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Risk Spillovers and Interconnectedness
between Systemically Important Institutions

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Abstract
In this paper we gauge the degree of interconnectedness and quantify the linkages between global and other systemically important institutions, and the global financial system. We document that the two groups and the financial system become more interconnected during the global financial crisis when linkages across groups grow. In contrast, during tranquil times linkages within groups prevail. Global systemically important banks contribute most to system-wide distress, but are also most exposed. There are more links coming from global systemically important banks to other systemically important institutions than the other way around, confirming the role of global systemically important banks as major risk transmitters in the financial system. Prior to the official designation of global systemically important banks and other systemically important institutions, the prevalent news sentiment was negative. The systemic importance and systemic exposure of G-SIBs and O-SIIs are perceived differently by the FSB and by the EBA, respectively.

Key words: systemic risk, interconnectedness, bank networks, Bayesian graphical VAR, textual analysis

JEL codes: G21; D85; G01
1. Introduction

The experience of the global financial crisis suggests that the architecture of the financial system plays a central role in shaping systemic risk (Acemoglu et al., 2015) and it reveals that regulators and market participants had very limited information about the network of obligations between financial institutions (Glasserman and Young, 2016). Previous studies indicate that the interconnectedness of global banks played a major role in the 2007–2009 financial crisis (Hale et al., 2019) and show that the complexity of financial networks may decrease the ability to mitigate systemic risk (Battiston et al., 2016). As a consequence of the growth of the global financial network and of the very high degree of integration and interconnectedness in the global financial system, when a bank experiences some financial stress, its troubles could spill over to other banks and threaten to contaminate the broader financial system leading to a global systemic crisis (Greenwood et al., 2015; Avdjiev et al., 2019; Park and Shin, 2019).

In this paper, we use various approaches to measure the spillover effects between global systemically important banks (G-SIBs) and other systemically important institutions (O-SIIs), on the one hand, and the global financial system, on the other. In particular we measure the spillovers: a) from G-SIBs to O-SIIs, and the financial system; b) from O-SIIs to G-SIBs, and the financial system; and c) from the financial system to G-SIBs, and O-SIIs.¹ Given that a key step in understanding systemic risk of any economy is to understand the interconnectedness of its large institutions (Basu et al., 2019) and realizing that the structure of financial networks can affect the capacity of regulators to assess the level of systemic risk (Roukny et al., 2019), our aim is thus to gauge the degree of interconnectedness and to quantify the linkages between the two groups of systemically important institutions and the financial system. In our paper, we measure the indirect connectedness between financial institutions based on investors’ perceptions reflected in equity prices, as opposed to direct linkages that can be captured through balance sheet exposures, such as interbank exposures that are often limited and available only to supervisory authorities (Bricco and

¹ Similar to Bostandzic and Weiß (2018), we use the MSCI World Financials Index as a proxy for the global financial system. It includes 226 large and mid-cap constituents from 23 developed countries as of July 30, 2021 from the following industries: (i) Diversified Financial Services, (ii) Consumer Finance, (iii) Capital Markets, (iv) Mortgage Real Estate Investment Trusts (REITs), and (v) Insurance. Part of both G-SIBs and O-SIIs are included in the index calculation, but G-SIBs have a greater weight given their larger size and global importance. As of July 30, 2021 the highest weights in the index are those of JP Morgan Chase & Co (5.93%), Berkshire Hathaway B (4.88%) and Bank of America (3.81%), where JP Morgan and Bank of America are both classified as G-SIBs.
Our analysis is related to that of Malik and Xu (2017) that investigate the interlinkages between global systemically important banks and insurers, and Abefidar et al. (2017) that compare systemic resilience of Islamic and conventional banks by employing systemic risk measures and graphical network models.

Our study covers the period from January 1, 2004 to September 29, 2017. Hence the sample period starts long before the release of the first list of G-SIBs (November 4, 2011) or the first list of O-SIIs (April 25, 2016). Thus, we are able to carry out an analysis concerning the systemic risk contribution and exposure of these institutions and to capture the spillover effects focusing especially on the contrast between the global financial crisis and prior tranquil times.

In addition to calculating the customary systemic risk measures that help us to identify the most contagious/subject to contagion institutions and their transmission channels (Giudici et al., 2020), we also employ several methods to quantify the degree of interconnectedness: Granger causality networks, cross-quantilograms, and Bayesian Graphical VAR models. The pairwise Granger-causality tests are based on stock return interconnections and are applied to identify the network of statistically significant Granger-causal relations among financial institutions over time. Cross-quantilograms measure the dependence structure of time series across quantiles for a large number of lags. They do not require any modelling assumptions and allow to detect simultaneously the direction, magnitude and the duration of dependence between (in our application) pairs of financial institutions. Moreover, they can be extended to capture the time-varying nature of the interconnectedness and applied to measure a public institution’s systemic risk contribution or a public institution’s exposure to system-wide distress based solely on their equity returns. Furthermore, we test whether the systemic riskiness of G-SIBs (dominated by the US banks) is perceived differently from that of the O-SIIs (European banks), given the components of both groups and the authorities that have carried out the assessment and disclosed the lists.

Quantifying interconnectedness with Granger-causality networks, we find that there was an increase in interconnectedness during the 2007-2009 global financial crisis and subsequent European sovereign debt crisis, more so across than within groups. We also find that as the system gets distressed, G-SIBs are instantly exposed and we detect spillover effects from G-SIBs to O-SIIs that are higher and propagate more rapidly than the other way around. Finally, we find that G-

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2 For the period before the official designation, that is, before November 4, 2011 for G-SIBs and before April 25, 2016 for O-SIIs we consider those institutions that were included for the first time on the lists as systemically important (as some G-SIBs are also O-SIIs, we exclude them from the O-SIIs list; see Table A1 from the Annexes for details).
SIBs are the main contributors to system-wide distress, but at the same time they are also more exposed, whilst both the contribution and the exposure of O-SIIs gets modulated. The O-SIIs on the other hand bear more individual market risk as measured by Value at Risk (VaR). In addition, using a more advanced approach using Bayesian graphical VAR, we report several periods of substantial interconnectedness associated with the global financial crisis and sovereign debt crisis in Europe events that affected the financial markets. This more robust technique highlights that there are more links coming from G-SIBs to O-SIIs than the other way around, confirming the role of some identified G-SIBs as major risk transmitters in the financial system.

The differences between the G-SIB and O-SII groups of financial institutions are further investigated considering the textual data from Reuters archive. The banks from G-SIBs most mentioned are mostly top tier international banks like Royal Bank of Scotland, Goldman Sachs and Credit Suisse, whereas for the O-SIIs group the textual analysis produces banks that have a strong national focus such as Alpha Bank, Banca Monte dei Paschi and Danske Bank. To uncover a more dynamic news linkage to G-SIBs and O-SIIs institutions, we employ time-varying news sentiment indices. Several periods with high negative sentiment values are identified, most notably the global financial crisis (in the case of G-SIBs) and close to the first dates of lists release (for both groups). Moreover, before the official designation of G-SIBs and O-SIIs, the prevalent news sentiment was negative. The listings between G-SIB and O-SII groups as determined by the main systemic risk measures are significantly different and this reflects the different points of view of FSB and of the EBA when gauging the systemic importance and systemic exposure of G-SIBs and O-SIIs, respectively.

In sum, the two groups perform differently within the wider financial system, highlighting once more the drawbacks of micro-prudential supervision where risk is taken to be exogenous to financial system and institutions non-contagious. Instead, a more encompassing set of regulations and practices through which financial institutions are regulated and supervised together, as part of the global financial system, should be the new desiderata for policy makers.

The remainder of this paper is structured as follows. In Section 2 we discuss the connection between systemic risk and contagion as it is reflected in the literature so far. In Section 3 we describe the data and in Section 4 we describe the systemic risk methodology we employ. Our empirical findings are contained in Section 5 and in Section 6 we present our conclusions.
2. Connecting Contagion and Systemic Risk

After the financial crisis, understanding contagion among financial institutions became priority for policy makers in order to foster financial stability thereby if not prevent at least modulate future financial crises (Liu et al., 2017). Supervisory and regulatory authorities (see for instance BCBS, 2010; EC, 2013; and OCC, 2013) have agreed that new measures such as capital surcharges, liquidity requirements, and resolution regimes are needed in order to assure a more resilient banking system that is capable to absorb future losses without making use of public money, to reduce systemic risk and, ultimately, to foster financial stability. Given these considerations, on November 4, 2011 at the G20 Summit in Cannes, the Financial Stability Board (FSB) in consultation with the Basel Committee on Banking Supervision (BCBS) published a list of 29 global systemically important banks (G-SIBs), which is a particular category of systemically important institutions (SIFIs). All these banks were required to increase their capital in a range that varies from 1% to 2.5% of their risk-weighted assets (with an empty bucket of 3.5% to discourage further systemic risk) in order to improve the loss absorption capacity (FSB, 2011). Moreover, the G-SIBs will be subject to a tighter and a more effective supervision, given their systemic importance. The G-SIBs list is updated and published every year in November by the FSB. In addition, the BCBS (2012) developed a framework for assessing the domestic systemically important banks (D-SIBs).

The European Banking Authority (EBA), outside the designation of G-SIBs adopted by the Basel Committee, established upon consultation with the European Systemic Risk Board (ESRB) its own guidelines for identifying other systemically important institutions (O-SIIs), that is, institutions “[...] that, due to their systemic importance, are more likely to create risks to financial stability4 for the European Union or a Member State. The identification process follows the principles of Basel Committee to deal with D-SIBs and it includes both national and supranational authorities. Therefore, the O-SIIs are the financial institutions that are systemically important at the European Union or Member State level. The criteria on which these institutions are selected are size, interconnectedness, relevance to the economy and complexity. Thus, the

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3 Besides financial intermediaries (banks), SIFIs include insurance companies (non-bank financial intermediaries), and other financial institutions. According to Zhou (2012), systemically important financial institutions may jeopardize financial stability through counterparty, liquidity and contagion risk.

interconnectedness is one of the five characteristics used by the EBA to determine systemically important financial institutions. The identified institutions must maintain a Common Equity Tier 1 (CET1) capital buffer of up to 2% of the total risk exposure they hold. The first official list was disclosed by the EBA on April 25, 2016 and it is updated on a yearly basis.

Given the systemic importance of the banks, a strand of literature has emerged, especially in the last decade, trying to quantify the systemic risk and to identify the institutions with a great contribution or exposure to systemic risk (for some surveys and comparisons of the measures of systemic risk, see for instance Bisias et al., 2012; Zhang et al., 2015; Benoit et al., 2017; Silva et al., 2017). Quantifying the risk of distress is important from both financial stability and macroeconomic standpoints, as financial crises tend to have significant and persistent negative effects on real economy (Acemoglu et al., 2012; Avdjiev et al., 2019). However, as systemic risk varies over time, institutions may prove not to be systemically important in some periods while remaining critical in others (Elliott and Litan, 2011) such that the systemic risk rankings may move in opposite directions (van de Leur et al., 2017). Moreover, most of the systemic risk measures proposed in the literature are market- and/or accounting-based. Löffler and Raupach (2018) for example point out that market-based measures’ ability to identify systemically important banks may have some pitfalls. Furthermore, many economists have agreed that imposing capital and/or liquidity surcharges based on institution’s contribution to systemic risk in order to absorb future losses may be a good tool to reduce negative externalities (e.g., Elliott and Litan, 2011; Ötker-Robe et al., 2011; Adrian and Brunnermeier, 2016; Acharya et al., 2017). Elliott and Litan (2011) argue that charging additional capital for SIFIs may not result in less risk-taking. In addition, Benoit et al. (2014) document that different measures of systemic risk may lead to conflicting results in the identification of systemically important financial institutions.5

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

5 For a discussion on systemic risk measures shortcomings, see Giudici et al. (2020).
Contagion is broadly defined as the spillovers triggered by extreme negative events (Dornbusch, and Park, 2001; Forbes and Rigobon, 2002; Pericoli and Sbracia, 2003; Forbes, 2012). Forbes (2012) contrasts contagion to interdependence - high correlations across markets during all states of the world, arguing that the former has deep roots in this globalized framework, being therefore “extremely difficult to stop”. Forbes and Rigobon (2002), analyzing the 1994 Mexican and the 1997 Asian crises, using a heteroskedasticity-adjusted correlation coefficient, report no contagion but find interdependence during both crises among 24 developed and emerging markets. More recently, De Bruyckere et al. (2013) use excess correlations to measure bank/sovereign risk spillovers in the European debt crisis and they found significant empirical evidence of contagion between bank and sovereign credit risk.

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

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

Recently, a new strand of literature has emerged, making use of network graphs in order to describe the interdependence between markets/institutions (for recent surveys about network and systemic risk, see Battiston and Martinez-Jaramillo, 2018; and Neveu, 2018). Fagiolo et al. (2010)

6 For some excellent reviews, see Pericoli and Sbracia (2003) and Chinazzi and Fagiolo (2015).
7 Besides VAR models, some authors apply Vector Error Correction (VEC) modes. See, e.g., Pagnottoni and Dimpfl (2019) and Giudici and Pagnottoni (2019, 2020),
are among the first to model financial system as a network, applying it to international trade flows.\textsuperscript{8} The relationship between the institutions acting within the financial system can be represented as a network,\textsuperscript{9} where these institutions are the nodes and edges represent the existence of credit/lending relationships between any two parties (Chinazzi and Fagiolo, 2015). More generally, graphical networks represent interactions among random variables in a system where nodes represent the variables and edges show their interactions (Giudici and Spelta, 2016). Billio et al. (2012) develop measures of connectedness based on principal-component analysis and Granger-causality networks and they apply the methodology to hedge funds, banks, broker/dealers, and insurance companies. Their findings indicate that banks are the main actors in transmitting shocks within four categories of financial institutions. Diebold and Yilmaz (2014) propose connectedness measures based on variance decomposition and apply them to US financial institutions’ stock return volatilities. Peltonen et al. (2015) employ macro-networks to measure the interconnectedness of the banking sector and document that a more central position of the banking sector in the network significantly increases the probability of a banking crisis. In the same vein, Constantin et al. (2016) develop early-warning models based on network linkages for European banks and find that these models outperform the benchmark, without networks. Ahelegbey et al. (2016) propose a Bayesian graphical VAR (BGVAR) model to investigate contemporaneous and temporal causal structures of the structural VAR (SVAR) model, and apply it to macroeconomic and financial datasets. They find that the BGVAR produces a better representation of the linkages between the financial and non-financial super-sectors in Europe than the Granger-causal inference approach. Ahelegbey et al. (2021) combine VAR with network models by analyzing both bilateral-based and market-based financial data and show that both bilateral exposures and market prices act as contagion channels in the transmission of shocks arising from a country to the overall system.

Finally, a recent stream of literature makes use of text analysis and categorization in the financial context to assess contagion patterns in the information flow. Cerchiello et al. (2017) combine financial news from Twitter with market data in a Bayesian approach and show that their

\textsuperscript{8} Easley and Kleinberg (2010), Acemoglu et al. (2012), Babus (2016) and Adamic et al. (2017) describe financial applications of network graphs, whereas Bardoscia et al. (2021) provide an excellent review on the physics of financial networks.

model is successful in predicting the default probability of a bank, conditionally on the others. In the same context, Cerchiello and Nicola (2018) use news archives from Reuters and Bloomberg and investigate causal effects in the diffusion of the news by means of Granger-causality tests and show that both the temporal dynamics and the spatial differentiation matter in the news contagion. Also, Wan et al. (2021) investigate the propagation of news sentiment in company networks and evaluate the associated market movements in terms of stock price and volatility, arguing that strong media sentiment towards one company may be a sign of significant change in media sentiment towards related companies.

3. Tools for Measuring Interconnectedness of Systemic Risk

In this section we describe how we assess and quantify the spillover effects from/to G-SIBs, O-SIIs, and the financial system. We focus on the following approaches: systemic risk indicators, network measures, and cross-quantilogram. For systemic risk indicators and network measures we use equity returns whereas for the cross-quantilogram we construct market capitalization-weighted indices of O-SIIs and G-SIBs.

3.1. Systemic Risk Indicators

We employ three well-known systemic risk metrics that are widely used in the literature: Conditional Value at Risk of Adrian and Brunnermeier (2016), Marginal Expected Shortfall of Acharya et al. (2017), and SRISK of Acharya et al. (2012) and extended by Brownlees and Engle (2017). Bisias et al. (2012) provide an extensive survey of 31 measures of systemic risk.

i. \( \Delta \text{CoVaR} \)

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

\[
\text{Market Assets}_t^i = \text{Total Assets}_t^i \times \frac{\text{Market Equity}_t^i}{\text{Book Equity}_t^i}
\] (1)
We focus on the daily change of the market assets of institution $i$ from $t-1$ to $t$ and define the return of each institution:

$$R^i_t = \frac{Market\ Assets^i_t - Market\ Assets^i_{t-1}}{Market\ Assets^i_{t-1}} \quad (2)$$

As total assets and book equity have a quarterly frequency whereas market equity has a daily frequency, we transform the former two accounting measures into daily frequencies through linear interpolation between two consecutive quarters.$^{10}$

Following Adrian and Brunnermeier (2016), we estimate CoVaR as the $q$th quantile of the system’s returns ($R^\text{system}_t$) distribution over a given period of time conditioned on the event that each financial institution registers the maximum possible loss of its returns for the same significance level $q$: $^{11}$

$$Pr\left(R^\text{system}_t \leq CoVaR_{q,t}^{\text{system}} | R^i_{\text{Market\ Assets},t} = VaR^i_{q,t} | R^i_{\text{Market\ Assets},t} = VaR^i_{q,t}\right) = q \quad (3)$$

In order to capture the time-variation of the financial institutions’ individual and systemic risk, we estimate the tail risk measures VaR and CoVaR using a vector of market indices ($M^i_t$) that contains information representative for the world financial markets. More specifically, we have employed the following market indices: $^{12}$ (i) the daily return of MSCI World index, (ii) the volatility index (VIX), (iii) the daily real estate sector return (MSCI World Real Estate) in excess of the banking sector return (MSCI World Banks), (iv) the change in the three-month T-bill rate, (v) the spread between three-month repo rate and three-month T-bill rate, (vi) the spread of change in 10-year bond yield and three-month T-bill rate and (vii) the change in the spread of Moody’s Baa corporate bond yield and 10-year bond yield.

In order to compute VaR and CoVaR we use quantile regression (QR) allowing us to estimate the dependent variable’s quantiles conditioned on the explanatory variables, being more robust in the presence of extreme market conditions (Nistor and Ongena, 2021). Moreover, we use the method of Machado and Santos Silva (2013) accounting for the standard errors to be asymptotically valid in the presence of heteroskedasticity and misspecification.

$$R^i_{\text{Market\ Assets},t} = \alpha^i + M^i_{t-1} \times \beta^i + \epsilon^i \quad (4)$$

$^{10}$ As a robustness check, we also perform the cubic spline interpolations and the findings remain robust.

$^{11}$ Here we define the system as MSCI World Financials Index. Alternatively, we re-estimate the quantile regressions using the assets market value of the sample. Following Adrian and Brunnermeier (2016), all our systemic risk indicators are estimated for a 5% quantile.

$^{12}$ Initially, all market variables have been tested for unit stationarity using the Augmented Dickey-Fuller test. When the series were not stationary, we used instead the change of variables or the spread.
\[ R_t^{system} = \alpha^{system|i} + \delta^{system|i} \times R_{t}^{Market\ Assets,i} + M_{t-1}^{i} \times \beta^{system|i} + \varepsilon_t^{system|i} \]  

(5)

\[ M_{t-1}^{i} \] is a \((1 \times k)\) vector of lagged market indices at time \( t-1 \), \( \alpha^{i} \), \( \alpha^{system|i} \), \( \beta^{i} \), \( \beta^{system|i} \), \( \delta^{system|i} \), \( \gamma^{i} \), \( \gamma^{system|i} \) are the parameters to be estimated and \( \varepsilon^{i} \) and \( \varepsilon^{system|i} \) are \( iid \) error terms. \( \delta^{system|i} \) reflects the conditional dependence of the system’s return on financial institution \( i \)'s return, a large coefficient being associated with an increased contribution of that institution to systemic risk and thus with large spillover effects.

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

\[ \hat{VaR}_{q,t}^{i} = \alpha_q^{i} + M_{t-1}^{i} \times \beta_q^{i} \]  

(6)

\[ \hat{CoVaR}_{q,t}^{i} = \alpha_q^{system|i} + \delta_q^{system|i} \times \hat{VaR}_{q,t}^{i} + M_{t-1}^{i} \times \beta_q^{system|i} \]  

(7)

In the end, each financial institution’s contribution to systemic risk (\( \Delta CoVaR \)) is defined as:

\[ \Delta CoVaR_{q,t}^{system|i} = CoVaR_{q,t}^{system|i} - CoVaR_{q,t}^{system|_{Market\ Assets=VaR_{50%}^{system}}} \]  

(8)

Rearranging Eq. (8) we get the exposure of the institution \( i \) to systemic risk, defined as:

\[ Exposure - \Delta CoVaR_{q,t}^{system|i} = CoVaR_{q,t}^{system|_{Market\ Assets=VaR_{q,t}^{system}}} - CoVaR_{q,t}^{system|_{Market\ Assets=VaR_{50%}^{system}}} \]  

(9)

Exposure-\( \Delta CoVaR \) works in the opposite direction compared to \( \Delta CoVaR \), and can be shortly defined as contribution of the financial system to institution \( i \)'s systemic risk.

ii. Marginal Expected Shortfall

Another systemic risk measure that we apply is the Marginal Expected Shortfall (MES) of Acharya et al. (2017), denoting the exposure of financial institutions to systemic risk as percent of market capitalization. MES is defined as the average return on financial institution’s market capitalization on the days the total market capitalization of the sample experienced a loss greater than a specified threshold \( C \) indicative of market distress:

\[ MES_{t-1}^{i} = E_{t-1}(R^i_t | R^{system}_t < C) \]  

(10)

where \( R^i_t \) is the return of financial institution \( i \) at time \( t \) and \( R^{system}_t \) is the return of the system, defined as MSCI World Financials Index. We model the bivariate process of firm and market returns as follows:
\[ R_t^{\text{system}} = \sigma_t^{\text{system}} \times \varepsilon_t^{\text{system}} \]  
(11)

\[ R_t^i = \sigma_t^i \varepsilon_t^i = \sigma_t^i \times \rho_t^i \times \varepsilon_t^{\text{system}} + \sigma_t^i \times \sqrt{1 - \rho_{t,t}^2} \times \xi_{t,t} \]  
(12)

\( \sigma_t^i \) and \( \sigma_t^{\text{system}} \) are the volatilities of financial institution \( i \) and system, respectively, \( \rho_t^i \) is the correlation coefficient between the return of institution \( i \) and the return of the system, and \( \varepsilon_t^{\text{system}}, \varepsilon_t^i \) and \( \xi_{t,t} \) are the i.i.d. error terms. It follows that:

\[ \text{MES}_{t-1}^i = E_{t-1}(R_t^i|R_t^{\text{system}} < C) = \sigma_t^i E_{t-1}(\varepsilon_t^i|\varepsilon_t^{\text{system}} < \frac{c}{\sigma_t^{\text{system}}}) = \sigma_t^i \]

\[ \rho_{t,t} E_{t-1}(\varepsilon_t^i|\varepsilon_t^{\text{system}} < \frac{c}{\sigma_t^{\text{system}}}) + \sigma_t^i \sqrt{1 - \rho_{t,t}^2} E_{t-1}(\xi_{t,t}^i|\varepsilon_t^{\text{system}} < \frac{c}{\sigma_t^{\text{system}}}) \]  
(13)

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

iii. Systemic Risk Index

Finally, our last indicator to consider in our analysis is the Systemic Risk Index (SRISK) introduced by Acharya et al. (2012) and extended by Brownlees and Engle (2017). As in the case of the \( \Delta \text{CoVaR} \), SRISK is a measure of contribution of a financial institution to the wide systemic risk, defined as the loss of a specific institution (capital shortfall), conditioned by the whole financial system being in distress. A major convenient of SRISK is that it is expressed in monetary units making it very reliable in monitoring systemic exposure. The capital shortfall of firm \( i \) at time \( t \) is defined as:

\[ CS_t^i = kA_t^i - E_t^i = k(L_t^i + E_t^i) - E_t^i \]  
(14)

\( E_t^i \) is the market capitalization of the institution (market value of equity), \( L_t^i \) is the book value of total liabilities, \( A_t^i \) is the implied value of total assets, and \( k \) is the prudential capital ratio.

As specified above, SRISK is the capital shortfall conditioned by a systemic event, which is the decline of the system below a threshold \( C \) over a time horizon \( h \). Combining these altogether, we have the following expression:

\[ \text{SRISK}_t^i = E_t(CS_{t+h}^i|R_{t+1:t+h}^{\text{system}} < C) = kE_t(R_t^i|R_{t+1:t+h}^{\text{system}} < C) - (1-k)E_t(E_{t+h}^i|R_{t+1:t+h}^{\text{system}} < C) \]  
(15)
Further, we assume that when a crisis hits the financial system, the debt cannot be renegotiated. It follows then that:

\[ SRISK_t^i = k LRMES_t^i - (1 - k) E_t^i (1 - LRMS_t^i) \]  \hspace{1cm} (16)

where \( LRMES_t^i \) is the long-run marginal expected shortfall, i.e., the expectation of the firm equity multi-period return conditional on the systemic event. Following Acharya et al. (2012), we compute LRMS as \( (1 - \exp^{-18 \times MES}) \). The capital prudential ratio, \( k \), is set at 8% in accordance with the Basel Accords. As in the case of the MES, SRISK is estimated using the GARCH-DCC framework. When the institution is in distress, the SRISK indicator will be positive, indicating insufficient working capital, whereas a negative value indicates a capital surplus.

3.2. Measures of Connectedness

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

In a Granger causality framework one can determine the directional return spillovers in the financial system (composed, in our case, from G-SIBs and O-SIIs). A time series \( j \) can Granger-cause another time series \( i \) if information contained in the past values of \( i \) and in the past values of \( j \) are better in predicting the value of \( i \) than the information based only on the past values of \( i \).

Defining the following relationships:

\[ (j \rightarrow i) = \begin{cases} 1 \text{ if } j \text{ Granger causes } i, \\ 0 \quad \text{otherwise} \end{cases} \]  \hspace{1cm} (17)

and \((j \rightarrow j) \equiv 0.\) Thus, based on these pairwise Granger causalities, one can construct the Granger-causality network. The network is defined as a set of nodes (G-SIBs and O-SIIs) connected by edges. It will be represented as an \( N_t \)-dimensional adjacency matrix \( A_t \) with the elements \( a_{ijt} \) zeros and ones, \( a_{ijt} = 1 \) if the node \( j \) Granger causes node \( i \) and \( a_{ijt} = 0 \) otherwise. Following Billio et al. (2012) we compute the Dynamic Causality Index (DCI) or the Degree of Granger Causality (DGC) with the following expression:

\[ \text{We employ the Bayesian Information Criterion (BIC)/Schwartz Information Criterion (SIC) as the model-selection criterion for determining the optimal number of lags in our analysis.} \]
\[ DCI_t = \binom{N_t}{2}^{-1} \sum_{i=1}^{N_t} \sum_{j=1}^{N_t} a_{ijt} \]  

(18)

DCI is defined as the proportion of Granger-causality relationships (at the 5% level of statistical significance) among all \( N(N-1) \) pairs of \( N \) financial institutions based on 252-days rolling window. We set the threshold of non-causal relationships at 0.06.\(^{14}\) An increase in the DCI indicates a higher level of interconnectedness between financial institutions (G-SIBs and O-SIIs, in our case).

Furthermore, we compute the In network degree measuring the number of financial institutions that significantly (at the 5% level) Granger-cause institution \( j \), the Out network degree that measures the number of financial institutions that are significantly (at the 5% level) Granger-caused by institution \( j \), and their sum, i.e., the In + Out network degree. Also, following Billio et al. (2012) we compute the In + Out – Other network degree condition on the type of financial institution (G-SIBs and O-SIIs, in our case).

Additionally, we present three of the most used centrality measures in network analysis: betweenness centrality, eigenvector centrality, and closeness centrality. The betweenness centrality measures the extent to which a financial institution lies on paths between other financial institutions. Very important, this measure can capture how susceptible a node (financial institution) is to shocks that spread through network. The eigenvector centrality quantifies the importance of a financial institution in a network by assigning relative scores to financial institutions dependant on how connected they are to the rest of the nodes in the network. Finally, the closeness centrality determines the mean distance from a financial institution to other financial institutions and captures how close a node is to other nodes in the graph.

3.3. The Cross-Quantilogram

The cross-quantilogram is a relatively new tool introduced by Han et al. (2016), continuing the work of Linton and Whang (2007) who proposed the quantilogram as measure for predictability in different parts of the distribution of a stationary time series based on the correlogram of “quantile hits” (Han et al., 2016). The cross-quantilogram measures the predictability of different quantiles of the distribution of a stationary time series,\(^{15}\) but this time into a bivariate setting and it can be

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\(^{14}\) The choice of threshold value follows the approach of Billio et al. (2012) which set it at 0.055, being the simulated distribution obtained under the hypothesis of no causal relationships.

\(^{15}\) We reject the null hypothesis of non-stationary for all series (G-SIBs, O-SIIs and the system) according to the Phillips–Perron test. The results are presented in Table 2.
used to study the tail risk interdependence between two time series. The cross-quantilogram is suitable for financial series that exhibit stylized facts, such as non-normality, fat tails, and asymmetry. In this framework we are able to simultaneously detect the direction, magnitude, and the duration of the dependence between two variables (Uddin et al., 2019). Unlike the mean-spillover Granger-causality relationships, the cross-quantilogram allows to estimate the association and directional predictability between two variables at different quantile levels for the whole conditional distribution, such as extreme market conditions (5% quantile) and tranquil state of the economy (95% quantile). Moreover, quantifying the quantile dependence between time series, the cross-quantilogram can also be employed for assessing systemic risk.

Consider two time series $\mathcal{E}_{1,t}$ and $\mathcal{E}_{2,t}$ as continuous returns for G-SIBs and O-SIIs weighted by market-capitalization with the conditional distribution functions $F_1$ and $F_2$ and the corresponding conditional quantile functions $q_1(\tau_1) = \inf \{u: F_1(u) \geq \tau_1\}$ and $q_2(\tau_2) = \inf \{u: F_2(u) \geq \tau_2\}$ for $\tau_1$ and $\tau_2 \in (0, 1)$. With the pairs $\tau = (\tau_1, \tau_2)$ we will estimate the dependence between $\{\mathcal{E}_{1,t} \leq q_1(\tau_1)\}$ and $\{\mathcal{E}_{2,t-k} \leq q_2(t-k)(\tau_2)\}$ for $k = \pm 1, \pm 2, \ldots$ Having the function $\psi_a(u) = I[u < 0] - a$, defining the quantile-hit process, the cross-quantilogram has the following form:

$$\rho_\tau(k) = \frac{E[\psi_{1,1}(\mathcal{E}_{1,t} - q_{1,1}(\tau_1)) \psi_{2,2}(\mathcal{E}_{2,t-k} - q_{2,2}(t-k)(\tau_2))]}{\sqrt{E[\psi_{1,1}^2(\mathcal{E}_{1,t} - q_{1,1}(\tau_1))] \sqrt{E[\psi_{2,2}^2(\mathcal{E}_{2,t-k} - q_{2,2}(t-k)(\tau_2))]}]}$$

(19)

The cross-quantilogram is able to capture cross-correlation of quantile-hit processes and in the case where $\mathcal{E}_{1,t} = \mathcal{E}_{2,t}$, the cross-quantilogram becomes the quantilogram of Linton and Whang (2007). In general, $\rho_\tau(k) \in [-1, 1]$ but if $\rho_\tau(k) = 0$, there is no directional predictability. If $\mathcal{E}_{1,t}$ and $\mathcal{E}_{1,t}$ are the market capitalization-weighted indices of G-SIBs and O-SIIs, respectively and $\rho_\tau(1) = 0$ this implies that if the returns on O-SIIs are below (above) a given quantile $q_1(\tau_1)$ at time $t-1$, there is no possibility of prediction whether the return on the G-SIBs is below (above) a given quantile $q_1(\tau_1)$ at time $t$.

To test the null hypothesis that the conditional correlations are not different from zero ($\rho_\tau(k) = 0$ for all $k \in \{1, 2, \ldots, p\}$) against the alternative hypothesis that they are different from

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16 Through this approach, we measure spillover effects from G-SIBs to O-SIIS, from O-SIIs to G-SIBs, from G-SIBs to the system, from the system to G-SIBs, from O-SIIs to the system, and from the system to O-SIIs, but we consider only G-SIBs and O-SIIs when presenting the methodological aspects.
zero \( (\rho_t(k) \neq 0 \text{ for some } k \in \{1, 2, \ldots, p\}) \) we use the Box-Ljung test statistic which can be presented as follows:

\[
\hat{Q}_T(p) = \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}^2(k)}{T-k} 
\]  

(20)

The critical values of the test are obtained using the stationary bootstrap procedure of Politis and Romano (1994) that takes into account the serial dependence in the data, where pseudo samples are constructed from blocks of data with random block lengths. Also, as in Han et al. (2016) confidence intervals are obtained with stationary bootstrapping.

To control for equity market volatility on the cross-quantile relationship between G-SIBs and O-SIIs, we apply the partial cross-quantilogram, which is an extended version of the cross-quantilogram. In this framework we control for intermediate events between \( t \) and \( t - k \) for the two series \( \{y_{1,t} \leq q_{1,t}(\tau_1)\} \) and \( \{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\} \). The control state variable is defined as \( z_t = [\psi_{\tau_3}(y_{3,t} - q_{3,t}(\tau_3)), \ldots, \psi_{\tau_l}(y_{l,t} - q_{l,t}(\tau_l))]^T \) for \( l \geq 3 \). The correlation matrix and its inverse function can be presented as follows:

\[
R^{-1}_\tau = E[h_t(\bar{\tau})h(\bar{\tau})^T]^{-1} = P_\tau 
\]  

(21)

where \( h_t(\bar{\tau}) = [\psi_{\tau_1}(y_{1,t}(\tau_1)), \ldots, \psi_{\tau_l}(y_{l,t} - q_{l,t}(\tau_l))]^T \) is the quantile-hit process, and \( P_\tau \) can be defined as

\[
\rho_{\tau \mid z} = \frac{-P_{\tau_{12}}}{\sqrt{P_{\tau_{11}}P_{\tau_{22}}}} 
\]  

(22)

Thus, \( \rho_{\tau \mid z} \) is the partial cross-quantilogram measuring the cross-quantilogram dependence that is conditional on the control variable \( z_t \).

3.4. One unified testing framework: Bayesian Graphical VAR

We discuss in this section a unified testing framework to embed the measures we have presented above.\(^{17}\) To this end, we follow the methodology developed by Ahelegbey et al. (2016) that propose a Bayesian graphical VAR (BGVAR) model where the contemporaneous and temporal causal structures of the structural VAR (SVAR) model are represented by two different graphs. This approach is very useful considering two aspects: (i) financial variables may change over time, especially during financial distress, and thus dynamic models could provide a convenient

\(^{17}\) We thank an anonymous referee for suggesting this approach.
framework to analyze their temporal behaviour and (ii) it provides a solution to the problem of over-parametrization in VAR models.

Consider the following SVAR model:

\[ Y_t = B_0 Y_t + \sum_{i=1}^{p} B_i Y_{t-1} + \sum_{i=1}^{p} C_i Z_{t-1} + \epsilon_t \]  

where \(Y_t\) is a \(n_y\) vector of response variables, \(Z_t\) is a \(n_z\) vector of predictor variables, \(B_0\) is a \(n_y \times n_y\) vector of structural contemporaneous coefficients, with zero diagonals, \(B_i\) and \(C_i\) are \(n_y \times n_y\) and \(n_y \times n_z\) matrices of structural coefficients, respectively with \(1 \leq i \leq p\), and \(\epsilon_t\) is an iid \(n_y\) vector of structural error terms. Let \(X_t = (X^1_t, X^2_t, ..., X^n_t)\), where \(X^i_t\) is a realization of the \(i\)th variable at time \(t\). Eq. (23) can be represented as a graphical model with a one-to-one correspondence between the coefficient matrices and a directed acyclic graph (DAG):

\[ X_j^{t-s} \rightarrow X^i_t \iff B^*_s,i,j \neq 0, \quad 0 \leq s \leq p \]  

where \(B^*_0 = B_0\) for \(s = 0\), and \(B^*_s = (B_s, C_s)\) for \(1 \leq s \leq p\). The relationship in Eq. (24) can be considered as temporal (lagged) dependence for \(1 \leq s \leq p\) and contemporaneous for \(s = 0\).

From Eq. (24) we define:

\[ B^*_s = (G_s \circ \Phi_s), \quad 0 \leq s \leq p \]  

where \(s = 0, B^*_0 = B_0\) is a \(n_y \times n_y\) structural coefficients of contemporaneous dependence, \(G_0\) is a \(n_y \times n_y\) binary connectivity matrix, and \(\Phi_0\) is a \(n_y \times n_y\) matrix of coefficients. For \(1 \leq s \leq p, B^*_s = (B_s, C_s)\) is a \(n_y \times (n_y + n_z)\) matrix of structural coefficients of temporal dependence, \(G_s\) is a \(n_y \times (n_y + n_z)\) binary connectivity matrix, and \(\Phi_s\) is a \(n_y \times (n_y + n_z)\) matrix of coefficients. Thus, \(G_0\) is the connectivity matrix of contemporaneous dependence and \(G_s\) is the matrix of temporal dependence. \(\circ\) is the element-by-element Hadamard’s product. There is a one-to-one correspondence between \(\Phi_s\) and \(B^*_s\) conditionally on \(G_s\):

\[ B^*_{s,i,j} = \begin{cases} \Phi_{s,i,j} & \text{if } G_{s,i,j}=1 \\ 0 & \text{if } G_{s,i,j}=0 \end{cases} \]  

Based on Eq. (25), Eq. (23) can be represented as:

\[ Y_t = (G_0 \circ \Phi_0) Y_t + \sum_{i=1}^{p} (G_0 \circ \Phi_0) X_{t-1} + \epsilon_t \]  

where \((G_0 \circ \Phi_0)\) are the graphical model structural coefficient matrices whose non-zero elements represent the value associated with the contemporaneous and temporal dependences, respectively. For estimating Eq. (27) one needs to specify the appropriate number of lags, \(p\) (we use BIC), inference of the causal structure, \(G = (G_0, G_1, ..., G_p)\), and the set of parameters, \(\{B_0, B^*_1, ..., B^*_p, \Sigma_\epsilon\}\)
from $\Sigma_x$. We assume that the prior on $G$ is uniform and that, given a complete graph, the prior on $\Omega_x = \Sigma_x^{-1}$ is a conjugate Wishart (for details, see Ahelegbey et al., 2016).

The reduced-form parameters of the standard VAR model can be mapped to that of the Bayesian graphical model as follows:

$$
A_0 = L_{n_y} - (G_0 \circ \Phi_0), A_i = (L_{n_y} - G_0 \circ \Phi_0)^{-1}(G_i \circ \Phi_i), i = 1, ..., p
$$

where $A_0$ is an $n_y \times n_y$ coefficient matrix conditional on $G_0$, and $A_i$ is a stacked reduced-form coefficient matrix. Let $B_+^*$ be a stacked form of $B_1^*, ..., B_p^*$. The connectivity matrix associated with $B_+^*$ can be expressed as $G_+$, a stacked form of $G_1, ..., G_p$, and the graph associated with $A_+$ can be represented as $G_+^* = (L_{n_y} - G_0)^{-1}G_+$ and $G_+^*$ are of dimension $n_y \times np$.

To sample the graph structures, we follow the approach described in Ahelegbey et al. (2016). Our interest is to investigate the temporal dependence and thus we will estimate $G_+ = (G_1, ..., G_p)$ based on the specification of $p$, the maximum number of lags computed with BIC. $G_+$ will be referred as multivariate autoregressive (MAR) structure. The likelihood of MAR structure is given by the probability density function of the normal distribution $\mathcal{N}(0, \Sigma_{x+})$, where $\Sigma_{x+}$ is the temporal covariance matrix.

3.5. The Influence of Financial News

To further disentangle the effect of a bank being included in the G-SIB or O-SII list, we follow the approach of Cerchiello and Nicola (2018) and besides market data we assess the textual data concerning these two groups of institutions\(^\text{18}\). Hence, we analyze the evolution of topics extracted from Reuters news archive from 2007 to 2016 by employing Structural Topic Model (STM), which is a modified version of the Latent Dirichlet Allocation (LDA), allowing for specific covariates.

The STM can be defined as follows:

$$
\theta_i|(C_i, \gamma, \Sigma) \sim \text{LogisticNorm}(C_i, \gamma, \Sigma) \quad (29)
$$

$$
\phi_{ik} \propto \exp(m + k_k + k_{ci} + k_{ki}) \quad (30)
$$

$$
z_{ij}|(\theta_i) \sim \text{Multinomial}(\theta_i) \quad (31)
$$

$$
x_{ij}|z_{ij} \sim \text{Multinomial}(\phi_{iz_{ij}}) \quad (32)
$$

where $C_i$ is the covariates matrix, $\gamma$ is the coefficient vector, $\Sigma$ is the covariance matrix, $\phi_{ik}$ is the word distribution for document $d_i$ and $k$th topic, $m$ is a reference log-word distribution, whereas

\(^{18}\) We thank an anonymous referee for suggesting this approach.
$k_k$, $k_g$ and $k_{gl}$ are the deviations from the baseline as a result of the topics, the covariates and their interaction effect, respectively.

The topic prevalence is modeled by the Eq. (29) through a logistic normal distribution with a mean that is not constant but depends on the covariates. The topical content is represented by Eq. (30) in which the word occurrences are modeled in terms of log-transformed rate deviations from a corpus based distribution $m$, where parameters $k_k$, $k_g$ and $k_{gl}$ are the deviations from the baseline as a result of the topics, the covariates and their interaction effect, respectively. The last two equations show the distribution of topics $z_{ij}$ and of words $x_{ij}$, both sampled from a Multinomial distribution. We follow Cerchiello and Nicola (2018) and include time (temporal dimension) and country (spatial dimension) specific variables as covariates.

The performance of the model depends particularly on the number of topics. Roberts et al. (2019) suggest several methods in choosing the appropriate number of topics. We employ the data-driven approach by indicating an interval from 5 to 20 topics, and select the optimal number based on held-out log-likelihood and semantic coherence.

Last but not least, based on the Reuters news archive, we derive time-varying news sentiment indices for both G-SIBs and O-SIIs. This approach is lexicon-based and takes into account valence shifters (negation and amplifiers / deamplifiers). In the end, it assigns different values for a news in a particular day which can be negative (more words with a negative polarity), 0 (neutral) or positive (more words with a positive polarity).

In Table 1 we provide a summary of the technique we apply, their main advantages and disadvantages, and the findings in short.

[Table 1 goes here]

4. Data and Empirical Results

4.1. Data

A complete description of the data used in our analysis is given in the Table 2. For systemic risk indicators we use total assets and total common equity with daily frequency derived from linear

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19 The analysis is performed using the `sentimentr` package in R.
interpolation from quarterly data, market capitalization, equity returns and market indices with
daily frequency.

[Table 2 goes here]

In Table 3 we report the descriptive statistics for market capitalization-weighted indices
disaggregated for G-SIBs and O-SIIs, and the global financial system. The mean of G-SIBs series
is -0.02% with a standard deviation of 1.62%, whereas the average of O-SIIs and the system is -
0.04% and 0%, respectively with a standard deviation of 2.10% and 1.35%, respectively. One can
also note from the table above that all three series exhibit negative skewness and excess kurtosis is
well above zero, meaning that all three series are not normally distributed.

[Table 3 goes here]

The same conclusion is reached by employing the Jarque-Bera test. The ARCH-LM test
applied for 1 lag according to Bayesian Information Criterion rejects the null hypothesis of
homoscedasticity for all three series up to fifth lag at the 1% level, whereas the Phillips-Perron test,
which accounts for potential serial correlation and heteroskedasticity in the residuals, rejects the
null hypothesis of non-stationarity. Therefore, a good methodology in quantifying the degree of
interconnectedness between financial institutions should take into account the non-normality, fat
tails, and asymmetry of the data.

4.2. Systemic Risk Rankings

Table 4 reports the main statistics of systemic and individual risk measures over the analyzed
period. In terms of contribution to systemic risk as defined by ΔCoVaR and SRISK, one can
observe that on average, G-SIBs contribute more to systemic-wide distress than O-SIIs with 0.33
p.p. in terms of ΔCoVaR. This difference is with respect to SRISK too, where on average G-SIBs
have a capital shortfall greater with approximately $50 billion than O-SIIs. In terms of exposure to
systemic risk, again G-SIBs are more exposed to systemic risk than O-SIIs, as indicated by MES
(by 0.39 p.p.) and Exposure-ΔCoVaR (by 0.33 p.p.).

[Table 4 goes here]
However, O-SIIs are riskier on average based on VaR as a measure of individual risk. Thus, we reiterate the necessity of a macroprudential supervision for financial institutions because metrics based on their stand-alone risk may be misleading as they ignore the spillover effects between institutions and the negative externalities posed by individual financial institutions. Macroprudential policies, however, focus on the system as a whole and try to limit the impact of the financial crises on real economy. Within this framework, the risk comes from inside of the financial system and propagates rapidly because institutions are interconnected, thus taking into account the spillover effects between them. The evolution over time of the main systemic risk measures is depicted in Figure 1, comparatively for the two main groups of institutions.

[Figure 1 goes here]

In the aftermath of the global financial crisis and the sovereign debt crisis in Europe all risk indicators increased in jointly, with greater spikes for G-SIBs, and therefore increased the spillover effects from G-SIBs and O-SIIs to the financial system (ΔCoVaR and SRISK), and from the financial system to G-SIBs and O-SIIs (MES and Exposure-ΔCoVaR). The vertical lines on each graph represent the date of first release of G-SIBs list (November 4, 2011) and the date of first release of O-SIIs list (April 25, 2016). We do not find evidence in the short run of an increase in systemic and individual risk when these designation lists were made public.

Going further, we follow the approach of Abefidar et al. (2017) and construct systemic risk networks (for ΔCoVaR and MES, that is, a measure of contribution and of exposure to systemic risk, respectively) based on their partial correlations. Partial correlation measures the correlation between systemic distress of two banks by controlling for all other banks from the sample, and consider only direct relationships. The link between any two nodes (banks) represents the presence of a significant partial correlation coefficient between them (at the 5% level), the thickness of the edge line shows the link magnitude, and the colour indicates its sign, with blue – positive partial correlation and with red – negative partial correlation.

[Figure 2 goes here]
We can on the graphs in Figure 2 note more pronounced positive partial correlations between and within the two groups of banks, both for ∆CoVaR and MES, than negative partial correlations. In terms of centrality measures – more specifically betweenness centrality (ranks the institutions based on how susceptible they are to shocks that go through network) and closeness centrality (indicates how close a node is to other nodes in the graph) – Bank of China (G-SIB), Bank of Cyprus (O-SII) and Mizuho Financial Group (G-SIB) exhibit higher contagion capacity through the lens of ∆CoVaR, and Bank of Ireland Group (O-SII), State Street (G-SIBs) and OTP Bank (O-SII) are the closest nodes in the network. When it comes to MES, Getting Noble Bank, Bank of Cyprus and Sydbank (all O-SIIs) have the highest betweenness centrality and thus the most exposed to systemic distress, whereas Bank of Cyprus, Getting Noble (both O-SIIs) and Goldman Sachs (G-SIB) display greater closeness centrality measure. Thus, systemic risk network can provide supplementary insights comparing to row estimates of systemic contribution and exposure of the banks.

4.3. Dynamic Causality Index Evolution and Measures of Connectedness

From the evolution of the Dynamic Causality Index depicted in Figure 3, we note that the highest values of the index are reached at the end of 2008 and 2011, confirming our previous results from Section 4.2, documenting an increase in interconnectedness between G-SIBs and O-SIIs during the global financial turmoil and sovereign debt crisis in Europe, even though at that time (2008) the lists of G-SIBs and O-SIIs were not published yet. The first list of G-SIBs was made public by the FSB of November 4, 2011 and the first list of O-SIIs was released by the EBA on April 25, 2016.

On the same figure we depict the number of \( In + Out \) network degree (i.e., the sum of the number of financial institutions that Granger-cause institution \( j \) at the 5% level and the number of financial institutions that are Granger-caused by institution \( j \) at the 5% level, and \( In + Out – Other \) network degree, i.e., the sum of the number of financial institutions that Granger-cause and that are Granger-caused by institution \( j \) at the 5% level, conditional on the type of financial institution (G-SIBs and O-SIIs, respectively), together with the Granger-causality threshold (0.06) in red.

[Figure 3 goes here]
[Figure 4 goes here]
In Figure 4 we provide robustness assessment for DCI by considering different p-values to detect significant directional relationships in the Granger-causality framework, i.e., 1%, 5% and 10%, respectively. One can note that in most of the cases our results show causal relationships (greater than the 0.06 threshold), except for several periods between 2004-2006 and 2013-2017 for the 1% p-value.

[Figure 5 goes here]

Figure 5 illustrates the network diagram of linear Granger-causality relationships between G-SIBs and O-SIIs over the whole period, indicated as straight lines, connecting an institution that at time \( t \) Granger-causes the return of another institution at time \( t+1 \). The number of Granger-causality relationships that are statistically significant at the 5% level is larger within groups than between groups, being dominated by the other systemically important institutions. In the network diagram, the size of the node is proportional to the betweenness centrality measure. The biggest nodes in terms of betweenness centrality which takes into account both direct and indirect linkages capturing the position of a node in the overall network (i.e., they are situated on many shortest paths) appear to be banks from G-SIBS group, i.e., Mizuho Financial Group (MIZH), Sumitomo Mitsui Financial Group (SMFI), Bank of America (BAC), and Bank of New York Mellon (BK). Hence, they are the most susceptible to shocks (i.e., their equity price fluctuation) that propagate through the network, and have the most connections with the O-SIIs group. In contrast, Banco Bilbao Vizcaya Argentaria (BBVA), Bank of Valletta (BOV), OTP Bank (OTP), Siauliu Bankas (SUB) and Wells Fargo (WFC) are situated on no shortest path (i.e., the betweenness centrality is equal to zero) and are the least susceptible to shocks that propagate through network.\(^{20}\)

Additionally, we perform the same analysis over three sub-periods: January 1, 2004 – July 31, 2007 (pre-crisis), August 1, 2007 – December 31, 2013 (crisis) and January 1, 104 – September 29, 2017 (post-crisis).\(^{21}\) These are pre-crisis, crisis and post-crisis periods, respectively and the crisis period also includes the sovereign debt crisis in Europe (Lane 2012; Cornille et al., 2019). The number of significant Granger-causality links over the whole period was 1,625, whereas during

\(^{20}\) These measures of centralities are obtained based on average Granger-causality relationships.
\(^{21}\) The network diagrams for these two sub-periods are presented in the Annexes section of this paper (Figure A1, A2 and A3, respectively).
January 1, 2004 – July 31, 2007 – 1,873, during August 1, 2007 – December 31, 2013 – 1,554, and during post-crisis period – 1,776. We observe an increase in the number of connections between G-SIBs and O-SIIs during the crisis period compared to the pre-crisis period and the whole period. More importantly, during the crisis time the number of connections between the groups (G-SIBs and O-SIIs) was higher than within the groups (G-SIBs and G-SIBs and O-SIIs and O-SIIs), and one can associate this pattern with an increase in the dynamic interconnectedness between the two groups.

[Figure 6 goes here]

In Figure 6 we show the three centrality measures normalized between 0 and 1: betweenness centrality, eigenvector centrality, and closeness centrality. Betweenness centrality can capture how susceptible a financial institution is to shocks that propagate through network, and it is based on geodesic, i.e., the shortest distance path between two nodes. The higher this measure is for a particular financial institution (in proportion to other financial institutions), the higher the shocks that go through that particular financial institution. The eigenvector centrality quantifies the importance of a financial institution in a network by assigning relative scores to financial institutions dependent on how connected they are to the rest of the nodes in the network, being sensitive to the eigenvector centrality of other nodes. The closeness centrality determines the mean distance from a financial institution to other financial institutions and indicates how close a node is to other nodes in the graph. Based on two centrality measures, i.e., the betweenness centrality and the eigenvector centrality, Mizuho Financial Group (MIZH), which is a member of the G-SIBs group, is the most susceptible to shocks that go through network, being also the most important actor that is connected with other central actors. In terms of closeness centrality, HSBC Bank Malta (HSB) and Bank of Valletta (BOV), both from the O-SIIs group, are the closest, on average, to other financial institutions within the network. The average centrality measures for G-SIBs are the following: betweenness centrality – 0.02, eigenvector centrality – 0.19, closeness centrality – 0.65, whereas for O-SIIs the average for betweenness measure is 0.07, for eigenvector centrality – 0.28, and for closeness centrality – 0.49. Our results are in line with those of Hué (2019) and Cerqueti et al. (2020), confirming the important systemic role played by the G-SIBs in the global banking network.
4.4. Cross-Quantilogram Results

To capture the time-varying nature of the interconnectedness between G-SIBs, O-SIIs and the system, and any potential shift in the cross-quantilogram over time, we develop the quantile-hit process using recursive subsample estimations, a procedure that presents several advantages to linear estimations against the backdrop of structural breaks in the relationship between two variables (see e.g., Uddin et al., 2019). In the recursive subsample analysis, the length of the first window period is set to 252 days, and the increment in the length of the window is one day. The results when all variables are at their 5% quantile are presented in Figure 7, where the blue lines are time-varying cross-quantilograms in the recursive subsamples whereas the red lines indicate the 95% bootstrap confidence intervals based on 100 iterations. Our findings indicate an increase in interconnectedness between the G-SIBs, O-SIIs and the financial system during global turmoil from 2007-2009, and a gradually declining trend afterwards where all six cross-quantilograms become flat. Thus, in contrast with the systemic risk measures analysis (see discussion in Section 5.1) and the Dynamic Causality Index discussion (see Section 5.2), we do not find evidence of an increase in interconnectedness between G-SIBs, O-SIIs and the global financial system during sovereign debt crisis in Europe, nor in the aftermath of G-SIBs and O-SIIs lists publication.

[Figure 7 goes here]

We undertake a similar approach with all variables being at their median quantile (50%), i.e., in a tranquil state (Figure A4 in the Annexes). Unlike the crisis state (5% quantile), the blue line is flat for almost the whole period, implying a cross-quantilogram around zero and a lack of interdependence.

Up till now, we have estimated the cross-quantile correlation when all variables are at their 5% quantile (bear market conditions). To better capture the mutual directionality and dependence structure of G-SIBs, O-SIIs and the system, we compute the cross-quantilograms for different lags and quantiles, and present them as heatmaps (Figure 8). In each heatmap, the vertical axis shows the quantiles of the first series, while that of the second series is presented on the horizontal axis. For example, for the G-SIBs-O-SIIs pair, the quantiles of the G-SIBs are shown on the vertical axis, whereas the quantiles of the O-SIIs are on the horizontal axis.
For all six pairs, the cross-quantilograms are the highest for lag one and when all of them are at their lower quantiles, i.e., in extreme market conditions. Moreover, the linkages are also present when the series’ returns are at their median to higher quantiles, implying an interconnection during normal times for a very short period of time. However, the effect weakens for higher lag structure (5, 20 and 60, respectively), but it is still persistent for lower and higher quantiles. These findings suggest that G-SIBs, O-SIIs and the financial system tend to boom and crush together for a period of up to sixty days (one quarter).

4.5. Bayesian Graphical VAR

In Figure 9 we report the temporal dynamics structure of MAR, averaged over the period January 1, 2004 – September 29, 2017. To estimate the BGVAR model, we have used 1 lag, according to Bayesian Information Criterion, and 40,000 Gibbs iterations. We find strong evidence of temporal dependence using daily returns (higher posterior probabilities), especially within G-SIBs group, which is depicted starting with bottom left-hand side angle of the chart. Following Ahelegbey et al. (2016), we also model the BGVAR for monthly returns, and the results are shown in Figure A5 from Annexes. The temporal dynamics for our banks is preserved also for one month, but with a smaller magnitude (lower posterior probabilities), findings that are in line with those from cross-quantilogram.

We also estimate total linkages, those coming from G-SIBs to O-SIIs and those coming from O-SIIs to G-SIBs based on a 252 days moving window (Figure 10). The number of linkages is computed by summing all the edges in the graph structure for each window. Using MAR, we observe several periods of large interconnectedness, especially those corresponding to global financial crisis and sovereign debt crisis in Europe. Moreover, the number of links coming from
G-SIBs to O-SIIs is much higher than the other way around, emphasizing the role of these global systemically important banks as risk transmitters.

4.6. The Influence of Financial News

To further disentangle the effect of being included in the G-SIB or O-SII list we analyze the textual data from Reuters archive concerning these two groups of institutions following the approach of Cerchiello and Nicola (2018). The number of topics selected using the algorithm described in Section 3.5 is as follows: 20 for G-SIBs and 18 for O-SIIs.

[Figure 11 goes here]

Figures 15 reports the most relevant words along the whole analyzed corpus for G-SIBs and O-SIIs, respectively, highlighting words connected to the topics. The bigger and bolder the word in the figure, the more often it is mentioned within Reuters news and the more important it is. Thus, we can note that for G-SIBs the most important words are “bank”, “suisse” (Credit Suisse), “morgan” (Morgan Stanley), “sach” (Goldman Sachs), “confer”, “plcform” (PLC and former), and “present”, whereas in the case of O-SIIs the most relevant words are “bank”, “regbank” (bank regulation), “ireland” (Bank of Ireland Group), “paschi” (Banca Monte dei Paschi) and “danks” (Danske Bank).

To further evaluate topics’ relevance, in Figure 11 we present the topics for both G-SIBs (left-hand side) and O-SIIs (right-hand side) sorted according to their prevalence, which represents the proportion of documents devoted to each topic, as well as the associated words for the first 10 topics ordered by FREX measure (i.e., words are weighted by their overall frequency and how exclusive they are to the topic). Thus, in the case of G-SIBs the main topics cover subjects related to Royal Bank of Scotland, Goldman Sachs and Credit Suisse, whereas for O-SIIs Alpha Bank, Banca Monte dei Paschi and Danske Bank are devoted larger proportion of documents in the Reuters news archive.

The news sentiment could indicate in advance the evolution of the market value of public companies. Indeed, Audrino et al. (2020) find that sentiment variables are able to improve volatility forecasts significantly, whereas Wan et al. (2021) demonstrate that there exists a weak but
statistically significant association between strong media sentiment and abnormal market return as well as volatility.

To analyze more in-depth how financial news influence G-SIBs and O-SIIs institutions, we derive time-varying news sentiment indices. This approach is lexicon-based and takes into account valence shifters (negation and amplifiers/deamplifiers). In the end, it assigns different values for a news in a particular day which can be negative (more words with a negative polarity), 0 (neutral) or positive (more words with a positive polarity). The results are showcased in Figure 12 showing several periods with high negative sentiment values, most notably the global financial crisis (in the case of G-SIBs) and close to the first dates of lists release (for both groups). Thus, before the official designation of G-SIBs and O-SIIs, the prevalent news sentiment was negative. As documented by Moenninghoff et al. (2015) and Andrieş et al. (2020), these two regulatory announcements negatively affected the market value of considered banks.

4.7. Further Analysis

In this section we test whether systemic riskiness of G-SIBs is perceived differently from that of O-SIIs. As we know, G-SIBs are global important financial institutions dominated by the US banks designated by the Financial Stability Board in consultation with the Basel Committee on Banking Supervision, and they are required to hold additional capital of 1% to 2.5% Common Equity Tier 1 to improve their loss absorption capacity. On the other hand, O-SIIs are financial institutions that are systemically important at the Member State of the European Union level, that are selected by the European Banking Authority based on the 12 principles of the Basel Committee in dealing with Domestic Systemically Important Banks, and that must maintain a Common Equity Tier capital buffer of up to 2% of their total risk exposure. Thus, we exploit whether perceived systemic risk of G-SIBs differs from perceived risk of O-SIIs (i.e., probability weighted by density). In this respect, we apply the bootstrap version of the Kolmogorov-Smirnov (KS) test developed by Abadie (2002) with the null hypothesis that the probability densities for both the treated and control groups are the same, where treated and control groups are alternatively G-SIBs and O-SIIs.
We compute the average of $\Delta$CoVaR and MES for G-SIBs and O-SIIs taking into consideration the new financial institutions that were added on the lists or those that were removed from the lists according to the new lists disclosed, making thus a dynamic index, reflecting the changing behavior of the institutions once the market participants become aware of their systemic importance. We perform the two-sided KS test with 1,000 bootstrap replications (see Abadie, 2002). The results are exhibited in Table 5. First, we assess whether the systemic risk of G-SIBs is perceived differently from systemic risk of O-SIIs for the whole period under investigation. For both $\Delta$CoVaR and MES we reject the null hypothesis of the test, meaning that the probability densities for G-SIBs and O-SIIs groups are not the same. In other words, systemic importance and systemic exposure of G-SIBs and O-SIIs are perceived differently by the FSB and by the EBA, respectively. Next, we investigate whether the systemic risk of these two groups 250 days before the first publication (i.e., the event date) is significantly different from the systemic risk 250 days after the event. Again, we reject the null hypothesis for both G-SIBs and O-SIIs under both systemic risk measures. Thus, the systemic risk of G-SIBs and O-SIIs is not the same before and after the event. In this case, one can anticipate in advance what institutions would be included on the new lists, and what institutions would be removed from the lists, based solely on their systemic risk contribution and exposure.

5. Conclusions

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

The balance sheet oriented systemic risk measures indicate that G-SIBs were, on average, the main contributors and the main exposed financial institutions to systemic-wide distress. However, O-SIIs were riskier in terms of individual market risk as measured by Value at Risk, and these findings highlight the idea that individual supervision is not without shortcomings. From a
network of Granger-relationships perspective there is evidence of an increase in interdependence between G-SIBs and O-SIIs especially during 2007-2013, a period associated with the subprime crisis and debt crisis in Europe. In addition, spillover effects seem to be more pronounced within the group rather than between the groups for the whole sample period, but not for the crisis periods.

Our analysis based on cross quantilograms point out to an increase in interconnectedness between the G-SIBS, O-SIIs and the financial system during the turbulent period 2007-2009, followed up by a gradually declining trend. Therefore, when using cross quantilograms as a tool of capturing dependency we do not find evidence of an increase in interconnectedness between G-SIBS, O-SIIs and the global financial system during sovereign debt crisis in Europe, nor in the aftermath of G-SIBs and O-SIIs lists publication.

As a robustness check we employ also the BGVAR and we observe several periods of large interconnectedness around the global financial crisis and the sovereign debt crisis in Europe. The number of links from G-SIBs to O-SIIs is superior to the number of links from O-SIIs to G-SIBs, emphasizing the role of G-SIBs as risk transmitters. Furthermore, the FSB and the EBA have a different quantification of the systemic importance and systemic exposure of G-SIBs and O-SIIs, respectively.

Last but not least, we analyze how financial news influence G-SIBs and O-SIIs institutions, using a text analysis approach looking at valence shifters (negation and amplifiers/deamplifiers). We identify several periods with high negative sentiment values, most notably the global financial crisis (in the case of G-SIBs) and close to the first dates of publication of lists (for both groups). Prior to the official designation of G-SIBs and O-SIIs, the prevalent news sentiment was negative.
References


