22.52	5	8,146
	STD		0.52		0.62		8.86		9,273
Portugal	Mean	12	0.50	12	0.77	12	12.78	11	-749
	STD		0.21		0.30		4.35		1,827
Slovakia	Mean	14	0.04	15	0.12	15	2.12	8	119
	STD		0.10		0.14		2.51		36
Spain	Mean	2	1.15	3	1.61	3	24.96	3	13,113
	STD		0.28		0.37		4.69		6,247
PIIGS	Mean	6	0.92	10	1.32	10	20.92	14	-6,544
	STD		0.31		0.41		5.39		20,843
Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.15	12	0.15	12	2.74	4	-46
	STD		0.05		0.05		0.84		12
Belgium	Mean	8	0.71	9	1.10	9	17.62	14	-10,771
	STD		0.35		0.49		6.42		2,674
Cyprus	Mean	5	0.76	8	1.10	8	17.85	6	-125
	STD		0.27		0.34		4.91		56
Finland	Mean	11	0.50	11	0.99	11	16.20	7	-213
	STD		0.21		0.29		4.05		31
France	Mean	6	0.74	7	1.12	7	17.94	13	-7,812
	STD		0.38		0.50		6.50		1,972
Germany	Mean	1	1.05	2	1.48	2	23.16	1	33,403
	STD		0.35		0.48		6.08		12,600
Greece	Mean	9	0.65	10	1.01	10	16.54	2	775
	STD		0.25		0.34		4.79		148
Ireland	Mean	10	0.63	6	1.23	6	19.36	5	-53
	STD		0.52		0.66		8.73		21
Italy	Mean	2	1.02	1	1.55	1	24.28	11	-5,444
	STD		0.21		0.28		3.72		1,184
Luxembourg	Mean	13	0.05	13	0.11	13	1.89	8	-796
	STD		0.11		0.14		2.37		129
Netherlands	Mean	7	0.72	5	1.30	5	20.55	9	-1,589
	STD		0.36		0.53		6.38		822
Slovenia	Mean	14	0.00	14	0.00	14	0.03	3	-4
	STD		0.00		0.00		0.04		2
Spain	Mean	4	0.88	3	1.35	3	21.55	10	-1,669
	STD		0.19		0.25		3.47		494
PIIGS	Mean	3	0.96	4	1.32	4	20.95	12	-6,670
	STD		0.30		0.40		5.29		1,832
Member State		**ΔCoVaR**		**MES**		**LRMES**		**SRISK**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	9	0.55	8	1.01	8	16.25	9	-1,800
	STD		0.38		0.51		6.86		1,009
Cyprus	Mean	10	0.42	11	0.59	11	10.13	6	-17
	STD		0.09		0.13		2.10		12
Finland	Mean	7	0.91	6	1.30	6	20.66	10	-1,832
	STD		0.28		0.32		4.58		1,511
France	Mean	1	1.76	1	2.05	1	30.65	2	16,048
	STD		0.32		0.38		4.38		3,341
Germany	Mean	3	1.30	3	1.71	3	26.39	1	27,386
	STD		0.28		0.36		4.48		11,292
Greece	Mean	8	0.55	9	0.93	9	14.29	5	-11
	STD		0.76		0.92		13.57		7
Ireland	Mean	11	0.28	10	0.63	10	10.68	7	-520

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Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
	STD		0.09		0.11		1.68		158
Italy	Mean	4	1.08	4	1.35	4	21.34	11	-2,566
	STD		0.34		0.40		5.46		2,332
Netherlands	Mean	2	1.64	2	1.98	2	29.72	3	5,350
	STD		0.38		0.45		5.35		1,361
Slovenia	Mean	12	-0.27	12	-1.21	12	-60.00	4	15
	STD		0.72		1.37		729.11		308
Spain	Mean	6	0.94	7	1.29	7	20.70	8	-1,268
	STD		0.17		0.23		3.11		1,118
PIIGS	Mean	5	1.00	5	1.30	5	20.60	12	-4,557
	STD		0.34		0.42		5.61		3,570

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (D): Real-estate									
Austria	Mean	11	0.12	11	0.21	11	3.68	11	-4,693
	STD		0.08		0.13		2.26		2,242
Belgium	Mean	8	0.28	10	0.49	10	8.35	6	-1,789
	STD		0.19		0.27		4.28		282
Cyprus	Mean	10	0.20	8	0.56	8	9.43	2	-103
	STD		0.19		0.26		4.16		56
Estonia	Mean	12	0.00	12	0.00	12	0.05	5	-1,650
	STD		0.00		0.00		0.03		3
Finland	Mean	1	0.82	1	1.41	1	21.74	4	-567
	STD		0.55		0.77		9.28		233
France	Mean	5	0.56	6	0.93	6	15.29	12	-7,234
	STD		0.23		0.34		4.94		2,473
Germany	Mean	9	0.27	9	0.50	9	8.45	8	-2,561
	STD		0.22		0.32		4.98		860
Greece	Mean	4	0.59	5	0.99	5	16.02	3	-382
	STD		0.40		0.53		7.40		160
Italy	Mean	2	0.73	2	1.35	2	21.05	7	-2,048
	STD		0.42		0.65		8.03		686
Malta	Mean	13	-0.01	13	-0.11	13	-2.03	1	-10
	STD		0.10		0.13		2.47		1
Netherlands	Mean	3	0.69	4	1.14	4	18.09	9	-3,057
	STD		0.39		0.58		7.65		626
Spain	Mean	6	0.56	3	1.16	3	18.19	10	-4,413
	STD		0.50		0.80		7.48		3,840
PIIGS	Mean	7	0.52	7	0.91	7	14.80	13	-7,238
	STD		0.31		0.42		6.01		4,752

Notes: The table ranks the average exposure to systemic risk measures according to *MES*, *SRISK and*Δ*CoVaR* of each member state in the Eurozone. Simple averages and standard deviations are computed within the pre-crisis period (Q3 2004-Q2 2007). Standard deviations and average *MES and*Δ*CoVaR* figures are expressed as a percentage while *SRISK* figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

Appendix I. Average systemic risk measures of each financial sector within member states (Post-crisis Period)

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (A): Banks									
Austria	Mean	9	2.49	6	2.97	6	40.68	10	6,192
	STD		0.76		0.92		8.85		2,345
Belgium	Mean	1	4.15	1	4.67	1	54.61	7	24,474
	STD		1.65		1.87		13.03		14,428
Cyprus	Mean	12	1.60	12	1.35	12	21.00	11	1,363
	STD		0.72		0.66		9.17		628
Finland	Mean	13	0.05	13	0.21	13	3.58	13	98
	STD		0.24		0.26		4.41		31
France	Mean	3	3.50	2	4.14	2	50.52	1	263,760
	STD		1.47		1.75		12.58		22,432
Germany	Mean	10	2.16	9	2.30	9	32.73	6	36,257
	STD		0.99		1.07		11.76		4,054
Greece	Mean	7	2.81	10	2.14	10	31.09	9	7,695
	STD		0.96		0.89		10.95		4,055
Ireland	Mean	8	2.55	11	2.11	11	30.77	15	-1,467
	STD		1.13		0.97		9.74		13,079
Italy	Mean	2	3.95	7	2.69	7	37.42	3	94,313
	STD		1.30		1.03		10.27		16,654
Malta	Mean	15	-0.10	15	-0.18	15	-3.27	14	-546

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Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
	STD		0.04		0.06		1.09		87
Netherlands	Mean	4	3.49	3	4.07	3	49.68	5	53,229
	STD		1.57		1.81		13.56		6,010
Portugal	Mean	11	1.97	8	2.34	8	33.48	8	9,067
	STD		0.82		0.97		10.15		922
Slovakia	Mean	14	0.01	14	-0.12	14	-2.29	12	323
	STD		0.25		0.27		4.99		28
Spain	Mean	5	2.99	4	3.08	4	41.92	4	69,582
	STD		0.78		0.82		8.11		11,984
PIIGS	Mean	6	2.94	5	3.02	5	41.24	2	169,209
	STD		0.82		0.85		8.39		22,905

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (B): Diversified Financial									
Austria	Mean	12	0.18	11	0.38	11	6.46	7	-62
	STD		0.15		0.24		3.88		21
Belgium	Mean	6	1.42	6	1.68	6	25.64	14	-5,757
	STD		0.52		0.60		7.44		2,564
Cyprus	Mean	10	0.41	12	0.32	12	5.67	6	-57
	STD		0.08		0.07		1.24		8
Finland	Mean	9	0.72	10	0.82	10	13.57	9	-193
	STD		0.32		0.36		5.33		27
France	Mean	4	1.86	4	2.21	4	31.62	13	-4,303
	STD		0.94		1.07		11.47		1,629
Germany	Mean	2	2.41	1	2.83	1	39.01	1	99,786
	STD		0.88		1.02		10.00		15,245
Greece	Mean	7	1.39	5	1.70	5	25.89	2	7,905
	STD		0.61		0.68		7.71		908
Ireland	Mean	11	0.22	9	0.83	9	13.88	8	-113
	STD		0.05		0.18		2.44		19
Italy	Mean	3	2.38	3	2.41	3	34.71	4	931
	STD		0.64		0.65		7.38		1,212
Luxembourg	Mean	14	-0.04	13	0.28	13	4.95	10	-1,061
	STD		0.02		0.10		1.67		48
Netherlands	Mean	8	0.98	8	1.31	8	20.64	12	-3,864
	STD		0.41		0.51		6.62		709
Slovenia	Mean	13	0.00	14	0.00	14	0.04	5	-3
	STD		0.00		0.00		0.04		1
Spain	Mean	5	1.60	7	1.66	7	25.27	11	-1,410
	STD		0.63		0.66		8.61		296
PIIGS	Mean	1	2.76	2	2.76	2	38.51	3	7,889
	STD		0.80		0.81		8.37		2,094

Member State		ΔCoVaR		MES		LRMES		SRISK	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (C): Insurance									
Austria	Mean	8	1.34	8	1.89	7	28.37	10	-449
	STD		0.49		0.66		7.85		778
Cyprus	Mean	12	0.04	11	0.20	11	3.47	7	-17
	STD		0.02		0.07		1.23		8
Finland	Mean	7	1.68	7	1.90	8	28.25	12	-6,041
	STD		0.68		0.78		9.33		2,131
France	Mean	2	2.97	2	3.38	2	44.08	1	36,258
	STD		1.22		1.37		11.69		5,786
Germany	Mean	6	2.04	6	2.47	6	34.66	2	14,871
	STD		0.96		1.15		11.50		9,298
Greece	Mean	10	0.46	10	0.69	10	11.51	6	-1
	STD		0.22		0.27		4.34		6
Ireland	Mean	9	0.67	9	1.06	9	17.32	9	-145
	STD		0.18		0.23		3.39		61
Italy	Mean	4	2.54	5	2.64	5	37.32	3	14,605
	STD		0.67		0.72		7.71		2,770
Netherlands	Mean	1	3.08	1	3.69	1	46.94	4	14,014
	STD		1.24		1.47		12.11		1,446
Slovenia	Mean	11	0.07	12	0.07	12	1.13	8	-81
	STD		0.21		0.23		3.92		21
Spain	Mean	5	2.47	3	2.87	3	39.95	11	-1,232
	STD		0.54		0.63		6.56		851
PIIGS	Mean	3	2.76	4	2.73	4	38.08	5	13,272

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Member State		Δ*CoVaR*		*MES*		*LRMES*		*SRISK*	
		Rank	%	Rank	%	Rank	%	Rank	Value
	STD		0.87		0.89		9.23		3,660

Member State		Δ*CoVaR*		*MES*		*LRMES*		*SRISK*	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (D): Real-estate									
Austria	Mean	6	1.44	6	1.86	6	27.78	9	-2,848
	STD		0.60		0.75		8.65		771
Belgium	Mean	7	0.77	9	0.91	9	14.88	10	-2,932
	STD		0.32		0.38		5.19		438
Cyprus	Mean	10	0.54	10	0.89	10	14.77	2	-39
	STD		0.10		0.17		2.54		16
Estonia	Mean	13	-0.01	13	0.03	13	0.54	8	-1,335
	STD		0.02		0.05		0.95		613
Finland	Mean	3	1.94	3	2.29	3	33.06	5	-786
	STD		0.74		0.86		8.73		254
France	Mean	5	1.56	5	1.92	5	28.06	13	-10,956
	STD		0.84		1.02		11.53		3,279
Germany	Mean	9	0.61	11	0.82	11	13.57	12	-3,627
	STD		0.20		0.26		3.73		571
Greece	Mean	11	0.42	8	0.91	8	14.98	3	-202
	STD		0.14		0.30		4.48		44
Italy	Mean	2	2.10	1	2.88	1	39.24	4	-416
	STD		0.89		1.16		11.66		253
Malta	Mean	12	0.10	12	0.17	12	2.88	1	-10
	STD		0.16		0.18		3.26		4
Netherlands	Mean	4	1.81	4	2.13	4	30.82	11	-3,407
	STD		0.83		0.99		11.08		902
Spain	Mean	8	0.77	7	1.03	7	16.68	6	-1,001
	STD		0.37		0.45		6.51		711
PIIGS	Mean	1	2.23	2	2.42	2	34.77	7	-1,278
	STD		0.65		0.74		8.14		891

Notes: The table ranks the average exposure to systemic risk measures according to *MES*, *SRISK and*Δ*CoVaR* of each member state in the Eurozone. Simple averages and standard deviations are computed within the post-crisis period (Q3 2010- Q2 2013). Standard deviations and average *MES and*Δ*CoVaR* figures are expressed as a percentage while *SRISK* figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

References

Abadie, A., 2002. Bootstrap tests for distributional treatment effects in instrumental variable models. J. Am. Stat. Assoc. 97 (457), 284–292.

Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2015. Systemic risk and stability in financial networks. Am. Econ. Rev. 105 (2), 564–608.

Acharya, V., 2009. A theory of systemic risk and design of prudential bank regulation. J. Financ. Stab. 5, 224–255.

Acharya, V., Engle, F., Pierret, D., 2014. Testing macroprudential stress tests: the risk of regulatory risk weights. J. Monet. Econ. 65, 36–53.

Acharya, V., Engle, R., Richardson, M., 2012. Capital shortfall: a new approach to ranking and regulating systemic risks. Am. Econ. Rev. 102 (3), 59–64.

Acharya, V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. Rev. Financ. Stud. 30 (1), 2–47.

Acharya, V.V., Yorulmazer, T., 2007. Too many to fail - an analysis of time-inconsistency in bank closure policies. J. Financ. Intermed. 16 (1), 1–31.

Adams, Z., Füss, R., Gropp, R., 2014. Spillover effects among financial institutions: a state-dependent sensitivity value-at-risk approach. J. Financ. Quant. Anal. 49 (3), 575–598.

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. Am. Econ. Rev. 106 (7), 1705.

Allen, D., Powell, R., Singh, A., 2016. Take it to the limit: innovative CVaR applications to extreme credit risk measurement. Eur. J. Oper. Res. 249 (2).

Allen, L., Bali, T., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Rev. Financ. Stud. 25, 3000–3036.

Andreev, A., Kanto, A., Malo, P., 2005. On the close form calculation of CVAR. Work. Pap. No. W389. Helsinky Sch. Econ.

Andrieş, A.M., Chiper, A.M., Ongena, S., Sprincean, N., 2024. External wealth of nations and systemic risk. J. Financ. Stab. 70, 101192.

Andrieş, A.M., Ongena, S., Sprincean, N., Tunaru, R., 2022. Risk spillovers and interconnectedness between systemically important institutions. J. Financ. Stab. 58, 100963.

Artzner, P., Delbaen, F., Eber, M., Heath, D., 1999. Coherent measures of risk. Math. Financ. 9, 203–228.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61 (4), 1645–1680.

Bakkar, Y., Nyola, A.P., 2021. Internationalization, foreign complexity and systemic risk: evidence from European banks. J. Financ. Stab. 55, 100892.

Balla, E., Ergena, I., Migueis, M., 2014. Tail dependence and indicators of systemic risk for large US depositories. J. Financ. Stab. 15, 195–209.

Bekaert, G., Harvey, C.R., 2002. Research in emerging markets finance: looking to the future. Emerg. Mark. Rev. 3 (4), 429–448.

Beltratti, A., Stulz, A., 2012. Why did some banks perform better? J. Financ. Econ. 105, 1–17.

Benoit, S., Colletaz, G., Hurlin, C., Perignon, C., 2013. A theoretical and empirical comparison of systemic risk measure. S. SSRN Work. Pap.

Benoit, S., Colliard, J., Hurlin, C., Perignon, C., 2017. Where the risks lie: a survey on systemic risk. Rev. Financ. 21 (1), 109–152.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of systemic risk in the finance and insurance sectors. J. Financ. Econ. 104, 535–559.

Bisias, D., Flood, M., Lo, A.W., Valavanis, S., 2012. A survey of systemic risk analytics. Annu. Rev. Financ. Econ. 4 (1), 255–296.

Boucher, C., Danielsson, J., Kouontchou, P., Maillet, B., 2014. Risk models–at–risk. J. Bank. Financ. 44, 72–92.

Brown, C.O., Dinc, I.S., 2014. Too many to fail? Evidence of regulatory forbearance when the banking sector is weak. Rev. Financ. Stud. 24 (4), 1378–1405.

Brownlees, C., Engle, R., 2012. Volatility, correlation and tails for systemic risk measurement. Work. Pap. N. Y. Univ.

Brownlees, C., Engle, R.F., 2017. SRISK: a conditional capital shortfall measure of systemic risk. Rev. Financ. Stud. 30 (1), 48–79.

Cao, Z., 2013. Multi CoVaR Shapley Value. A Syst. Risk Meas. Banq. De. Fr. Work. Pap.

Carrington, T., 1984. U.S. Won't Let 11 Biggest Banks in Nation Fall. Wall St. J. September 20.

Chen, R.R., Zhang, X., 2024. From liquidity risk to systemic risk: a use of knowledge graph. J. Financ. Stab. 70, 101195.

Chuanliang, J., 2012. Does tail dependence make a difference in the estimation of systemic risk? ΔCoVaR and MES. Econ. Dep. Boston Coll.

Cline, W., Wolff, G., 2012. Resolving the European Debt Crisis. Peterson Inst. Int. Econ.

Cont, R., Moussa, A., Santos, E.B., 2013. Network structure and systemic risk in banking systems. In: Fouque, J.-P., Langsam, J.A. (Eds.), Handb. Syst. Risk. Cambridge Univ. Press; 2013, pp. 327–368.

Curcio, D., Gianfrancesco, I., Vioto, D., 2023. Climate change and financial systemic risk: evidence from US banks and insurers. J. Financ. Stab. 66, 101132.

Drehmann, M., Tarashev, N., 2011. Measuring the systemic importance of interconnected banks. Bank Int. Settl. Work. Pap. 342.

Duffie, D., Pan, J., 1997. An overview of value at risk. J. Deriv. 4, 7–49.

Dungey, M., Milunovich, G., Thorp, S., 2010. Unobservable shocks as carriers of contagion: a dynamic analysis using identified structural GARCH. J. Bank. Financ. 34, 1008–1102.

Durbin, J., 1973. Distribution Theory for Tests Based on the Sample Distribution Function. Soc. Ind. Appl. Math.
Ellis, L., Haldane, A., McAndrews, J., Moshirian, F., 2014. Liquidity shocks, governance, systemic risk and financial stability. J. Bank. Financ. 45, 171–174.
Ellis, S., Sharma, S., Brzeszczyński, J., 2022. Systemic risk measures and regulatory challenges. J. Financ. Stab. 61, 100960.
Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. 20, 339–350.
Engle, R., 2009. Anticipating Correlations: A New Paradigm for Risk Management. Princeton Univ. Press.
Engle, R.F., Siriwardane, E.N., 2018. Structural GARCH: the volatility-leverage connection. Rev. Financ. Stud. 31 (2), 449–492.
Engle, R., Jondeau, E., Rockinger, M., 2015. Systemic risk in Europe. Rev. Financ. 19 (1), 145–190.
Financial Stability Board, 2011. Policy Measures to Address Systemically Important Financial Institutions. FSB Publ.
Forbes, K., Rigobon, R., 2001. Measuring contagion: conceptual and empirical issues. In: Claessens, S., Forbes, K. (Eds.), Int. Financ. Contagion. Kluwer Acad. Publ., Boston, pp. 43–66.
Forbes, K., Rigobon, R., 2002. No Contagion only interdependence: measuring stock market comovements. J. Financ. doi: 10:1111/0022-1082.0094.
Furfine, C., 2003. Interbank exposures: quantifying the risk of contagion. J. Money Credit Bank. No 35 (1), 111–128.
Giot, P., Laurent, S., 2003. Value-at-risk for long and short trading positions. J. Appl. Econ. 18, 641–664.
Girardi, G., Ergün, T., 2013. Systematic risk measurement: multivariate GARCH estimation of CoVaR. J. Bank. Financ. 37 (8), 3169–3180.
Hanson, S.G., Kashyap, A.K., Stein, J.C., 2011. A macroprudential approach to financial regulation. J. Econ. Perspect. 25 (1), 3–28.
Jin, X., De Simone, F.N., 2020. Monetary policy and systemic risk-taking in the Euro area investment fund industry: a structural factor-augmented vector autoregression analysis. J. Financ. Stab. 49, 100749.
Jorion, P., 2007. Value at Risk: The New Benchmark for Managing Financial Risk, 3rd Edition. McGraw-Hill.
Kanas, A., Molyneux, P., Zervopoulos, P.D., 2023. Systemic risk and CO2 emissions in the US. J. Financ. Stab. 64, 101088.
Kashyap, A., Stein, J., 2000. What do a million observations on banks say about the transmission of monetary policy? Am. Econ. Rev. 90, 407–428.
Kim, T., White, H., 2004. On more robust estimation of Skewness and Kurtosis. Financ. Res. Lett. 1, 56–70.
King, M., Wadhwani, S., 1990. Transmission of volatility between stock markets. Rev. Financ. Stud. 3 (1), 5–33.
Leong, S.H., Pellegrini, C.B., Urga, G., 2020. The contribution of shadow insurance to systemic risk. J. Financ. Stab. 51, 100778.
Lopez-Espinosa, G., Moreno, A., Rubia, A., Valderrama, L., 2013. Short-Term Wholesale Funding and Systemic Risk: A Global CoVaR Approach. J. Bank. Financ.
Markose, S., Giansante, S., Gatkowski, M., Shaghaghi, A., 2010. Too Interconnected To Fail: Financial Contagion and Systemic Risk in Network Model of Cds and Other Credit Enhancement Obligations Of US Banks. Work. Pap., Univ. Essex.
Meuleman, E., Vander Vennet, R., 2020. Macroprudential policy and bank systemic risk. J. Financ. Stab. 47, 100724.
Mies, M., 2024. Bank opacity, systemic risk and financial stability. J. Financ. Stab. 70, 101211.
Mitchell, J., 1997. Strategic Creditor Passivity, Regulation, and Bank Bailouts. William Davidson Inst. (WDI), Work. Pap.
Morelli, D., Vioto, D., 2020. Assessing the contribution of China's financial sectors to systemic risk. J. Financ. Stab. 50, 100777.
Pellegrini, C.B., Cincinelli, P., Meoli, M., Urga, G., 2022. The contribution of (shadow) banks and real estate to systemic risk in China. J. Financ. Stab. 60, 101018.
Pichler, A., Poledna, S., Thurner, S., 2021. Systemic risk-efficient asset allocations: minimization of systemic risk as a network optimization problem. J. Financ. Stab. 52, 100809.
Poledna, S., Martínez-Jaramillo, S., Caccioli, F., Thurner, S., 2021. Quantification of systemic risk from overlapping portfolios in the financial system. J. Financ. Stab. 52, 100808.
Rodriguez-Moreno, M., Pena, J.I., 2013. Systemic risk measures: the simpler the better? J. Bank. Financ. 37, 1817–1831.
Roesch, D., Scheule, H., 2014. Systemic risk in commercial bank lending. SSRN Work. Pap.
Scaillet, O., 2004. Nonparametric estimation and sensitivity analysis of expected shortfall. Math. Financ. 14 (1), 115–129.
Scaillet, O., 2005. Nonparametric estimation of conditional expected shortfall. Insur. Risk Manag. J. 74 (1), 639–660.
Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. J. Financ. 52 (1), 35–55.
Siebenbrunner, C., Guth, M., Spitzer, R., Trappl, S., 2024. Assessing the systemic risk impact of bank bail-ins. J. Financ. Stab., 101229
Sigmund, M., Siebenbrunner, C., 2024. Do interbank markets price systemic risk? J. Financ. Stab., 101223
Singh, A., Allen, D., Robert, P., 2013. Extreme market risk and extreme value theory. Math. Comput. Simul. 94, 310–328.
Straetmans, S., Chaudhry, S., 2015. Tail risk and systemic risk of US and Eurozone financial institutions in the wake of the global financial crisis. J. Int. Money Financ. 58, 191–223.
Thomson, J., 2009. On systemically important financial institutions and progressive systemic mitigation. DePaul Bus. Comm. LJ 8, 135.
Vallascas, F., Keasey, K., 2013. Does bank default risk increase with information asymmetry? Evidence from Europe. ERN: Econ. Stud. Corp. Gov.
Weiß, G., Bostandzic, D., Neumann, S., 2014. What factors drive systemic risk during international financial crises? J. Bank. Financ. 41, 78–96.
Xiao, S., Zhu, S., Wu, Y., 2023. Asset securitization, cross holdings, and systemic risk in banking. J. Financ. Stab., 101140
Zhang, W., Li, C., Ye, Y., Li, W., Ngai, E.W., 2015. Dynamic business network analysis for correlated stock price movement prediction. IEEE Intell. Syst. 30 (2), 26–33.
Zhang, X., Fu, Q., Lu, L., Wang, Q., Zhang, S., 2021. Bank liquidity creation, network contagion and systemic risk: evidence from Chinese listed banks. J. Financ. Stab. 53, 100844.