Measuring Network Systemic Risk Contributions: A Leave-one-out Approach

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June 30, 2018

Abstract

Granger-causality measures of interconnectedness between financial institutions are useful indicators of systemic risk (Billio et al., 2012, Journal of Financial Economics), as they help to evaluate to which extent the distress of one institution disseminates across the whole financial system due to the network. This article provides a critical assessment of Granger-causality networks, showing that they can lead to inconsistent measures of systemic risk contributions due to the presence of spurious causalities arising from indirect contagion effects. Traditional solutions to control for these effects - via inference on conditional Granger-causality - lead however to the curse of dimensionality. To solve this issue, we provide a measure of financial network systemic risk contributions based on the leave-one-out (LOO) concept. For a given financial institution, the new measure evaluates to which extent the total number of significant Granger-causality breakdowns when this institution is excluded from the system. We control for spurious causalities between the remaining institutions due to the indirect contagion effect of the excluded financial institution using a conditional Granger-causality test, which is free of the curse of dimensionality. Empirical applications are conducted using daily market returns for a sample of the world's largest banks. Results show that our measure gives a meaningful ranking of the systemic importance of financial institutions which is consistent with the ranking of global systemically important banks (G-SIBs) provided by the Financial Stability Board (FSB). Moreover, our measure appears as a robust significant early-warning indicator of large losses in the case of a systemic event, and is strongly driven by balance-sheet variables related to size, business model and profitability.

JEL Codes: G12, G29, C51
Keywords: Systemic risk, Interconnectedness, Financial networks, Granger-causality, Spurious causalities, Curse of dimensionality, Leave-one-out, Early warning indicators.

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We thank the ANR program MultiRisk (ANR- 16-CE26-0015-01) for supporting our research.

1 Introduction

The US financial market turmoil that began in August 2007 and amplified by the collapse of Lehman Brothers had spread to the global financial market, with severe impacts on the worldwide real economy. The amplitude of these negative externalities and the related social costs in most countries raised the need for new macro-prudential devices for a more efficient stabilization of systemic risk in the financial sector. The Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) as regulatory authorities, responded to these challenges initiating a number of reforms, with the main element of the agenda being the identification of the so-called global systemically important financial institutions (G-SIFIs). The objective is to allocate G-SIFIs into buckets according to their required level of additional loss absorbency. In a country-level, a set of principles had also been established to allow national authorities to identify domestic systemically important financial institutions (D-SIFIs).

Methodologically, the identification of SIFIs requires a deep knowledge of the nature of systemic risk and the development of suitable tools for its measurement. In this line, the academic literature has evolved over recent years, offering different models or methodologies to evaluate the level of systemic risk for financial institutions. The profusion of the different methodologies springs from the fact that systemic events can have different sources or facets, including size, contagion or interconnectedness, lack of substitute financial products, global cross-jurisdictional activity, and complexity of business models. Indeed, Bisias et al. (2012) in their survey of systemic risk analytics, identify thirty one (31) quantitative measures of systemic risk in the economics and finance literature, that can be classified in six (06) homogenous groups: macroeconomic measures like credit-gap indicators, cross-sectional measures including among others, the delta conditional value-at-risk (CoVaR) of Adrian and Brunnermeier (2016) and the systemic expected shortfall (SES) of Acharya et al. (2017), forward-looking risk measures like contingent claims analysis, measures of illiquidity and insolvency, stress tests scenarios, and network measures.

In this article, our interest lies on the last group, i.e., network measures based on the interconnections between financial institutions. Even though this group of measures represents only a small part of the literature, the related subject has always been and is still the interest of major studies. On the theoretical ground, the literature on network measures of systemic risk is related to financial contagion with major contributions including among others, Allen and Gale (2000), Freixas et al. (2000), Dasgupta (2004), Acemoglu et al. (2015) and Glasserman and Young (2015). The core of these papers is to analyze the role played by the linkages among financial institutions in the amplification of exogenous shocks that hit the system. The analyses are generally undertaken under various angles related either to the shape of the network (complete or incomplete), the level of uncertainty prevailing in the financial markets, the complexity and concentration of the network (for a recent review, see Chinazzi and Fagiolo, 2015). Empirical papers on network measures of systemic risk contributions are also broad and can be categorized in two main groups depending on the nature (private, public) of the input data sets. The first category of measures uses private data on contractual obligations that measure the counterparty connections, to establish the so-called counterparty network graph. An illustrative example of such a graph is described in International Monetary Fund (2009), with the systemic importance of a financial institution approximated by the degree of connectivity of its associated node in the graph. The second category is based on publicly available data such as asset returns or credit default swaps. The differences between the many contributions arise from the econometrical or statistical methodologies used to establish the network, which range from variance decomposition (Diebold and Yılmaz, 2014; Demirer et al., 2018) to tail risk dependencies (Hautsch et al., 2015; Betz et al., 2016), the combination of both approaches (Härdle et al., 2016) and Granger-causality inference (Billio et al., 2012; Basu et al., 2017; Etesami et al., 2017).

This article is specifically devoted to the last group of contributions, that tries to evaluate systemic risk contributions based on Granger-causality network. The seminal paper is Billio et al. (2012) who propose to evaluate the systemic risk contribution of a given financial institution by its importance in a network based on pair-wise Granger-causality tests. Precisely, they define a statistics equal to the frequency of statistically significant pair-wise Granger-causality relations (regardless of the direction of causality) in which an institution is involved. Thus, higher (lower) values of this statistics correspond to more (less) systemic financial institutions. This statistics can be further disentangled focusing on the direction of causality. With empirical applications using monthly returns data for hedge funds, broker/dealers, banks and insurers, they show that these statistics help identifying financial crisis periods, and have good out-of-sample predictive powers.

Nevertheless, some recent papers provide a critical assessment of Granger-causality networks *à la* Billio et al. (2012) for measuring systemic risk contributions (Basu et al., 2017; Etesami et al., 2017). The focal point of the criticism is the pair-wise Granger-causality inference that underlies this approach, which can lead to spurious causalities driven by the existence of indirect contagion effects. Indeed, as underlined by Basu et al. (2017), the pair-wise approach evaluates the statistical association between any two institutions A and B, focusing on the direct connectivity between them, as well as indirect connectivities through all the other nodes (institutions) in the network. Therefore, Granger-causality networks based on the direct and indirect effects do not reveal the most systemic institutions, i.e., those that are central in spreading shocks in the whole system. The consequences on the empirical side is that the pair-wise approach generally leads to networks that are highly dense, due to spurious causalities, with potentially misleading ranking of the systemic importance of financial institutions. This stylized fact is well known in the statistical literature about Granger-causality inference and is usually tackled using conditional Granger-causality (Geweke, 1984) in a vector autoregressive (VAR) model. Precisely, the autoregressive equations of the bivariate Granger-causality tests, are extended using controlling variables that correspond to lagged values of the returns on the other $n-2$ institutions, with n the total number of institutions in the system. However, with realistic large values of n, one has to deal with a large dimensional VAR model, with traditional estimation via the least squares method subject to overfitting. As proposed by Basu et al. (2017), penalized least squares methods can be used to overcome the curse of dimensionality, but with a no less important challenge related to the choice of the penalty parameter. Indeed, there are many methods to calibrate the penalty parameter (information criteria, cross-validation), and it is known in the statistical literature, that estimation results can be sensitive to the retained choice.

Our main goal in this article is to rehabilitate the pair-wise Granger-causality approach for the evaluation of systemic risk contributions, adressing these two shortcomings (indirect causalities and curse of dimensionality). Indeed, we show that this approach when combined with the leave-one-out (LOO) concept is still valuable in providing consistent measures of systemic risk contributions. Formally, for a given financial institution A, we introduce a new measure of systemic risk importance, which evaluates to which extent the total number of significant Granger-causality breakdowns when this institution is excluded from the system. We control for causalities between the remaining $n-1$ institutions which are due to the indirect effect of the excluded financial institution A, using a conditional Granger-causality test. Remark that the use of the conditional version for each of the $(n-1)(n-2)$ pair-wise Granger-causality tests in the system that excludes the financial institution A, allows us to clean all spurious causalities between the remaining $n-1$ institutions and which arise from the indirect effect of the institution A. Moreover and importantly, this conditional version is free of the curse of dimensionality, as it only involves lagged values of the returns on the financial institution A.

Empirical applications are conducted using daily market returns for a sample of 90 large banks worldwide. The data range from September 12, 2003 to February 19, 2018, and include the global financial crisis of 2007-2008. The data set includes almost every global systemically important banks (G-SIBs) identified by the Financial Stability Board (FSB). Results show that our measure gives meaningful ranking of the systemic importance of financial institutions, that is found to be consistent with the ranking of G-SIBs provided by the FSB. Moreover, the new measure of systemic importance from the viewpoint of interconnectedness, appears as a robust significant early-warning indicator of large losses in the case of a systemic event. The predictive power is larger than the one associated to the measures in Billio et al. (2012). These results demonstrate that the pair-wise approach is more valuable when the effects of indirect causalities are clean out in a meaningful way.

Lastly we search for the economic contents of our measure by estimating panel regression models with balance-sheet variables as predictors. Results show that our measure of systemic risk importance is strongly related to the size, the business model and the profitability of banks. In line with the existing literature on systemic risk, we find a positive and significant relationship between the size, as measured by the logarithm of total assets, and our measure of systemic risk contribution. We also assess whether the business model of banks drives our measure of systemic risk. Similarly to Brunnermeier et al. (2012) and Laeven et al. (2016), our results suggest that banks specialized in market-based activities tend to have a higher level of systemic risk than banks specialized in traditional intermediation activities. Furthermore, we investigate the link between the profitability of banks, proxied by the return on equity, and their contribution to systemic risk. We find a positive and statistically significant relationship between these two variables.

It is worth noting that the use of the LOO approach in the literature of systemic risk measures is not new. Indeed, Zedda and Cannas (2017) employ this methodology to analyze the systemic risk and the determinants of contagion in a banking system. Formally, they base their approach on a simulated distribution of losses of the entire system, and of each subsystem in which one bank was removed. Recently, Li et al. (2017) also use the LOO concept applied to the z-score, as measured by the return of asset (ROA) plus equity-to-assets ratio divided by the standard deviation of ROA. They define an aggregate z-score for the whole system, and the so-called "Minus one bank z-score" which represents the z-score of the system when one bank is removed. The difference between these two measures is the contribution of the removed bank to the systemic risk of the system. Note that as underlined by Zedda and Cannas (2017), the LOO methodology presents some similarities with the Shapley value (Shapley, 1953), which is used by many authors to measure systemic risk contributions (Tarashev et al., 2010; Drehmann and Tarashev, 2013). Nonetheless, to our knowledge, our paper is the first that mobilizes the LOO concept for measuring systemic risk contributions based on Granger-causality networks.

The remainder of the article is structured as follows. Section 2 is devoted to a review of literature on network measures of systemic risk, covering both theoretical and empirical issues. Second 3 provides, in the line of Basu et al. (2017), a critical assessment of systemic risk contribution's measures based on pair-wise Granger-causality tests. In Section 4, we present the new measure based on the LOO approach, and assess its reliability using real data sets in Section 5. Section 6 searches for the microeconomic determinants of the LOO measure using balance-sheet data, and the last section concludes the article.

2 Literature Review

2.1 Theoretical Literature

The theoretical literature on network measures of systemic risk is related to contagion, induced from direct or indirect linkages. Most of the works[1] on network contagion focuses on risk channels issued from direct linkages, such as credit exposures, financial market relationships (Allen and Gale, 2000; Freixas et al., 2000; Eisenberg and Noe, 2001; Dasgupta, 2004; Leitner, 2005; Vivier-Lirimont, 2006; Brusco and Castiglionesi, 2007; Nier et al., 2007; Gai et al., 2011; Acemoglu et al., 2015; Glasserman and Young, 2015). The literature can be categorized depending on the dimension of the contagion analyzed, such as the density of the network (complete or incomplete), the level of uncertainty in the markets, the complexity and concentration of the network.

Pioneering works from Allen and Gale (2000) and Freixas et al. (2000) focus on the first dimension, studying the effect of the density of the network on the resilience of the system to the insolvency of an individual bank. For instance, Allen and Gale (2000) set up a basic network structure involving four banks in a model *à la* Diamond and Dybvig (1983). In order to protect themselves against liquidity shocks (due to the uncertainty about the timing of this shock), banks hold inter-regional claims on each other. While those cross-holdings of deposits increase the resilience of the network (since the proportion of the losses of one bank is spread across multiple agents) it exposes the system to contagion. More precisely, the degree of contagion depends on the pattern of interconnectedness between banks. A fully connected network spreads the liquidity shock across the network and reduces its impact, while an incomplete (not fully connected) network increases its impact and leads to contagion. Freixas et al. (2000) also propose a model in the tradition of Diamond and Dybvig (1983) with banks facing liquidity shocks. However, they are connected through interbank credit lines due to uncertainty about the location of withdrawal deposits. As in Allen and Gale (2000), they find that interconnections increase the resilience of the network to the insolvency of a single bank.

[1]See Allen and Babus (2009), Chinazzi and Fagiolo (2015) and Hüser (2015) for surveys on financial networks contagion.

Nevertheless, these theoretical predictions should be contrasted to those of Vivier-Lirimont (2006) and Brusco and Castiglionesi (2007) who obtain opposite results. Considering network structures *à la* Allen and Gale (2000) with multiple regions and one representative bank per region, Brusco and Castiglionesi (2007) study the contagion of financial crises across regions in which banks are connected through cross-holdings of deposits. However, contrary to Allen and Gale (2000), bankruptcies are caused by the moral hazard problem instead of a liquidity shock. They find that a more connected interbank deposit market increases the number of regions hit by bankruptcies as compared to the case where an incompletely connected market is considered. Similar conclusions can be found in Vivier-Lirimont (2006) who analyzes the optimal network architecture where transfers through the interbank market improve the utility of the depositors. He finds that the higher is the network density, the higher is the likelihood of the system to collapse.

Acemoglu et al. (2015) try to reconciliate these opposite results by analyzing the network as a contagion mechanism in which institutions can be exposed to counterparty risk due to unsecured debt contracts shared among each others. They observe that the resilience of the network depends on an endogenous threshold for the number of shocks. Precisely, if the magnitude or the number of shocks are below this threshold, the more interconnected the network is, the less fragile is the system. However, as the magnitude or the number of shocks become higher than the threshold, the opposite result appears, i.e., more financial interconnections make the system more sensitive and more prone to contagion.

This branch of the literature about contagion arising from direct linkages has evolved with the years. The debate around the connectivity of the network and its resilience to negative shocks has spread beyond the form of the network (complete or incomplete). Indeed, other features of the network have been studied, such as its complexity, concentration or leverage (Gai and Kapadia, 2010; Nier et al., 2007; Glasserman and Young, 2015). For example, Gai et al. (2011) observe that the complexity and the concentration are important characteristics. They propose a network of 250 banks linked through unsecured claims and subject to funding liquidity shocks. Based on different simulations' scenarios, they find that complex and concentrated networks are more sensitive to financial shocks and may amplify their effects.

Another part of the literature studies the contagion process of a negative shock via indirect linkages arising from exposure to common assets and mark-to-market losses from fire sales (Lagunoff and Schreft, 2001; De Vries, 2005; Elliott et al., 2014; Cabrales et al., 2014; Caccioli et al., 2015). For instance, Lagunoff and Schreft (2001) build a model in which agents have portfolios whose returns depend on the portfolio allocations of others. Some agents are subject to shocks which lead them to reallocate their portfolios, and consequently to break the links between them. They exhibit two types of crises. The first one happens gradually. Agents do not anticipate the possible losses and thus do not instantaneously break links. Losses spread across the network and break more and more links. The second one happens instantly, as agents foresee losses and preemptively break links to avoid losses from contagion. More recently, Elliott et al. (2014) propose a model in which institutions are linked through cross-holdings of shares (debt or liabilities). If the value of an institution become low enough that it falls below a failure threshold, this one fails and affects its counterparties which then propagate the initial failure. The authors identify two main features of the cross-holdings that impact the probability of cascades and their extent: integration and diversification. The integration corresponds to how much an institution is privately held - cross-held by other institutions. The diversification represents how much the cross-holdings of a single institution are spread out through the network (by only a few ones or by a high number of them). Another example is Cabrales et al. (2014) who analyze the trade-off between risk sharing and contagion. They consider a model in which firms are linked through the exchanges of assets they are endowed with, and more precisely, the securitization of mortgage loans sold to other firms. These exchanges allow firms to diversify, but expose them to counterparties' default. They stress two alternatives that allow to reduce the contagion. The first one is by isolating the firms in each component (which represents a region of the network). The second one is by reducing the number of firms to which a firm is linked to. They observe that when the probability distribution of the shocks has fat tails (high probability of large shocks), the optimal network is the most segmented one with small components. However, when the tails are thin, the best one is a single component with the minimum segmentation in order to maximize risk sharing.

It is worth noting that the analysis of only direct or indirect linkages is not realistic. Indeed in practice, banks have many simultaneous direct and indirect linkages. Drawing on this stylized fact, some authors incorporated both type of linkages in their models (Cifuentes et al., 2005; Nier et al., 2007; Gai and Kapadia, 2010; Caballero and Simsek, 2013; Glasserman and Young, 2015; Caccioli et al., 2015). Cifuentes et al. (2005) build a complete network combining direct linkages via mutual credit exposures, and indirect linkages through overlapping asset banks' portfolios. They find that the effect of an initial shock can be substantial and amplified if the prices of fire-sold assets can change endogenously. Indeed, the initial failure of one bank leads to the sale of the remaining assets of this bank. Under certain condition, this can decrease the market prices of these assets, and thus, spreads the initial shock across the network, particularly to the banks that hold the same assets. Finally, Gai and Kapadia (2010) propose an interbank network with direct exposures based on the models used in the epidemiological literature. They find two interesting facts. First, rare shocks can have significantly large impacts on the network when they occur. Second, the impact of a shock, regardless of its size, depends on the node of the network it hits. Indeed, more central node, i.e., more interconnected ones, facilitate and amplify the contagion. To take into consideration indirect linkages, they also include the setup used in Cifuentes et al. (2005). However, they find that it does not modify the result of their initial model.

2.2 Empirical Literature

On the empirical side, the many contributions available in the literature differ by the type (private or public) of data used as well as by the econometrical or statistical methods mobilized to construct the network and to extract measures of systemic risk contributions. For instance, in the spirit of theoretical works, Drehmann and Tarashev (2013) use direct and indirect linkages to measure the systemic importance of banks in a network. More precisely, they propose two measures. The first one quantifies the losses that a bank imposes on its non-bank investors (participation approach), and the second one corresponds to the contribution of this bank to the contagion of an idiosyncratic shock, i.e., its degree of connectedness (contribution approach). Using balance sheet data of 20 international banks, they highlight that interconnectedness is an important feature as it increases banks' systemic importance, and that both approaches allocate risk differently between banks.

Another representative paper is that of Diebold and Yılmaz (2014). They develop networks based on variance decompositions and proposed various interconnectedness measures. By focusing on major American financial institutions from May 1999 to April 2010, they show that Citigroup has the highest value of connectedness, and more generally the largest commercial banks are the most interconnected. However, their methodology is sensible to the curse of dimensionality, and they limit the sample to only a small part of G-SIBs. Demirer et al. (2018) extend this methodology to compute high-dimensional networks. Indeed, they consider penalization methods to reduce the dimensionality of the network, and render the model estimable even in presence of a high number of banks. Thus, in their empirical applications, they consider a sample of 96 international banks from the world's top 150, and find that there are strong clusters within and between countries.

Other studies focus on firms' tail risk to build networks. For example, Hautsch et al. (2015) initially propose the "realized systemic risk beta" which corresponds to the marginal effect of the value-at-risk of a given institution on the value-at-risk of the network. Using the 57 largest financial institutions from North America, they find a high degree of interconnectedness and a rise of their measure of systemic risk contributions during the 2007-2008 financial crisis. This work is extended to a dynamic setup by Hautsch et al. (2014) to compute time-varying realized systemic risk. Their empirical results based on a sample of 20 banks and insurers from Europe, highlight country-specific risk channels, as well as cross-country and industry-specific channels. Betz et al. (2016) extend both previous papers by allowing their methodology to be feasible in presence of high-dimensional financial systems. They apply their model to European banks and show that the network's density increases during the financial crisis but decreases afterward, and that the size, leverage and degree of interconnectedness increase banks' systemic importance. In the same vain, Härdle et al. (2016) combine firms' tail risk with variance decomposition. They build their network by using the approach of Diebold and Yılmaz (2014), but the so-called adjacency matrix (with elements indicating whether pairs of vertices are adjacent or not in the graph) is based on the value-at-risk of institutions instead of conditional correlations. Using 100 US financial institutions (depositories, insurers, broker-dealers and others), they find that the banking (insurance) sector is the one that gives more (less) the pace in risk transmission.

Another empirical approach that gains interest in recent years is Granger-causality networks. A representative contribution is Billio et al. (2012) who use pair-wise Granger-causality tests to measure the systemic risk contributions of financial institutions. To build their network, they consider linear and nonlinear versions of these tests and develop several measures of interconnectedness. Using data from the 25 largest banks, hedge funds, broker-dealers and insurers, they show that these sectors are strongly interconnected, and that the connections are dynamic. Moreover, their findings suggest that the banking and insurance sectors might have a central position in the network. The pair-wise approach is recently extended to a multivariate setting to deal with indirect causalities (Basu et al., 2017; Etesami et al., 2017; Barigozzi and Brownlees, 2013). These works consider large dimensional vector autoregressive model estimated via penalization to deal with the issue of dimensionality. For instance, Barigozzi and Brownlees (2013) propose two network representations for large sparse VARs and a new algorithm based on the Lasso method. The first one is a combination of directed linkages, represented through Granger-causality connections, and undirected ones, corresponding to partial contemporaneous correlation connections. The second one is made up of undirected linkages which represents long run partial correlation connections. Considering ninety US bluechips, they find that the most interconnected institutions are the largest ones, such as AIG, Bank of America or Citigroup. As already stressed, our paper focuses on this last group of works, i.e., measures of systemic risk contributions based on Granger-causality networks.

3 Measuring Systemic Risk via Granger-Causality Network: a Critical Assessment

This section motivates our contribution to the literature on network systemic risk contributions. The first part of the section describes the concept of Granger-causality inference, the building block of Granger-causality networks, and the second part shows through an illustrative example and Monte Carlo simulations, the negative effect of indirect causalities in measuring systemic risk contributions through Granger-causality networks.

3.1 Granger-Causality Inference

Consider a system of n interconnected financial institutions, and denote $y_{k,t} \equiv \Delta \log P_{k,t} = \log P_{k,t} - \log P_{k,t-1}$ the market returns as measured by the log-difference of market prices for the financial institution number k, with $k = 1, ..., n$. With two financial institutions i and j, the Granger-causality test as formalized by the seminal paper of Granger (1969) can be used to check whether information conveyed by $y_{j,t}$ the returns of the financial institution j helps predict the dynamics of $y_{i,t}$ the returns of the financial institution i. The null hypothesis corresponds to

$$\mathbb{H}_0 : \Pr\left(y_{i,t} < y \left| \mathcal{F}_{t-1} \right.\right) = \Pr\left(y_{i,t} < y \left| \mathcal{F}_{i,t-1} \right.\right), \tag{1}$$

for all values of y, where the information sets $\mathcal{F}_{t-1}$ and $\mathcal{F}_{i,t-1}$ are given by

$$\mathcal{F}_{t-1} = \left\{ (y_{i,s}, y_{j,s})', s \leq t-1 \right\}, \tag{2}$$

$$\mathcal{F}_{i,t-1} = \left\{ y_{i,s}, s \leq t-1 \right\}. \tag{3}$$

Remark that the concept of causality carried out by this null hypothesis is strong, as it aims of testing for the lack of predictive content over the whole distribution. Since the seminal paper of Granger (1969), the academic literature has evolved focusing on some weak versions of the concept, i.e., causality in specific moments of the conditional distribution (mean, variance, tail). For instance, the well-known concept of Granger-causality in mean (Granger, 1980, 1988; Sims, 1972, 1980) is based on the following modified null hypothesis

$$\mathbb{H}_{0,1} : \mathbb{E}\left(y_{i,t} \left| \mathcal{F}_{t-1} \right.\right) = \mathbb{E}\left(y_{i,t} \left| \mathcal{F}_{i,t-1} \right.\right), \tag{4}$$

which can be tested in a parametric framework relying on the following test statistics

$$U_{j \to i} = T \log(\frac{\widehat{\sigma}^2_{i,2}}{\widehat{\sigma}^2_{i,1}}), \tag{5}$$

where T is the sample length, $\widehat{\sigma}_{i,1}^2$ and $\widehat{\sigma}_{i,2}^2$ are respectively the sample variances of the fitted residuals $\widehat{\varepsilon}_{i,1}$ and $\widehat{\varepsilon}_{i,2}$, from the following autoregressive models

$$y_{i,t} = c_1 + \sum_{s=1}^{M} \phi_s y_{i,t-s} + \sum_{s=1}^{M} \gamma_s y_{j,t-s} + \varepsilon_{i,1,t}, \tag{6}$$

$$y_{i,t} = c_2 + \sum_{s=1}^{M} \alpha_s y_{i,t-s} + \varepsilon_{i,2,t}, \tag{7}$$

with M the lag-order, c_1, c_2, ϕ_s, γ_s, α_s, $s = 1, ..., M$ some parameters. Under the null hypothesis $\mathbb{H}_{0,1}$ of absence of Granger-causality in mean, the test statistics $U_{j\to i}$ has an asymptotic chi-square distribution with degree of freedom equal to M. Hence, if $U_{j\to i} > \chi^2_{1-\eta}(M)$, one rejects the null hypothesis of no Granger-causality in asset returns from the financial institution j to the financial institution i, with $\chi^2_{1-\eta}(M)$ the fractile of order $1-\eta$ of the chi-square distribution with M degree of freedom, η being the nominal significance level.

Note that Granger et al. (1986) also introduce the concept of Granger-causality in variance to test for transmission in the second order moment.[2] More recently, some papers focus on testing for Granger-causality in extreme quantiles or tail-events to capture spillover effects on higher-order moments like skewness and kurtosis (Hong et al., 2009; Jeong et al., 2012; Han et al., 2016; Candelon and Tokpavi, 2016). In this paper, our contribution to the literature on network systemic risk contributions is developed (without loss of generality) around the concept of Granger-causality in mean as described above.

3.2 Indirect Causalities and Network Systemic Risk Contributions

For a system of n financial institutions, Granger-causality tests can be used for all pairs of financial institutions to assess the existence of interconnectedness. This issue is investigated in the literature by Billio, Getmansky, Lo and Pellizon (2012) (hereafter BGLP) to establish the network of a financial system, and to derive global as well as institution-specific measure of systemic risk. Following their approach, we can measure the systemic importance of a financial institution k by its contribution to the Granger-causality network as follows

$$\text{InOut}_k = \frac{1}{2\,(n-1)} \sum_{\substack{j=1 \\ j\neq k}}^{n} \left[\mathbb{I}\left(U_{k\to j} > \chi^2_{1-\eta}(M)\right) + \mathbb{I}\left(U_{j\to k} > \chi^2_{1-\eta}(M)\right) \right], \tag{8}$$

where $U_{k\to j}$ corresponds to the statistics of the Granger-causality test in mean from the financial institution k to the financial institution j, as defined in (5), and $\chi^2_{1-\eta}(M)$ the fractile of order $1-\eta$ of the chi-square distribution with M degree of freedom. The first term in the bracket measures the number of financial institutions that are significantly Granger-caused by the reference institution k (Out-part of the measure), while the second term measures the number of financial institutions that significantly Granger-causes the institution k (In-part of the measure). Hence, the statistics InOut_k measures the fraction of the total number of financial institutions that are involved in

[2] See also Engle and Ng (1988), Engle et al. (1990), Cheung and Ng (1996), Hong (2001), Sensier and van Dijk (2004), to cite but a few.

a significant connection with the financial institution k. Note that higher (resp. lower) values of the statistics InOut_k correspond to more (resp. less) systemic institution from the viewpoint of interconnectedness.

A central point that motivates our paper, is that the statistics InOut_k can lead to inconsistent rankings of financial institutions in term of systemic risk, due to the existence of indirect causalities. To give more insight on this statement, let us consider a simple financial system with $n = 3$ institutions 1, 2 and 3. The connections between the three financial institutions are displayed in Figure 1.

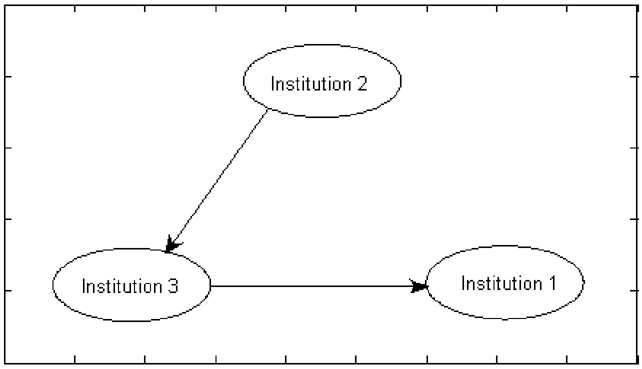

Figure 1: True network for a system of three financial institutions

In this simplified financial system, there is transmission in asset returns from the financial institution 2 to the financial institution 3 and from the institution 3 to the institution 1. This form of network can arise from indirect contagion due to common assets (Greenwood et al., 2015), overlapping portfolios (Caccioli et al., 2014, 2015) and linked portfolio returns (Lagunoff and Schreft, 2001), with propagation of shocks driven by fire sales. Precisely, the institution 2 facing an idiosyncratic shock that impacts negatively its equity, sells its assets to maintain its target level of leverage. In case of illiquid assets, fire sales depress prices, and this in turn can impact the equity of the financial institution 3 due to common exposures to those assets. The same phenomenon involving institutions 3 and 1 would take place with common exposures to other assets, leading to this type of network.

Using (8), the true levels of the contribution of each financial institution to the Granger-causality network are thus equal to

$$\text{InOut}_2 = \frac{1}{4} = 0.25, \text{InOut}_3 = \frac{2}{4} = 0.5, \text{InOut}_1 = \frac{1}{4} = 0.25. \tag{9}$$

Hence, the financial institution number 3 is the most systemic. Nevertheless, the network that would arise most often from the application of the Granger-causality test is depicted in Figure 2. In fact, an indirect spillover effect should be detected from the financial institution 2 to the financial institution 1, due to the financial institution 3.[3] The information one extracts from this network is that all three financial institutions

[3]Note that the probability with which one detects this indirect effect is theoretically equal to the power of the Granger-causality test.

are systemically equivalent, because we have

$$\text{InOut}_2 = \frac{2}{4} = 0.5, \text{InOut}_3 = \frac{2}{4} = 0.5, \text{InOut}_1 = \frac{2}{4} = 0.5. \tag{10}$$

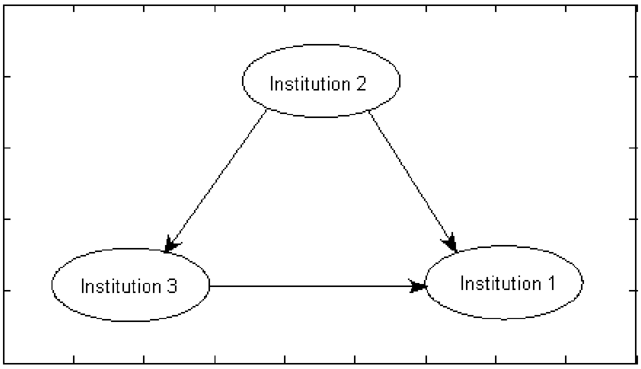

Figure 2: Detected network using Granger-causality tests

The following Monte Carlo experiments give more insights about this point. We consider that the data generation processes of asset returns for our three financial institutions 1, 2 and 3 are as follows

$$\begin{cases} y_{2,t} = 0.5y_{2,t-1} + u_{2,t} \\ u_{2,t} = \sigma_{2,t}v_{2,t} \\ \sigma^2_{2,t} = 0.05 + 0.85\sigma^2_{2,t-1} + 0.1u^2_{2,t-1}, \end{cases} \tag{11}$$

$$\begin{cases} y_{3,t} = 0.5y_{3,t-1} + 0.2y_{2,t-1} + u_{3,t} \\ u_{3,t} = \sigma_{3,t}v_{3,t} \\ \sigma^2_{3,t} = 0.05 + 0.85\sigma^2_{3,t-1} + 0.1u^2_{3,t-1}, \end{cases} \tag{12}$$

$$\begin{cases} y_{1,t} = 0.5y_{1,t-1} + 0.2y_{3,t-1} + u_{1,t} \\ u_{1,t} = \sigma_{1,t}v_{1,t} \\ \sigma^2_{1,t} = 0.05 + 0.85\sigma^2_{1,t-1} + 0.1u^2_{1,t-1}, \end{cases} \tag{13}$$

where each $v_{k,t}$, $k = 1, 2, 3$, follows a Student-t distribution with degree of freedom equal to 5. Thus we make the assumption that each serie of asset returns follows an AR(1)-GARCH(1,1) model. This model is calibrated to capture important stylized facts in the dynamics of asset returns such as autocorrelation, heteroskedasticity, and fat taildness. Moreover, we suppose that there is causality in mean from the financial institution 2 to the financial institution 3, and from the financial institution 3 to the financial institution 1. Hence, with the application of the Granger-causality test in mean, one should detect a significant connection from 2 to 3 and from 3 to 1. Hence, the specified data generation processes are consistent with the true network in Figure 1.

However as we stress above, although there is no connection between 2 and 1, the Granger-causality test in mean should detect an indirect spillover effect from the financial institution 2 to the financial institution 1. Figure 3 reports the rejection frequencies over $1,000$ simulations of the Granger-causality test in mean from 2 to 1, at the nominal significance level $\eta = 5\%$. Results are displayed for different values of the sample size $T \in \{100, 250, 500, 1000, 1500, 2000, 2500, 3000\}$. The lag-order M for the computation of the test statistics in (5) is set to $M = 5$. We observe in Figure 3 that the rejection frequencies of the test are high and increase with the sample size. To summarize, outcomes from our Monte Carlo experiments show that the ranking of financial institutions using the statistic InOut_k can indeed be misleading due to the detection of spurious indirect causalities in the network.

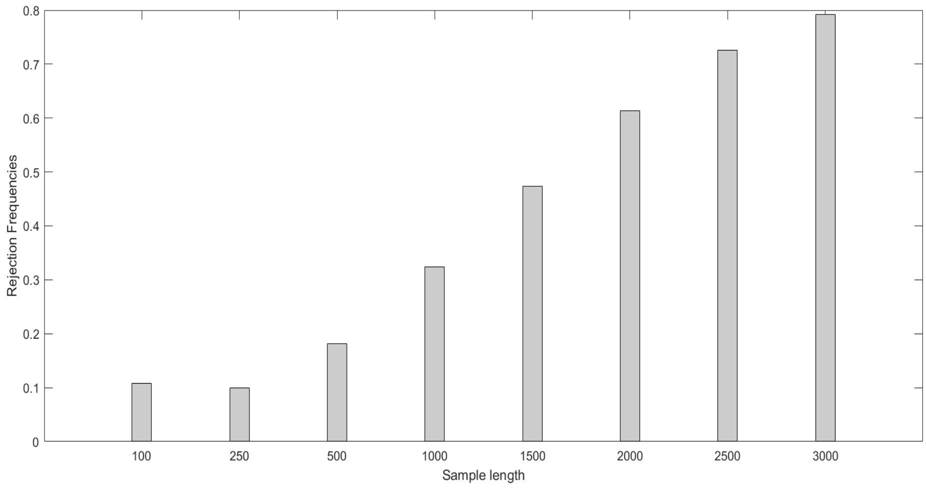

Figure 3: Rejection frequencies of the Granger-causality test from 2 to 1

A traditional solution to deal with this issue would be to consider network based on *conditional* Granger-causality test. Indeed, the conditional Granger-causality test introduced by Geweke (1984) has the ability to resolve whether the interaction between two time series is direct or is mediated by another time series. From a computational point of view, the test statistic $U_{j\to i|k}$ for the Granger-causality test in mean from j to i conditionally to k is identical to its unconditional version $U_{j\to i}$ in (5), that is

$$U_{j\to i|k} = T\log(\frac{\widetilde{\sigma}^2_{i,2}}{\widetilde{\sigma}^2_{i,1}}), \tag{14}$$

where again T is the sample length, $\widetilde{\sigma}^2_{i,1}$ and $\widetilde{\sigma}^2_{i,2}$ are respectively the sample variances of the fitted residuals $\widehat{u}_{i,1}$ and $\widehat{u}_{i,2}$, from the autoregressive models

$$y_{i,t} = c_1 + \sum_{s=1}^{M} \phi_s y_{i,t-s} + \sum_{s=1}^{M} \gamma_s y_{j,t-s} + \sum_{s=1}^{M} \psi_s y_{k,t-s} + u_{i,1,t}, \tag{15}$$

$$y_{i,t} = c_2 + \sum_{s=1}^{M} \alpha_s y_{i,t-s} + \sum_{s=1}^{M} \theta_s y_{k,t-s} + u_{i,2,t}, \tag{16}$$

with ψ_s, θ_s, $s = 1, ..., M$, some additional parameters. These two specifications are the extended versions of the autoregressive models in (6-7), where the residuals are cleaned out from the effect of the time series $y_{k,t}$ that is suspected to drive the causality.

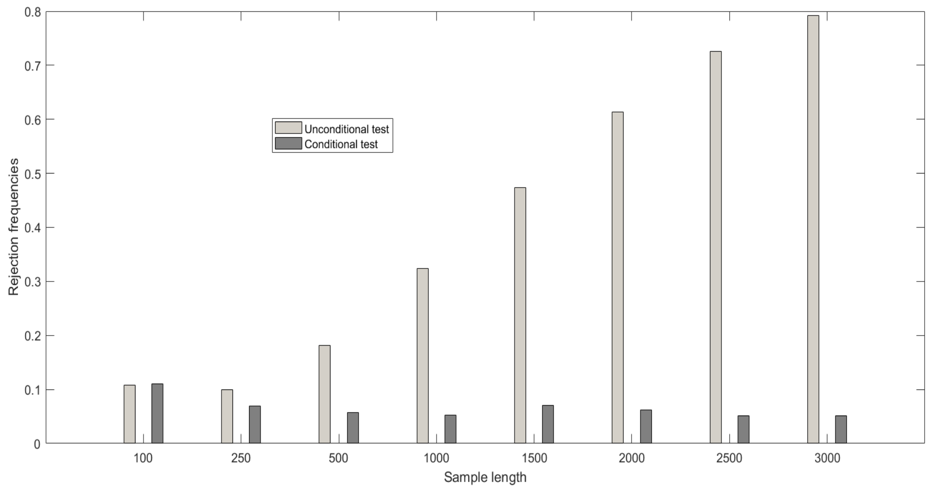

Figure 4: Comparison of conditional and unconditional Granger-causality tests

To illustrate the relevance of the conditional test in managing indirect causalities, we consider once again the simplified network depicted in Figure 1 along with the associated data generating processes in (11-13). The rejection frequencies (at the nominal risk level $\eta = 5\%$) over $1,000$ simulations of the Granger-causality test from the financial institution 2 to the institution 1, conditionally to the institution 3 are displayed in Figure 4. The lag-order is set to $M = 5$ and we consider different sample sizes $T \in \{100, 250, 500, 1000, 1500, 2000, 2500, 3000\}$. For comparison, we also report the rejection frequencies of the unconditional test for the same experiments. We observe that while the rejection frequencies of the unconditional test are high and increase with the sample size, the rejection frequencies of the conditional test are low and converge to the nominal significance level $\eta = 5\%$ at the highest sample length. Hence, based on the statistics InOut_k, the conditional test would lead to a consistent ranking of the systemic importance of the three financial institutions, as it is designed to exclude the spurious causality from the institution 2 to the institution 1, due to the effect of the indirect contagion.

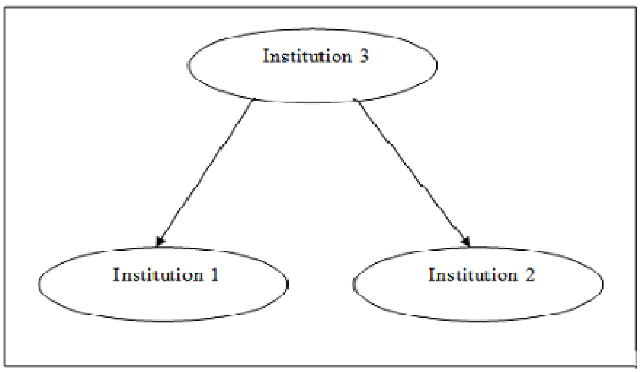

Figure 5: True network for a system of three financial institutions: second scenario

The conditional test as described above is also adapted to manage another form of indirect causality resulting from the joint exposure of the financial institutions 1 and 2 to the institution 3. The related true network is depicted in Figure 5, with the institution 3 that Granger-causes both institutions 1 and 2, but with a time-delay. The following data generating processes are consistent with this network, with $y_{1,t}$, $y_{2,t}$ and $y_{3,t}$ simulated as

$$\begin{cases} y_{3,t} = 0.5y_{3,t-1} + u_{3,t} \\ u_{3,t} = \sigma_{3,t}v_{3,t} \\ \sigma^2_{3,t} = 0.05 + 0.85\sigma^2_{3,t-1} + 0.1u^2_{3,t-1}, \end{cases} \tag{17}$$

$$\begin{cases} y_{2,t} = 0.5y_{2,t-1} + 0.2y_{3,t-1} + u_{2,t} \\ u_{2,t} = \sigma_{2,t}v_{2,t} \\ \sigma^2_{2,t} = 0.05 + 0.85\sigma^2_{2,t-1} + 0.1u^2_{2,t-1}, \end{cases} \tag{18}$$

$$\begin{cases} y_{1,t} = 0.5y_{1,t-1} + 0.2y_{3,t-2} + u_{1,t} \\ u_{1,t} = \sigma_{1,t}v_{1,t} \\ \sigma^2_{1,t} = 0.05 + 0.85\sigma^2_{1,t-1} + 0.1u^2_{1,t-1}, \end{cases} \tag{19}$$

where again $v_{k,t}$, $k = 1, 2, 3$, follows a Student-t distribution with degree of freedom equal to 5. Based on these data generating processes, rejection frequencies (over 1000 simulations) of the conditional and the unconditional Granger-causality tests from the financial institution 2 to the financial institution 1 are displayed in Figure 6. We observe once again that the conditional version of the test helps to control for the spurious causality arising from indirect contagion, while the unconditional test fails to do so with strong rejections of the null hypothesis.

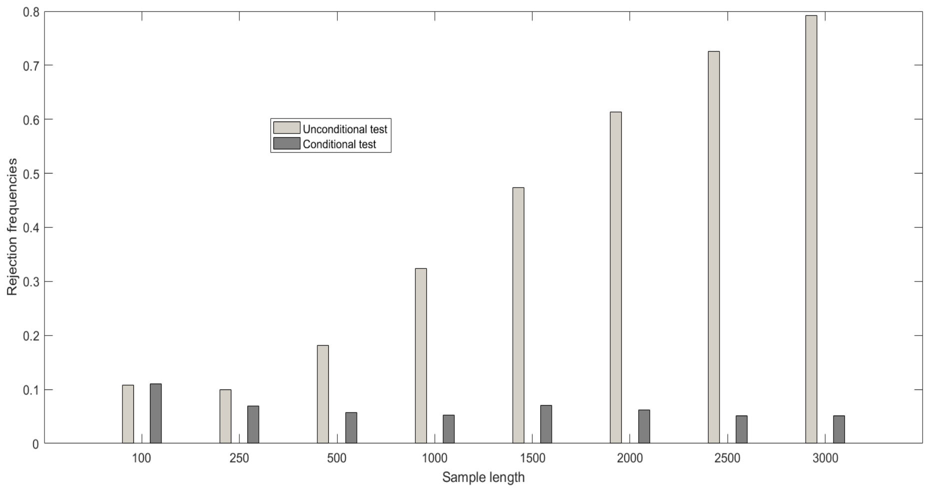

Figure 6: Comparison of conditional and unconditional Granger-causality tests: second scenario

Nevertheless, one can notice that if the conditional test is simple to implement in our simplified financial system including $n = 3$ institutions, its implementation for real system with many institutions will lead to the curse of dimensionality. Indeed, the conditional Granger-causality test from the financial institution j to the institution i should be run by controlling for the potential indirect effects coming from all other $n-2$ institutions. This leads to the following two autoregressive models

$$y_{i,t} = c_1 + \sum_{s=1}^{M} \phi_s y_{i,t-s} + \sum_{s=1}^{M} \gamma_s y_{j,t-s} + \sum_{k=1}^{n-2} \sum_{s=1}^{M} \psi_{k,s} y_{k,t-s} + u_{i,1,t}, \tag{20}$$

$$y_{i,t} = c_2 + \sum_{s=1}^{M} \alpha_s y_{i,t-s} + \sum_{k=1}^{n-2} \sum_{s=1}^{M} \theta_{k,s} y_{k,t-s} + u_{i,2,t}, \tag{21}$$

with $\psi_{k,s}$, $\theta_{k,s}$, $s = 1, ..., M$, $k = 1, ..., n-2$, the parameters of the controlling autoregressive terms. These specifications involve many explanatory variables. Indeed, in each model, the number of controlling variables is equal to $M(n-2)$, and even with a financial system of limited size, the estimation of both equations will be subject to multicollinearity and over-fitting. As analyzed by Basu et al. (2017), these issues can be handled within a lasso penalized vector auto-regressive (LVAR) model, which is designed to provide estimates of large dimensional vector autoregressive model with sparse coefficients. Their empirical applications based on a set of large US financial institutions show indeed that the LVAR succeeds in controlling for spurious indirect causalities, and hence helps recovering less dense networks in comparison to the BGLP approach. Note that in their work, a multivariate instead of the pair-wise approach of BGLP is adopted, with a VAR model specified for all firms simultaneously, taking into account all interactions in the system. See also Etesami et al. (2017) for a similar approach in the context of systemic risk, and Barigozzi and Brownlees (2013) in a more general context of network modeling.

4 Breaking the Curse of Dimensionality: a Leave-One-Out Approach

In this section, we show that the pair-wise approach of BGLP when combined with the leave-one-out (LOO) concept can still be used to consistently estimate Granger-causality network systemic risk contributions. As it will appear clearer in the sequel, the LOO methodology allows us to deal with the issue of indirect causalities, without facing the inherent curse of dimensionality arising in the multivariate approach (Basu et al., 2017; Etesami et al., 2017).

To present our LOO measure of systemic risk contributions, let us first define the following statistics which summarizes the level of Granger-causality (LGC) in the system, i.e., the number of statistically significant Granger-causality relationships among all $n(n-1)$ pairs of financial institutions in the system

$$\text{LGC} = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \mathbb{I}\left(U_{j \to i} > \chi^2_{1-\eta}(M)\right). \tag{22}$$

This statistics can be considered as a global measure of systemic risk in the system, from the viewpoint of interconnectedness. Now, for a given financial institution k, consider the system of size $n-1$ which includes all the n institutions, except the institution number k. We can similarly define as in (22), the level of Granger-causality in this system, yielding

$$\mathrm{LGC}_{(-k)} = \sum_{\substack{i=1\\ i\neq k}}^{n-1} \sum_{\substack{j=1\\ j\neq k, j\neq i}}^{n-1} \mathbb{I}\left(U_{j\to i} > \chi^2_{1-\eta}(M)\right). \tag{23}$$

The statistics $\mathrm{LGC}_{(-k)}$ measures the number of remaining significant connections in asset returns, when the financial institution k is excluded from the system. One can notice however that this statistics removes direct causalities in the network due to the financial institution k, but fails to clean indirect causalities between the remaining $n-1$ financial institutions which are due to the financial institution k. To overcome this shortcoming, we re-define the statistics $\mathrm{LGC}_{(-k)}$ as follows

$$\mathrm{LGC}_{(-k)} = \sum_{\substack{i=1\\ i\neq k}}^{n-1} \sum_{\substack{j=1\\ j\neq k, j\neq i}}^{n-1} \mathbb{I}\left(U_{j\to i|k} > \chi^2_{1-\eta}(M)\right), \tag{24}$$

where $U_{j\to i|k}$ is the conditional Granger-causality test as defined in (14). Remark that the use of the conditional version for each of the $(n-1)(n-2)$ pair-wise Granger-causality tests in the system that excludes the financial institution k, allows us to clean all spurious causalities that exist in the remaining $n-1$ institutions and which arise from the indirect effect of the institution k. Moreover and importantly, this conditional version is free of the curse of dimensionality, as it involves, as controlling variables, only lagged values of the returns on the financial institution k (see equations 15-16).

Based on the two statistics LGC and $\mathrm{LGC}_{(-k)}$, we define our LOO measure of the systemic importance of the financial institution k as follows

$$\Delta\mathrm{LGC}_k = \frac{\left(\mathrm{LGC} - \mathrm{LGC}_{(-k)}\right)}{\mathrm{LGC}}. \tag{25}$$

This statistics evaluates to which extent the total number of significant Granger-causality breakdowns when the institution k is excluded from the system, and hence appears as a proxy of its systemic importance. Note that the statistics $\Delta\mathrm{LGC}_k$ takes positive values, and higher (resp. lower) values correspond to more (resp. less) systemic institutions. Moreover, dealing with spurious causalities arising from indirect contagion effects, it should lead to consistent ranking of the systemic importance of financial institutions.

To provide some supports to the relevance of the LOO approach, we consider the true network depicted in Figure 1 along with the associated data generating processes in (11-13). Recall that from the viewpoint of interconnectedness, in this simplified financial system including three institutions, the most systemic is the third (3), with the other two (1 and 2) being systemically equivalent. Based on the true data generating processes, we simulate the returns of the three financial institutions, and compute both measures of systemic risk contributions InOut_k and $\Delta\mathrm{LGC}_k$, $k = 1, 2, 3$. Figure 7 displays the box plots of these measures obtained over $1,000$ simulations.

The first panel of the figure that displays the measures InOut_k for the three institutions, shows that the median values (emphasized in red color) are equal, confirming that this measure leads to inconsistent ranking of the financial institutions. Indeed, the equality of the median values means that with a high frequency, one will conclude

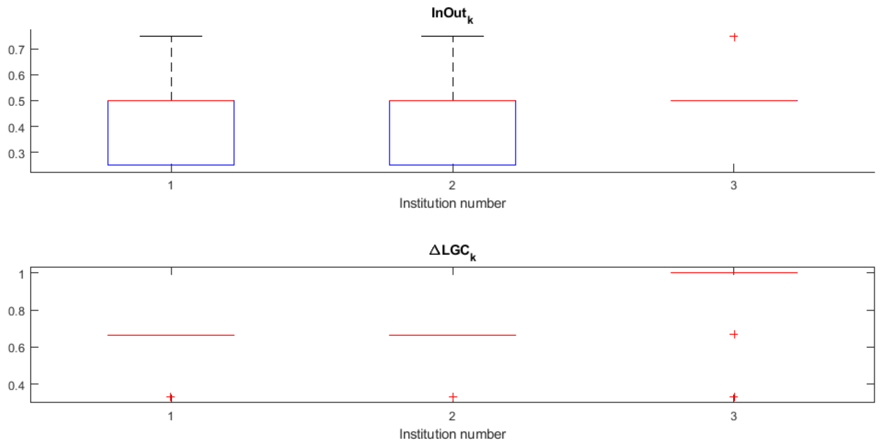

Figure 7: Box plots of alternative measures of systemic risk contributions

that the three institutions are systemically equal. In contrast, the box plots of our statistics ΔLGC_k confirm the relevance of the LOO approach. Indeed, the median values are equal for the institutions 1 and 2. This means that most frequently (across the $1,000$ simulations), these two institutions are found to be systemically equivalent. Moreover and importantly, the median value for the institution 3 takes the highest value, with the consequence that this institution is diagnosed as the most systemic in most simulations. Hence, these Monte Carlo experiments show that the ranking from the LOO measure is consistent, as least for the considered simulation setup. The next section is devoted to a thorough analysis of the new measure of systemic risk contributions using real data.

5 Reliability of the New Measure

In this section, we first introduce the data used to illustrate our new measure and give some summary statistics. Then, we compare the new measure to the one of BGLP and highlight the differences between the two measures. Finally, we evaluate its predictive power, that is, to what extent it can be considered as an early-warning indicator of the fragility of financial institutions in the case of a systemic event.

5.1 Data and Summary Statistics

To analyze the performance of our measure, we use daily assets returns, denominated in local currency, of 90 banks from 28 countries worldwide. The data are downloaded from Datastream, and range from September 12, 2003 to February 19, 2018, with a total of 3766 daily observations. The banks are mostly from developed countries: 80 are from 21 developed countries and 10 from 7 emerging countries. The sample of banks considered is the one used by Demirer et al. (2018), except six banks: CIMB Group Holdings (Malaysia), Pohjola Bank (Finland), Woori Finance Holdings (Korea), Bank of Yokohama (Japan), Banco Popular (Spain), and Banco Espirito Santo (Portugal). These banks are excluded for various reasons including data availability, failure or merger and acquisition. Table B1 in Appendix B displays the list of banks with their respective country and label.

One important feature of our data set is that it includes almost every G-SIBS identified by the Financial Stability Board (FSB). This will allow us to compare the banks that we identify as the "most systemic" based on our new measure, to those identified by the FSB. Starting from September 2003 to February 2018, our data set is large enough for sub-samples analyzes. For further analysis, we will thus consider three sub-periods: pre-crisis, crisis and post-crisis. We follow Laeven et al. (2016) by setting the beginning of the crisis period to July 2007 and the ending of the crisis to June 2009, which corresponds to the recovery of financial markets. Table B2 in Appendix B reports for the full sample and each sub-sample, the mean, the standard deviation, the skewness and the kurtosis of the banks' asset returns regrouped by continent. As expected, the average returns highly decreased for all regions during the crisis period and became negative except for Africa. The standard-deviation also increased during this period, and particularly for American's and European's banks.

5.2 Comparative Assessment

As underlined in the previous sections, spurious causalities arising from indirect contagion, can severely impair the results of Granger-causality tests, and can lead to inconsistent rankings of the systemic importance of financial institutions based on Granger-causality network. This is particularly the case for the measure InOut_k of BGLP. We thus introduced a new measure we denoted ΔLGC_k based on the LOO concept. The goal of this section is to highlight the differences between our measure and that of BGLP. To this end, we compute these two measures for our three sub-periods.[4]

Remark that both the BGLP measure InOut_k and our LOO measure ΔLGC_k are summaries of outcomes from multiple pair-wise Granger-causality tests, and hence are subject to data snooping (White, 2000), a phenomenon that occurs when the same dataset is used more than once for inference. Data snooping should be taken with cautious, since with multiple testing, there is an increased probability of rejecting the null hypothesis (here, absence of causality) just by chance, with an inflation of the overall significance level. Hence, we correct both measures for multiple testing problem, using the two-stage linear step-up procedure of Benjamini et al. (2006). Appendix A is devoted to a brief review of the data snooping problem, along with the motivation underlying our choice of this procedure.

Tables 1-3 provide the ten most systemic banks identified by both measures as well as the ten less systemic, for the three sub-periods. For the pre-crisis period (see Table 1), JPMorgan Chase & Co appears as the most systemic bank identified by our LOO approach, with the value of the measure ΔLGC_k equal to 0.938. This means that when this institution is excluded from the system, controlling for the impact of spurious causalities, the number of significant connections in the system has dropped by 93.8%. This decline is notable, and reflects the importance of this institution in the network. Figure 8 displays for the pre-crisis period, the network for the whole system including all of the 90 banks in the sample. The number of significant connections, i.e., the statistics LGC is equal to 1312. The same network excluding JPMorgan Chase &

[4]Following BGLP and Basu et al. (2017), we control the two measures for the presence of heteroskedasticity in asset returns, basing both the unconditional and conditional Granger-causality tests to the filtered returns innovations obtained from the estimation of GARCH models.

Table 1: Comparison of rankings during the pre-crisis period

BLGP Approach			Leave-One-Out		
10 Most Systemic Institutions (by Rank)					
Bank Name	Country	$InOut_k$	Bank Name	Country	ΔLGC_k
JPMorgan Chase & Co	US	0.320	JPMorgan Chase & Co	US	0.938
Goldman Sachs Group	US	0.309	Morgan Stanley	US	0.898
Shizuoka Bank	Japan	0.303	Goldman Sachs Group	US	0.860
Bank of New York Mellon	US	0.292	State Street Corporation	US	0.820
PNC Financial Services Group	US	0.292	Citigroup	US	0.800
Morgan Stanley	US	0.287	Bank of New York Mellon	US	0.781
BB&T Corp	US	0.287	BB&T Corp	US	0.778
State Street Corporation	US	0.275	American Express	US	0.758
American Express	US	0.275	Deutsche Bank	Germany	0.697
Nomura Holdings	Japan	0.275	PNC Financial Services Group	US	0.682
10 Less Systemic Institutions (by Rank)					
Royal Bank of Canada	Canada	0.034	National Australia Bank	Australia	0.059
Canadian Bank of Commerce	Canada	0.034	Hokuhoku Financial Group	Japan	0.056
Unipol Gruppo Finanziario	Italy	0.034	Resona Holdings	Japan	0.053
Ping An Bank	China	0.034	Yamaguchi Financial Group	Japan	0.053
Banco de Sabadell	Spain	0.034	Shanghai Pudong Development Bank	China	0.045
China Minsheng Banking Corp	China	0.028	Hua Xia Bank	China	0.043
Hua Xia Bank	China	0.028	Malayan Banking Berhad	Malaysia	0.042
China Merchants Bank	China	0.022	China Merchants Bank	China	0.037
Banco Comercial Portugues	Portugal	0.022	China Minsheng Banking Corp	China	0.033
Shanghai Pudong Development Bank	China	0.011	Ping An Bank	China	0.031

Note : This Table displays the 10 most (less) systemic banks identified by the BGLP measure $InOut_k$ and our new measure ΔLGC_k of systemic risk contributions. Both measures are compared over the pre-crisis period ranging from September 2003 to June 2007 with a total of 991 daily returns.

Table 2: Comparison of rankings during the crisis period

BLGP Approach			Leave-One-Out		
10 Most Systemic Institutions (by Rank)					
Bank Name	Country	$InOut_k$	Bank Name	Country	ΔLGC_k
BB&T Corp	US	0.669	Citigroup	US	0.886
Bank of America	US	0.517	Bank of America	US	0.758
Bank of Montreal	Canada	0.461	JPMorgan Chase & Co	US	0.738
U.S. Bancorp	US	0.449	Wells Fargo	US	0.678
Citigroup	US	0.438	Capital One Financial	US	0.661
Royal Bank of Canada	Canada	0.438	American Express	US	0.654
National Bank of Greece	Greece	0.438	U.S. Bancorp	US	0.631
Capital One Financial	US	0.427	BB&T Corp	US	0.613
SunTrust Banks	US	0.421	Morgan Stanley	US	0.592
United Overseas Bank	Singapore	0.416	PNC Financial Services Group	US	0.570
10 Less Systemic Institutions (by Rank)					
Banca Monte Dei Paschi di Siena	Italy	0.230	Yamaguchi Financial Group	Japan	0.075
Bank of Baroda	India	0.225	Fukuoka Financial Group	Japan	0.073
China Minsheng Banking Corp	China	0.219	Industrial Bank of Korea	Korea	0.072
Banco de Sabadell	Spain	0.213	China Merchants Bank	China	0.068
Commerzbank	Germany	0.208	Malayan Banking Berhad	Malaysia	0.067
Banco Popolare	Italy	0.202	Shizuoka Bank	Japan	0.063
Shanghai Pudong Development Bank	China	0.197	China Minsheng Banking Corp	China	0.060
State Bank of India	India	0.163	Shanghai Pudong Development Bank	China	0,053
Ping An Bank	China	0.107	Ping An Bank	China	0.049
Hua Xia Bank	China	0.051	Hua Xia Bank	China	0.036

Note : This Table displays the 10 most (less) systemic banks identified by the BGLP measure $InOut_k$ and our new measure ΔLGC_k of systemic risk contributions. Both measures are compared over the crisis period ranging from July 2007 to June 2009 with a total of 522 daily returns.

Table 3: Comparison of rankings during the post-crisis period

BLGP Approach			Leave-One-Out		
10 Most Systemic Institutions (by Rank)					
Bank Name	Country	InOut_k	Bank Name	Country	$\Delta\text{LGC}_\text{k}$
Mitsubishi UFJ Financial Group	Japan	0.472	JPMorgan Chase & Co	US	0.590
Sumimoto Mitsui Trust Holdings	Japan	0.444	Wells Fargo	US	0.554
Hokuhoku Financial Group	Japan	0.444	Bank of America	US	0.541
Nomura Holdings	Japan	0.427	Morgan Stanley	US	0.533
Sumimoto Mitsui Financial Group	Japan	0.416	Citigroup	US	0.524
HSBC Holdings	UK	0.416	Goldman Sachs Group	US	0.504
United Overseas Bank	Singapore	0.416	SunTrust Banks	US	0.496
Fukuoka Financial Group	Japan	0.410	U.S. Bancorp	US	0.487
National Bank of Greece	Greece	0.410	BNP Paribas	France	0.440
Resona Holdings	Japan	0.399	Bank of New York Mellon	US	0.434
10 Less Systemic Institutions (by Rank)					
Banco Bradesco	Brazil	0.230	Shinhan Financial Group	Korea	0.059
State Bank of India	India	0.225	State Bank of India	India	0.059
Toronto-Dominion Bank	Canada	0.219	China Merchants Bank	China	0.053
Royal Bank of Canada	Canada	0.213	Industrial Bank of Korea	Korea	0.051
Bank of Nova Scotia	Canada	0.213	Bank of Baroda	India	0.050
Banco de Sabadell	Spain	0.213	China Minsheng Banking Corp	China	0.048
Commerzbank	Germany	0.208	Hua Xia Bank	China	0.037
Sberbank Rossii	Russia	0.208	Ping An Bank	China	0.035
Banca Monte Dei Paschi di Siena	Italy	0.174	Shanghai Pudong Development Bank	China	0.034
Turkiye Is Bankasi	Turkey	0.163	Malayan Banking Berhad	Malaysia	0.034

Note : This Table displays the 10 most (less) systemic banks identified by the BGLP measure InOut_k and our new measure $\Delta\text{LGC}_\text{k}$ of systemic risk contributions. Both measures are compared over the post-crisis period ranging from July 2009 to February 2018 with a total of 2253 daily returns.

Co is exhibited in Figure 9, with the statistics $\text{LGC}_{(-k)}$ equal to 81. Hence, when this institution is excluded from the system, the number of significant connections drops from 1312 to 81, with our measure ΔLGC_k taking value $(1312 - 81)/1312 = 93.8\%$. This result should be contrasted with the one obtained for the least systemic institution (Ping An Bank) with the statistics ΔLGC_k equal to 0.031. Figure B1 in Appendix B displays the network that excludes this institution. As we can see, the network is indistinguishable from the one that includes all institutions (see Figure 8). Indeed the number of statistically significant connections in the system that excludes Ping An Bank is equal to 1271 and therefore very close to 1312.

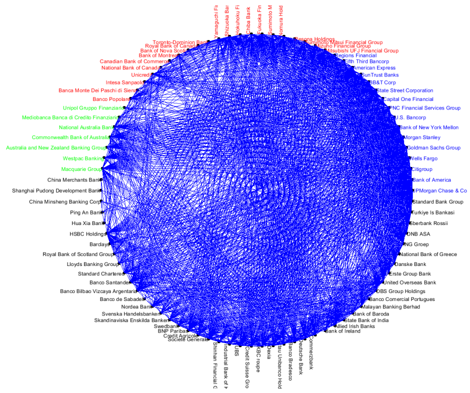

Figure 8: Network for all 90 banks: pre-crisis period

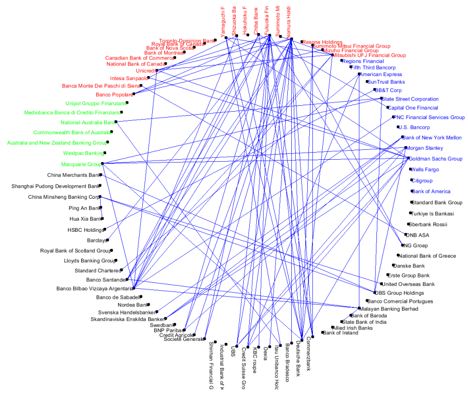

Figure 9: Network for the system excluding JPMorgan Chase & Co: pre-crisis period

Results in Table 1 also indicate that the most systemic banks identified are mostly American for both measures, whereas the less systemic are from Japan and China for the measure ΔLGC_k, but from China, Europe and Canada for the measure InOut_k. The differences between the most systemic institutions are thus weak. However, when one considers all of the 90 financial institutions, some divergences appear between the two measures of systemic risk contributions, as illustrated in Figure 10 which displays the scatter plot of the ranks of financial institutions. The most (less) systemic institution is ranked one (90) for both measures. We observe that if both measures identify American banks as the most systemic during the pre-crisis period, some differences exist for the rest of the sample.[5] Indeed, banks from Asia and Pacific, except from China

[5]The overall correlation between the ranks is equal to 0.423.

and India, are identified as much more systemic by the InOut_k measure than by the ΔLGC_k measure. This difference arises mainly from the negative impact of spurious indirect causalities on the measure InOut_k. In other words, the unconditional Granger-causality test that underlines the measure InOut_k detects many spurious causalities involving many banks from Asia and Pacific.

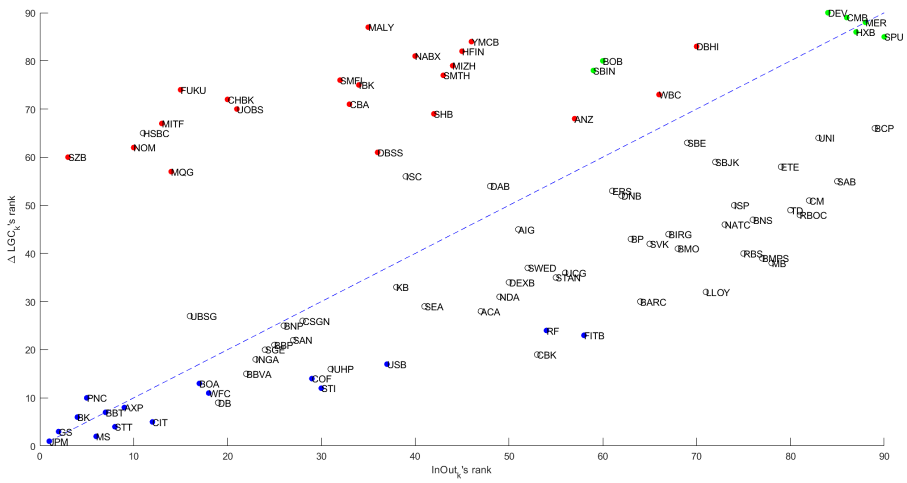

Figure 10: Comparison of the ranks of InOut_k and ΔLGC_k: pre-crisis period

Note : This figure represents the ranks of banks for both measures over the pre-crisis period. Banks from US are filled in blue, Australia, Japan, Korea, Malaysia and Singapore in red, China and India in green, and the others are not filled.

The patterns are different when analyzing the results for the crisis period displayed in Table 2. Indeed, while our measure still identifies American banks as the most systemic, the measure InOut_k from BGLP identifies banks from US and Canada. Moreover, banks from China, India, Europe and Canada are ranked as the less systemic by the latter measure, while our measure still identifies banks from China and Japan. The overall picture of the differences between the two measures are displayed in Figure 11 which represents the scatter plot of the ranks. The figure shows a clear cut divergence between both measures with the value of the correlation between ranks that drops from 0.423 (pre-crisis period) to 0.127. As already stressed, this result arises from indirect spurious causalities, which seems most prominent in the crisis period. Lastly, results in Table 3 (see also Figure B2 in Appendix B) confirm the divergence between both measures of systemic risk, with an overall rank correlation equal to 0.058.

As the true levels of systemic risk contributions are latent, one can wonder whether our measure is more accurate to that of BGLP. One way to convince the reader is to compare both rankings to the one provided by the Financial Stability Board (FSB). Indeed, since 2011, this institution publishes each year a ranking of the most systemic banks worldwide, denoted as G-SIBs (global systemically important banks), organized by buckets. The latter differ by the required level of additional common equity loss absorbency as a percentage of risk-weighted assets that each G-SIB will be required to hold. We thus consider the last ranking of G-SIBs published in 2017 by the FSB

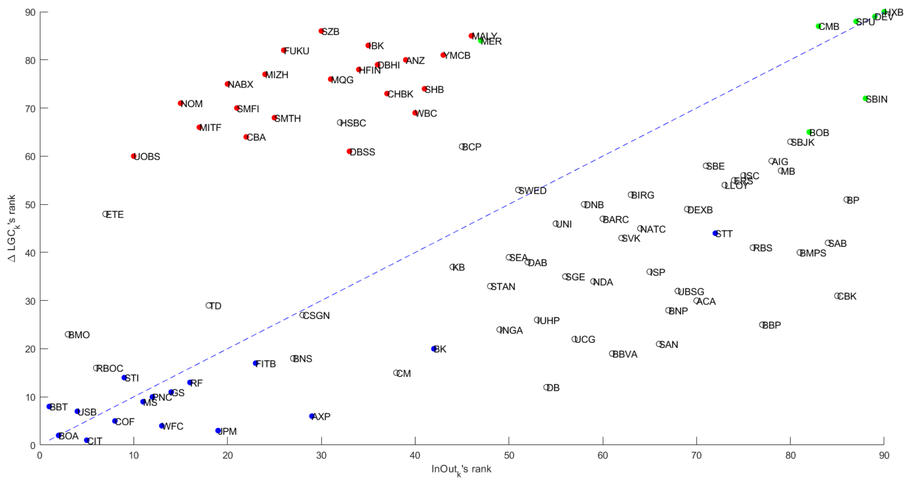

Figure 11: Comparison of the ranks of InOut_k and ΔLGC_k: crisis period

Note : This figure represents the ranks of banks for both measures over the crisis period. Banks from US are filled in blue, Australia, Japan, Korea, Malaysia and Singapore in red, China and India in green, and the others are not filled.

and make a comparison with our ranking and that from the BGLP approach over the 2016-2017 period. We consider this period as it includes the time-span over which the 2017 FSB ranking is generated. As our sample does not include (for lack of data over the whole sample) four Chinese banks among the G-SIBs identified in 2017 by the FSB (Bank of China, China Construction Bank, Industrial and Commercial Bank of China Limited and Agricultural Bank of China), we do not consider these banks for the purpose of comparison. This leads to a total of 26 G-SIBs over the 30 identified by the FSB.

The first two columns in Table 4 display these 26 G-SIBS, along with the associated buckets according to the FSB, while the third (fourth) column indicates whether each G-SIB is identified as systemic by the ΔLGC_k (InOut_k) measure, with the related rankings in parentheses (between 1 and 26). Among the 26 banks, our measure identifies 16 of them (61.54%). This represents a large proportion, and especially, most of those not identified (Mizuho Financial Group, Nordea Bank, Royal Bank of Canada, Royal Bank of Scotland, Standard Chartered, State Street Corporation, Sumimoto Mitsui Financial Group) are classified by the FSB as the less systemic institutions among the 26 banks (bottom bucket). In contrast, the measure from BGLP only identifies 6 of these G-SIBs, which corresponds to a low level of accuracy percentage (23.08%). Moreover, those not identified are not only from the bottom bucket, but also from the top buckets (most systemic banks). One illustrative example is JPMorgan Chase & Co (top systemic institution according to the FSB) that is not identified. Moreover, Bank of America, another top systemic institution is only present by a small margin as it is identified at the 23th place. These stylized facts are in accordance with the results in Table 3 (post-crisis period) which show that the most systemic banks identified by the ΔLGC_k are mostly from the US, while those identified by the InOut_k are mainly from

Table 4: Comparison of G-SIBs identifid by InOut_k and ΔLGC_k

Bucket	G-SIBS 2017	ΔLGC_k (ΔLGC_k's rank)	InOut_k (InOut_k's rank)
4	JPMorgan Chase & Co	X (5)	
	Bank of America	X (1)	X (23)
3	Citigroup	X (10)	
	Deutsche Bank	X (16)	
	HSBC Holdings		X (9)
2	Barclays		
	BNP Paribas	X (12)	
	Goldman Sachs Group	X (21)	
	Mitsubishi UFJ Financial Group		X (8)
	Wells Fargo	X (7)	
1	Bank of New York Mellon	X (25)	
	Credit Suisse Group	X (20)	
	Credit Agricole	X (23)	
	ING Groep	X (9)	
	Mizuho Financial Group		X (5)
	Morgan Stanley	X (2)	
	Nordea Bank		X (22)
	Royal Bank of Canada		
	Royal Bank of Scotland		
	Banco Santander	X (15)	
	Societe Generale	X (13)	
	Standard Chartered		
	State Street Corporation		
	Sumimoto Mitsui Financial Group		X (3)
	UBS	X (6)	
	Unicredit	X (26)	
		Number of G-SIBS identified	Number of G-SIBS identified
		16 [61.54%]	6 [23.08%]

Note : This Table displays the G-SIBs identified by the FSB with their respective buckets. We also report those identified by the systemic risk contributions statistics InOut_k and ΔLGC_k over the period 2016-2017 (followed by their respective ranking in parentheses), as well as the total number identified (percentage in brackets).

Japan. As the G-SIBs and especially the most systemic ones are mostly American banks, our measure appears as a more reliable indicator of systemic risk.

5.3 Predictive Power

As stressed by Sedunov (2016), an institution-level measure of systemic risk should be a good forecast of a financial institution's performance in crisis period. In other words, any consistent measure of the systemic risk profile of an institution should be an early-warning indicator of losses in the case of a systemic event. In this section, we check whether this characteristic is fulfilled by our measure $\Delta \mathrm{LGC}_k$ of systemic risk contributions. More precisely, we focus on the crisis period, i.e., the period ranging from July 2007 to June 2009, with a total of $T_c = 522$ daily observations. Over the crisis period, we compute for each bank its performance given by the average of downside returns. For a given financial institution $k = 1, ..., 90$, the performance is given by

$$\mathrm{Perf}_k = \frac{1}{m} \sum_{t=1}^{T_c} y_{k,t} Z_{k,t}, \tag{26}$$

for $t = 1, ..., T_c$, where $y_{k,t}$ is the return at time t on the asset of bank k, $Z_{k,t}$ a downside indicator at time t defined as

$$Z_{k,t} = \begin{cases} 1 & \text{if} \quad y_{k,t} < \delta \\ 0 & \text{else,} \end{cases} \tag{27}$$

with $\delta < 0$ a threshold. The parameter m is the number of times $Z_{k,t}$ takes value one over the crisis period, i.e.,

$$m = \sum_{t=1}^{T_c} Z_{k,t}. \tag{28}$$

The performance measure in (26) gives the average value of the losses experienced by the bank k in the crisis period. Since our goal in this section is to check whether banks with high levels of systemic risk perform more poorly (out-of-sample) than banks with low levels of systemic risk, we consider the following regression

$$[\mathrm{Perf}_k] = \beta_0 + \beta_1 [\mathrm{InOut}_k] + \beta_2 [\mathrm{In}_k] + \beta_3 [\mathrm{Out}_k] + \beta_4 [\Delta \mathrm{LGC}_k] + \epsilon_k, \tag{29}$$

where $[\mathrm{Perf}_k]$ is the rank (in ascending order) of the performance of bank k, with the less (most) performing bank taking value 1 (90). The variable $[\Delta \mathrm{LGC}_k]$ is the rank (in descending order) of our measure $\Delta \mathrm{LGC}_k$ for the bank k, over the pre-crisis period ranging from September 2003 to June 2007, with the most (less) systemic bank taking value 1 (90). Hence, in the case of predictive content, we expect a positive sign for β_4, i.e., more (less) systemic institutions in the pre-crisis period have higher (lower) realized losses in the crisis period.

Remind that our institution-level measure of systemic risk contribution is built on the pitfall of the measure InOut_k of BGLP in ranking institutions. Indeed, we argued that the ranking of financial institutions based on the latter measure can be misleading in the presence of spurious indirect causalities. Therefore, to evaluate the relevance of this statement, we include in the regression the rank (in descending order) of the measure InOut_k. We also consider the two components of the latter measure, separately, i.e., the statistics In_k and Out_k, with their respective ranks (in descending order). Therefore, as for the parameter β_4, the other slope parameters should also take positive values in the case of predictive content.[6]

Table 5 exhibits the estimation results for $\delta = -3\%$. The estimations are performed using ordinary least squares with inference based on White's robust method (White, 1980). We consider three values of the lag-order M in running the Granger-causality tests, with $M \in \{3, 5, 10\}$. For each value of M we display the results of eight different specifications. In specifications [1] to [4], we consider separately each of the alternative systemic risk measures. In specifications [5] to [7], we include our measure of systemic risk and each of the three measures of BGLP. Finally, in the column [8], we report the results from a specification that includes the four alternative measures of systemic risk.

First, as we can see in specifications [1] to [4], the slope parameter associated with each measure of systemic risk is statistically significant at the conventional levels. This means that, individually, each measure of systemic risk contributions is significantly related to the losses suffered by banks in the case of a systemic event. The BGLP measures (InOut_k and Out_k) and our measure (ΔLGC_k) appear with the expected sign: the riskier is a bank in the pre-crisis period, the more severe are the losses during the crisis period. Surprisingly, the measure In_k of BGLP appears with a negative sign, which indicates that banks with a higher systemic risk level are more resilient during the crisis. Furthermore, it is worth noting that our measure seems to predict a larger part of the variance of those losses compared to the three measures of BGLP. Indeed the values of the adjusted R-squared are always higher. For instance, with $M = 3$, the adjusted R-squared is equal to 31.3% with our measure ΔLGC_k, while it is equal to 28.2%, 7.5%, and 3.2% for the BGLP measures Out_k, InOut_k and In_k, respectively. Second, if we turn to specifications [5] to [7], we can see that the coefficients associated with the three measures of BGLP loose their statistical significance, while the one associated with our measure remains significant. This result is very important, as it suggests that all the information conveyed by the three measures of BGLP is included in our measure, with an additional information which probably arises from our methodology to clean indirect spurious causalities. This result is robust when we consider jointly the four measures of systemic risk (see specification [8]).

Table 6 presents the same results with $\delta = -5\%$. Results are qualitatively similar to those obtained in Table 5. Through Tables 5 and 6, we observe that the lag-order M does not seem to have a substantial impact neither on the estimated parameters nor on the adjusted R-squared. This is also the case for the parameter δ that measures the severity of the losses. Figures B3 and B4 in Appendix represent for the case $(\delta, M) = (-5\%, 3)$ the performance of each bank as measured by the mean of realized losses as a function of the systemic risk contribution measures InOut_k and ΔLGC_k, respectively. We observe that there is almost no correlation between the average realized losses and the measure InOut_k, whereas on the contrary, our new measure ΔLGC_k can predict the average realized losses relatively well.

[6] We consider using the ranks of the variables instead of their true values to avoid possible multi-collinearity between the measures InOut_k, In_k and Out_k. See Billio et al. (2012) for a similar approach.

Table 5: Predictive content of systemic risk measures for realized mean losses, δ = -3%

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
				$M=3$				
Constant	32.173***	54.876***	21.014***	19.796***	17.693***	10.725	19.515***	4.961
	(4.485)	(4.646)	(4.232)	(3.898)	(3.997)	(7.994)	(4.052)	(10.452)
InOut_k	0.293***				0.078			-0.045
	(0.088)				(0.090)			(0.119)
In_k		-0.206**				0.130		0.217
		(0.102)				(0.107)		(0.159)
Out_k			0.538***				0.090	0.303
			(0.074)				(0.249)	(0.275)
ΔLGC_k				0.565***	0.534***	0.634***	0.481**	0.416*
				(0.068)	(0.078)	(0.092)	(0.231)	(0.233)
$\overline{R}^2$	0.075	0.032	0.282	0.311	0.309	0.316	0.305	0.309
				$M=5$				
Constant	32.607***	54.786***	21.432***	19.907***	19.445***	13.716*	19.725***	7.400
	(4.587)	(4.606)	(4.194)	(3.889)	(3.955)	(7.494)	(4.023)	(9.584)
InOut_k	0.283***				0.019			-0.123
	(0.090)				(0.102)			(0.135)
In_k		-0.204*				0.092		0.216
		(0.102)				(0.103)		(0.150)
Out_k			0.529***				0.055	0.239
			(0.074)				(0.224)	(0.251)
ΔLGC_k				0.562***	0.553***	0.607***	0.512**	0.505**
				(0.067)	(0.084)	(0.087)	(0.207)	(0.231)
$\overline{R}^2$	0.070	0.031	0.272	0.309	0.301	0.307	0.301	0.300
				$M=10$				
Constant	35.927***	53.117***	23.941***	20.243***	20.666***	13.345*	21.007***	10.212
	(4.788)	(4.809)	(4.230)	(3.910)	(4.093)	(7.597)	(3.982)	(9.271)
InOut_k	0.210***				-0.016			-0.167
	(0.094)				(0.094)			(0.122)
In_k		-0.167				0.104		0.222
		(0.108)				(0.105)		(0.155)
Out_k			0.474***				-0.190	-0.027
			(0.080)				(0.229)	(0.242)
ΔLGC_k				0.555***	0.561***	0.602***	0.728***	0.748***
				(0.069)	(0.079)	(0.087)	(0.218)	(0.230)
$\overline{R}^2$	0.033	0.017	0.216	0.300	0.292	0.301	0.298	0.298

Note : This Table displays the results (parameter estimates followed by the standard errors in parentheses) of various predictive regressions, with the dependent variable measuring the rank of realized losses for each of the 93 financial institutions in the crisis period (July 2007-June 2009). We approximate the realized losses by the average value of returns below a given threshold $\delta = -3\%$. The regressions differ by the number of predictors considered, among a set including the ranks of systemic risk contributions statistics InOut_k, In_k, Out_k and ΔLGC_k, measured over the pre-crisis period (September 2003-June 2006). We consider different configurations of the lag-order M for causality tests, with $M \in \{3, 5, 10\}$. For the causality tests used to compute the predictors, inference is based on the two-stage linear step-up procedure of Benjamini et al. (2006). Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

Table 6: Predictive content of systemic risk measures for realized mean losses, δ = -5%

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
				$M = 3$				
Constant	32.122***	54.554***	21.218***	20.252***	17.982***	11.011	19.857***	4.495
	(4.543)	(5.059)	(4.203)	(3.926)	(3.944)	(7.652)	(4.074)	(9.710)
InOut_k	0.294***				0.084			-0.044
	(0.086)				(0.092)			(0.129)
In_k		-0.199*				0.133		0.228
		(0.104)				(0.099)		(0.148)
Out_k			0.534***				0.127	0.351
			(0.076)				(0.230)	(0.243)
ΔLGC_k				0.555***	0.521***	0.625***	0.437**	0.367*
				(0.068)	(0.085)	(0.083)	(0.208)	(0.200)
$\overline{R}^2$	0.076	0.029	0.277	0.300	0.298	0.305	0.294	0.301
				$M = 5$				
Constant	32.151***	53.971***	22.363***	20.245***	19.365***	12.786*	20.383***	8.774
	(4.471)	(5.014)	(4.169)	(3.884)	(3.932)	(7.175)	(4.007)	(9.418)
InOut_k	0.293***				0.037			-0.094
	(0.086)				(0.103)			(0.146)
In_k		-0.186*				0.110		0.196
		(0.103)				(0.095)		(0.147)
Out_k			0.509***				-0.041	0.128
			(0.078)				(0.233)	(0.257)
ΔLGC_k				0.555***	0.537***	0.609***	0.593***	0.577***
				(0.066)	(0.090)	(0.078)	(0.211)	(0.222)
$\overline{R}^2$	0.076	0.024	0.250	0.300	0.293	0.302	0.292	0.289
				$M = 10$				
Constant	35.254***	52.346***	24.231***	20.642***	20.471***	12.668*	21.367***	9.854
	(4.801)	(5.242)	(4.296)	(3.897)	(4.089)	(7.162)	(4.042)	(9.005)
InOut_k	0.225***				0.006			-0.148
	(0.091)				(0.099)			(0.146)
In_k		-0.150				0.121		0.226
		(0.110)				(0.097)		(0.150)
Out_k			0.467***				-0.180	-0.020
			(0.085)				(0.237)	(0.268)
ΔLGC_k				0.546***	0.544***	0.601***	0.710***	0.726***
				(0.068)	(0.086)	(0.076)	(0.211)	(0.215)
$\overline{R}^2$	0.040	0.012	0.210	0.291	0.282	0.294	0.288	0.288

Note : This Table displays the results (parameter estimates followed by the standard errors in parentheses) of various predictive regressions, with the dependent variable measuring the rank of realized losses for each of the 93 financial institutions in the crisis period (July 2007-June 2009). We approximate the realized losses by the average value of returns below a given threshold $\delta = -5\%$. The regressions differ by the number of predictors considered, among a set including the ranks of systemic risk contributions statistics InOut_k, In_k, Out_k and ΔLGC_k, measured over the pre-crisis period (September 2003-June 2006). We consider different configurations of the lag-order M for causality tests, with $M \in \{3, 5, 10\}$. For the causality tests used to compute the predictors, inference is based on the two-stage linear step-up procedure of Benjamini et al. (2006). Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

6 Determinants of Network Systemic Risk Contributions

Following the existing empirical literature on the determinants of systemic risk, we attempt in this last section to understand why some banks tend to contribute more to the global systemic risk than others. Indeed, since the last financial crisis, there is a considerable debate about the potential channels and drivers of transmission of financial distress between banks. In particular, some recent studies investigate whether the size and business model of banks significantly drive their contribution to systemic risk. They find strong evidence that large and market-oriented financial institutions are more prone to contribute to the build-up of systemic risk in the financial system than their peers.

Against this background, we check whether we find results in line with the existing literature when we consider our measure of systemic risk as dependent variable. This issue is particularly interesting in our case as our measure of systemic risk is a measure of interconnections between financial institutions, and then is more likely to be driven by size and activities of banks than other "traditional" measures of systemic risk, such as the marginal expected shortfall (MES), the SRISK or the ΔCoVaR. To this end, we consider a panel data framework and regress different balance-sheet variables on our measure of systemic risk. We consider annual data over the 2004-2017 period. More precisely, we consider seven non-overlapping sub-periods: 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15, 2016-17. For each bank of our sample, we then compute our systemic risk measure for these different sub-periods, while we use a two-year average for balance sheet data. Individual balance sheet data are taken from Thomson Reuters Worldscope.

We start our empirical investigation by assessing the link between bank size and our measure of systemic risk. Indeed, as highlighted above, a number of recent empirical studies find strong evidence that systemic risk increases with bank size (see, e.g., De Jonghe, 2010; Brunnermeier et al., 2012; Kleinow and Nell, 2015; Black et al., 2016; Laeven et al., 2016; Varotto and Zhao, 2018). As it is usual in the literature, bank size is measured by the logarithm of total assets. Specifically, we estimate the following benchmark regression specification:

$$\Delta LGC_{k,t} = \alpha + \beta_1 Size_{k,t-1} + \mu_k + \gamma_t + \lambda_c + \varepsilon_{k,t} \tag{30}$$

where k and t are respectively the bank and time period indicators, $\Delta LGC_{k,t}$ is our measure of systemic risk contribution, and $Size_{k,t-1}$ represents the bank size. Following Brunnermeier et al. (2012) and Laeven et al. (2016), the right-hand side variable is lagged one period to reduce a potential endogeneity bias associated with reverse causality. The term μ_k is an individual specific effect, γ_t is an unobserved time effect included to capture common time-varying factors, λ_c is a country fixed effect, and $\varepsilon_{k,t}$ is the random error term. Country-specific effects are included to control for cross-country differences in financial regulation and supervision. Because bank fixed effects and country fixed effects are perfectly collinear, we cannot use a fixed effects (FE) estimator, and then estimate Equation (30) using the random effects (RE) estimator.

Results that we obtain are reported in the first column of Table 7. As we can see, we find a positive and significant relationship between bank size and our measure of systemic risk. As higher values of our statistics mean more systemic institutions, this result suggests that the systemic risk contributions of banks increase with their size. As Laeven et al. (2016) argue, this result is consistent with the view that large banks enjoy "too big to fail" subsidies, making them pay less attention to the risks they take, and then creating strong externalities in the market when they are distressed. Moreover, as larger banks are often highly interconnected with their competitors, this result is consistent with the measure of network systemic risk we propose in this paper.

In a second step, we extend our previous findings by investigating whether the business model of banks drive their contribution to systemic risk. To this end, we augment our benchmark regression specification by considering an additional regressor capturing differences in banking activities. More precisely, we distinguish between traditional intermediation activities and non-traditional banking activities, such as investment banking, venture capital and trading activities. By this way, we distinguish between retail-oriented and market-oriented banks, and then assess the effect of banks asset structure on systemic risk. We proxy the importance of traditional activities by the loans to assets ratio, while the share of non-interest income to total income is used as a proxy for non-core activities. As shown by Laeven et al. (2016), the loans to assets ratio is negatively related to the systemic risk, while Brunnermeier et al. (2012) find that banks with higher non-interest income tend to have a higher contribution to systemic risk than traditional banks.

Results that we obtain are reported in the columns [2] and [3] of Table 7. As we can see in the column [2], similarly to Laeven et al. (2016), we find that the relationship between the loans to assets ratio and our systemic risk measure is negative and statistically significant. This suggests that traditional intermediation activities tend to reduce the systemic risk contribution of banks as lending-based activities make banks less exposed to common shocks. On the contrary, results reported in the column [3] show a positive and significant relationship between the share of non-interest income to total income and our measure of systemic risk. This result is consistent with the view that banks with more market-based activities are more prone to contribute to systemic risk. Indeed, in contrast to lending exposures, market-based exposures are relatively more correlated across banks, increasing the risk of contagion from a distressed bank.

Finally, we assess the influence of banks' profitability on systemic risk. We proxy for the profitability of a bank using the return on equity (ROE). However, as Weiß et al. (2014) and Kleinow and Nell (2015) argue, the link between the profitability of a bank and its contribution to systemic risk remains unclear. On the one hand, one may expect that a higher profitability shields banks from the risk of defaulting, and then should be associated with a lower systemic risk contribution. On the other hand, a higher profitability could be the result of the bank engaging in risky "side activities", such as market-based investments and trading activities. Furthermore, as our previous results suggest, profits from non-lending activities significantly drive our measure of systemic risk. As a consequence, a higher profitability could induce a higher systemic risk contribution. As we can see in the column [4] of Table 7, the estimated coefficient associated with ROE appears positive and statistically significant, confirming the fact that the profitability of a bank increases its contribution to the systemic risk.

Table 7: Determinants of systemic risk

	(1)	(2)	(3)	(4)
Dependent variable	ΔLGC	ΔLGC	ΔLGC	ΔLGC
Size $(t-1)$	2.931***	2.290**	2.233***	2.921***
	(0.858)	(0.944)	(0.861)	(0.880)
Loans to assets ratio $(t-1)$		-0.114*		
		(0.063)		
Non-interest income $(t-1)$			0.213***	
			(0.060)	
ROE $(t-1)$				0.074***
				(0.017)
Constant	-43.262***	-24.218	-36.306**	-44.279***
	(16.200)	(18.857)	(15.977)	(16.521)
Nb. of observations	621	557	570	605
Nb. of banks	90	85	84	90
R-squared	0.781	0.778	0.789	0.781

Note: Robust standard errors clustered at bank level are reported below their coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Due to the magnitude of the estimated coefficients, the dependent variable $\Delta LGC_{k,t}$ is multiplied by 100.

To conclude, results that we obtain suggest strong evidence that bank size is one of the key driver of systemic risk. This result is not surprising if we refer to the recent academic literature on systemic risk (see, e.g., Laeven et al., 2016). In line with the existing literature, we also find that the specialization and business model of banks, but also their profitability, are significant drivers of systemic risk. In particular, our results support the fact that traditional lending activities reduce the risk of contagion.

7 Conclusion

In the wake of the recent global financial crisis, a wide variety of systemic risk measures have been proposed to quantify the risk contribution of financial institutions to the financial system, and then identify the so-called G-SIBs (global systemically important banks). Among these measures, some of them focus on one fundamental aspect of systemic risk: the connectedness of financial firms. Indeed, the linkages between banks can act as a contagion channel during a crisis. However, measuring interconnectedness in relatively large and complex financial systems is empirically challenging. Especially, the fact that linkages between firms and contagion in the financial system can stem from both direct and indirect exposures to counterparties is of critical importance.

However, to the best of our knowledge, there are few measures in the existing literature on systemic risk that try to explicitly take into account the existence of indirect contagion effects. In their seminal paper, Billio et al. (2012) propose to evaluate the systemic risk contribution of a given financial institution using a pair-wise Granger causality approach. Within this framework, a financial institution is defined as highly systemic if a large number of firms in the network are involved in a significant connection with this financial institution. The main shortcoming of such an approach is that the existence of indirect contagion effects can lead to spurious causalities, and then a misleading ranking of systemically important financial institutions. More recently, Basu et al. (2017) propose to address this shortcoming of the pair-wise approach by estimating a large dimensional VAR model that includes all firms simultaneously, and then that takes into consideration all interactions in the system. An inherent computational difficulty with this type of modeling is the curse of dimensionality, since the number of parameters grows quickly with the size of the network.

Against this background, the aim of this paper is to propose an alternative measure of systemic risk contribution that overcomes these two shortcomings. It formally manages indirect causalities between firms in the network and breaks the curse of dimensionality. To this end, we combine the pair-wise Granger-causality approach with the leave-one-out (LOO) concept. More precisely, our approach is based on a conditional Granger causality test and consists of measuring the extent to which, the proportion of statistically significant connections in the system breakdowns when a given financial institution is excluded, controlling for the indirect effects of this latter institution. Hence, the systemic risk contribution of this given institution is high when this proportion is large.

Using daily assets returns for a sample of the world's largest banks from September 12, 2003 to February 19, 2018, we then assess the reliability of our systemic risk measure in different ways. First, we rank the systemic importance of each bank of our sample using our systemic risk measure and that developed by Billio et al. (2012). Results that we obtain show substantial differences between the two rankings. More importantly, when we compare both rankings with the ranking of G-SIBs published in 2017 by the Financial Stability Board (FSB), we observe that our measure is better able to identify the G-SIBs than that proposed by Billio et al. (2012). Indeed, among the 26 G-SIBs included in our sample, our measure identifies 16 of them (61.54%), while the measure of Billio et al. (2012) identifies 6 (23.08%). Second, we assess the predictive power of our systemic risk measure and show that our measure is a robust and significant early-warning indicator of downside returns during the last financial crisis. Its predictive power is larger than the one associated with the measure of Billio et al. (2012). These findings reinforce the idea that a pairwise Granger causality approach is more reliable when the effects of indirect causalities are cleaned out in a meaningful way.

Finally, as it is usual in the literature on systemic risk, we empirically investigate the potential drivers of the systemic risk contribution of banks. To this end, we consider a panel data framework and regress different balance-sheet variables on our measure of systemic risk. Following the previous results in the literature, we primarily focus our analysis on the size of banks. Results that we obtain suggest that systemic risk increase with bank size. This result clearly indicates that the largest banks are more prone to contribute to systemic risk. We also find that the degree of specialization in non-traditional banking activities is an important driver of systemic risk. Indeed, our results indicate that the systemic risk contribution is higher for banks with more market-based activities. On the contrary, we find a negative relationship between the specialization in lending-based activities and our systemic risk measure. Furthermore, we find that profitability of a bank significantly increases its contribution to the systemic risk.

Of course, a systemic event like the last global financial crisis is a rare phenomenon.

Consequently, an interesting extension of this work would be to consider a Granger-causality network based on the transmission of tail risks. Precisely, our leave-one-out (LOO) metrics for measuring systemic risk contributions could be extracted from a network generated using Granger-causality tests in tail events or extreme risk. An example of such a test can be found in Hong et al. (2009). In this context, the main challenge to resolve is the extension of this test to a conditional setup. We leave this as an issue for future research.

Appendix

Appendix A: The Multiple Testing Problem

The measures InOut_k and ΔLGC_k are summaries of outcomes from multiple pair-wise Granger-causality tests and are obviously subject to the multiple testing problem. This phenomenon arises when several hypotheses are tested simultaneously. Among the different hypotheses tested, some of the null hypotheses are false and thus some will be rejected. In a perfect world, every false hypothesis and only these ones would be rejected. However, in reality, all false hypotheses will not be rejected and among those rejected, some will be mistakenly rejected. This issue is of great interest because it can mislead authors to wrong conclusions. Therefore, to solve this problem, one might want to reduce false rejections and make as many true ones as possible. The literature provides many methods to control for the problem of multiplicity in statistical inference, with two main alternative controlling methods: the Family Wise Error Rate (FWE) and the False Discovery Rate (FDR).

The FWE is defined as the probability of rejecting at least one of the true null hypothesis. To control the FWE, it requires that its value is lower or equal to the significance level α, at least asymptotically. Different methodologies have been developed to control FWE and the most widely used is the Bonferroni method. Its popularity comes from two main reasons. First, it is really simple as it consists only to compare all p-values to a single critical value. More precisely, each null hypothesis is rejected if the p-value is no bigger than α/M, with M the total number of hypotheses tested. Second, this method can be applied to any statistical test.

However, the FWE (and therefore the Bonferroni correction as well), substantially loses power as the number of hypotheses increases. Indeed, the critical values become very small, making it difficult to barely reject at least one hypothesis. For example, for each institution, $(n-1)(n-2)$ hypotheses are tested using our LOO measure, resulting in $M = 7832$ hypotheses for our sample of $n = 90$ institutions. Applying the Bonferroni correction in this set-up would lead to compare every p-values to the threshold 0.05/7832, and obviously some false null hypotheses will not be rejected due to this very small significance level. Some less conservative methods have been developed in the literature (Šidák, 1967; Holm, 1979; Hommel, 1988; Hochberg, 1988) but failed to do so as they are still conservative. Thus, the traditional approach is to control the FWE when the number of tested hypotheses is relatively small, and to control the FDR when this number becomes very large.

The FDR is defined as the expected proportion of false rejections among all hypotheses tested. Indeed, in some applications, a certain number F of false-positives is tolerable if there is a large number R of total rejections. The main idea is to relax the worst-case approach underlying the FWE methodology by allowing a small proportion of false rejections. In this case, one can base the error control on the False Discovery Proportion (FDP) defined as FDP = F/R if R > 0, and 0 otherwise. Then, the FDR is finally the expected value of FDP. The most popular method to control the FDR is the linear step-up procedure from Benjamini and Hochberg (1995) that is very simple. First, order each individual p-value from the smallest to the largest : $p_1 \leq p_2 \leq \ldots$ and define $i^\star = max\{i : p_i \leq \gamma_i\}$, with $\gamma_i = \gamma i/M$, with γ the level of control. If such $i^\star$ exists, reject the $i^\star$ respective hypotheses for each p-value below $\gamma_{i^\star}$, otherwise do not reject any hypothesis.

Benjamini and Hochberg (1995) show that under p-values independence, their linear step-up procedure controls the false discovery rate at precisely $\gamma M_0/M$, where the unknown parameter M_0 is the number of true null hypotheses among the M hypotheses.[7] From this result, it is obvious that if the true value of M_0 is known, an improved (in power) linear step-up procedure can be obtained using the level of control $\gamma^\star = \gamma M/M_0$. Indeed the FDR bound in this case will be equal to $\gamma^\star M_0/M = \gamma$. Benjamini et al. (2006) suggest using as an estimate for M_0, $\widehat{M}_0 = M - R$, with R the number of rejected hypothesis in the linear step-up procedure. This leads to their two-stage linear step-up procedure that works as follows:

- Use the linear step-up procedure at level $\gamma' = \gamma/(1+\gamma)$. Let R be the number of rejected hypotheses. If $R = 0$ do not reject any hypothesis and stop; if $R = M$ reject all M hypotheses and stop; otherwise continue.
- Let $\widehat{M}_0 = M - R$.
- Use the linear step-up procedure with $\gamma^\star = \gamma' M/\widehat{M}_0$.

For both measures InOut_k and ΔLGC_k, we use this two-stage linear step-up procedure to correct the many pair-wise Granger-causality tests for multiple testing. We prefer this method because it is less conservative and more powerful than the FWE methods as the number of hypotheses tested is very large, and for its better power property (as discussed above) compared to the one-step procedure of Benjamini and Hochberg (1995). Moreover, Monte Carlo simulations in Stevens et al. (2017) show that the two-stage linear step-up procedure of Benjamini et al. (2006) performs better in comparison to alternative FDR procedures, under various forms of p-values dependences.

It is worth mentioning that among both types of methodologies (FWE and FDR), there is a class of controlling methods based on resampling procedures. For example, to control for the FWE, White (2000) proposes the Bootstrap Reality Check (BRC) and Romano and Wolf (2005) the StepM method. See also Lehmann and Romano (2005) who develop a bootstrap method to control for the FDR. However, the deployment of such approaches can be computationally demanding when the number of hypotheses tested is very large. As this is the case for both measures used in this paper, we cannot use such a class of approach. Indeed, for each institution, $(n-1) \times (n-2) = 7832$ hypotheses are tested for our LOO measure, and $n \times (n-1) = 8010$ for the one of BGLP.

[7] Note that Benjamini and Yekutieli (2001) also show that the bound $\gamma M_0/M$ holds under some type of positive dependences.

Appendix B: Additional Tables and Figures

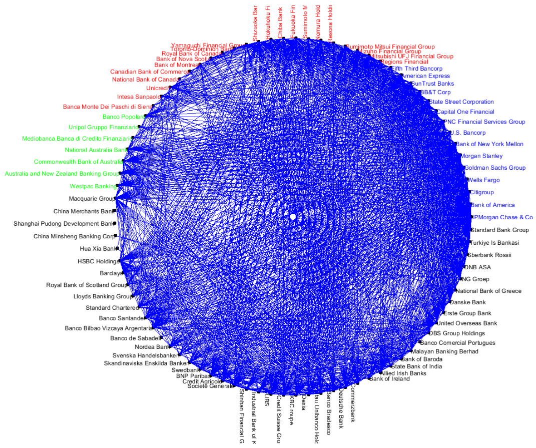

Figure B1: Network for the system excluding Ping An Bank: pre-crisis period

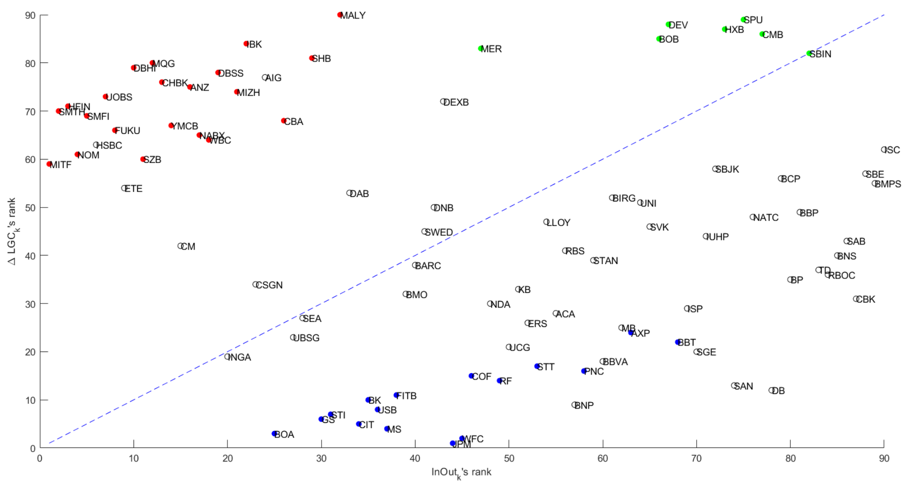

Figure B2: Comparison of the ranks of InOut$_k$ and ΔLGC$_k$: post-crisis period

Note : This figure represents the ranks of banks for both measures over the post-crisis period. Banks from US are filled in blue, Australia, Japan, Korea, Malaysia and Singapore in red, China and India in green, and the others are not filled.

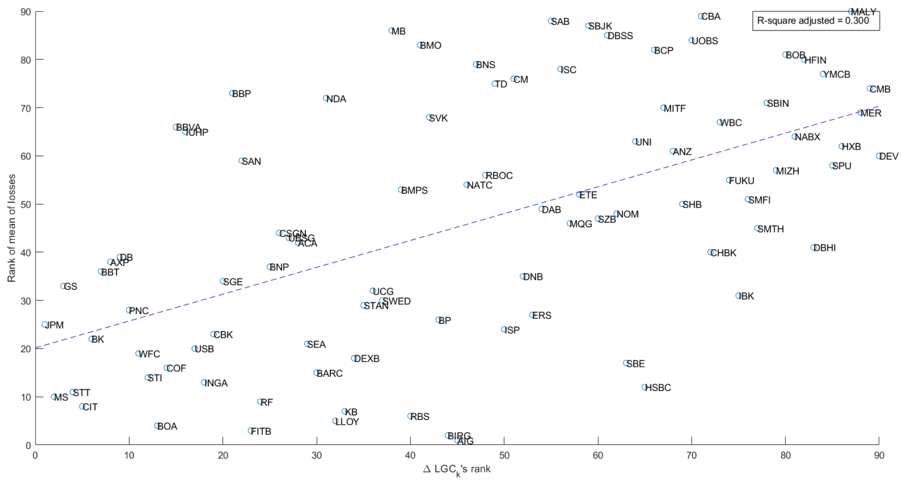

Figure B3: Systemic risk contributions ΔLGC_k and mean of realized losses: $\delta = -5\%$

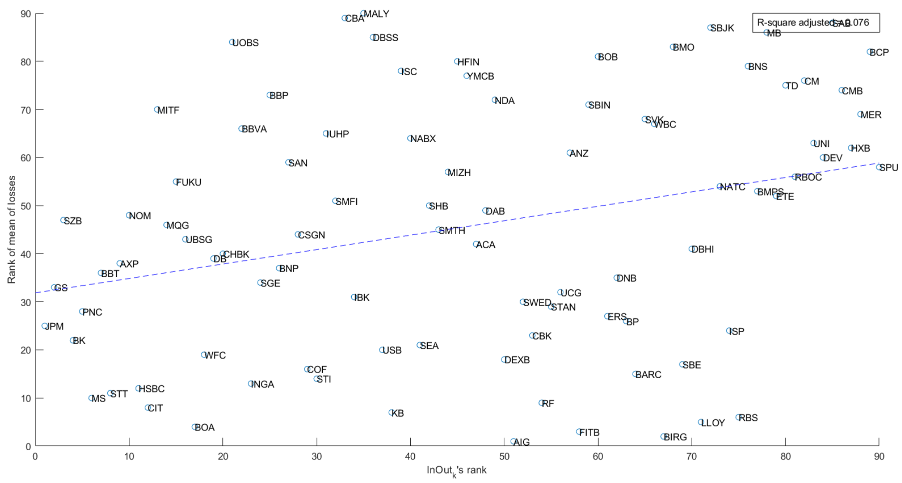

Figure B4: Systemic risk contributions InOut_k and mean of realized losses: $\delta = -5\%$

Table B1: Sample of Banks Analysed

America

Bank Name	Country	Label
Banco Bradesco	Brazil	BBP
Itau Unibanco Holding	Brazil	IUHP
Bank of Montreal	Canada	BMO
Bank of Nova Scotia	Canada	BNS
Canadian Bank of Commerce	Canada	CM
National Bank of Canada	Canada	NATC
Royal Bank of Canada	Canada	RBOC
Toronto-Dominion Bank	Canada	TD
American Express	US	AXP
Bank of America	US	BOA
Bank of New York Mellon	US	BK
BB&T Corp	US	BBT
Capital One Financial	US	COF
Citigroup	US	CIT
Fifth Third Bancorp	US	FITB
Goldman Sachs Group	US	GS
JPMorgan Chase & Co	US	JPM
Morgan Stanley	US	MS
PNC Financial Services Group	US	PNC
Regions Financial	US	RF
State Sreet Corporation	US	STT
SunTrust Banks	US	STI
U.S. Bancorp	US	USB
Wells Fargo	US	WFC

Africa

Bank Name	Country	Label
Standard Bank Group	South Africa	SBJK

Europe

Bank Name	Country	Label
Erste Group Bank	Austria	ERS
KBC roupe	Belgium	KB
Dexia	Belgium	DEXB
Danske Bank	Denmark	DAB
BNP Paribas	France	BNP
Credit Agricole	France	ACA
Societe Generale	France	SGE
Deutsche Bank	Germany	DB
Commerzbank	Germany	CBK
National Bank of Greece	Greece	ETE
Bank of Ireland	Ireland	BIRG
Allied Irish Banks	Ireland	AIG
Unicredit	Italy	UCG
Intesa Sanpaolo	Italy	ISP
Banca Monte Dei Paschi di Siena	Italy	BMPS
Banco Popolare	Italy	BP
Unipol Gruppo Finanziario	Italy	UNI
Mediobanca Banca di Credito Finanziario	Italy	MB
ING Groep	Netherlands	INGA
DNB ASA	Norway	DNB
Banco Comercial Portugues	Portugal	BCP
Sberbank Rossii	Russia	SBE
Banco Santander	Spain	SAN
Banco Bilbao Vizcaya Argentaria	Spain	BBVA
Banco de Sabadell	Spain	SAB
Nordea Bank	Sweden	NDA
Svenska Handelsbanken	Sweden	SVK
Skandinaviska Enskilda Banken	Sweden	SEA
Swedbank	Sweden	SWED
UBS	Switzerland	UBSG
Credit Suisse Group	Switzerland	CSGN
Turkiye Is Bankasi	Turkey	ISC
HSBC Holdings	UK	HSBC
Barclays	UK	BARC
Royal Bank of Scotland Group	UK	RBS
Lloyds Banking Group	UK	LLOY
Standard Chartered	UK	STAN

Asia and Pacific

Bank Name	Country	Label
National Australia Bank	Australia	NABX
Commonwealth Bank of Australia	Australia	CBA
Australia and New Zealand Banking Group	Australia	ANZ
Westpac Banking	Australia	WBC
Macquarie Group	Australia	MQG
China Merchants Bank	China	MER
Shanghai Pudong Development Bank	China	SPU
China Minsheng Banking Corp	China	CMB
Ping An Bank	China	DEV
Hua Xia Bank	China	HXB
State Bank of India	India	SBIN
Bank of Baroda	India	BOB
Mitsubishi UFJ Financial Group	Japan	MITF
Mizuho Financial Group	Japan	MIZH
Sumimoto Mitsui Financial Group	Japan	SMFI
Resona Holdings	Japan	DBHI
Nomura Holdings	Japan	NOM
Sumimoto Mitsui Trust Holdings	Japan	SMTH
Fukuoka Financial Group	Japan	FUKU
Chiba Bank	Japan	CHBK
Hokuhoku Financial Group	Japan	HFIN
Shizuoka Bank	Japan	SZB
Yamaguchi Financial Group	Japan	YMCB
Shinhan Financial Group	Korea	SHB
Industrial Bank of Korea	Korea	IBK
Malayan Banking Berhad	Malaysia	MALY
DBS Group Holdings	Singapore	DBSS
United Overseas Bank	Singapore	UOBS

Table B2: Summary Statistics

Full sample				
	Mean (%)	St.dev (%)	Skewness	Kurtosis
Africa	0.07%	1.82%	0.145	6.217
America	0.05%	2.30%	0.948	35.402
Asia and Pacific	0.04%	2.06%	0.296	10.341
Europe	0.02%	2.78%	0.483	22.707
Pre-Crisis				
	Mean (%)	St.dev (%)	Skewness	Kurtosis
Africa	0.13%	1.73%	0.208	4.469
America	0.05%	1.09%	0.121	7.178
Asia and Pacific	0.10%	1.87%	0.159	7.155
Europe	0.08%	1.29%	0.012	5.646
Crisis				
	Mean (%)	St.dev (%)	Skewness	Kurtosis
Africa	0.03%	2.74%	0.349	4.291
America	-0.01%	4.92%	0.726	11.167
Asia and Pacific	-0.03%	3.32%	0.312	5.770
Europe	-0.11%	4.26%	0.508	10.154
Post-Crisis				
	Mean (%)	St.dev (%)	Skewness	Kurtosis
Africa	0.05%	1.59%	-0.139	6.659
America	0.06%	1.60%	-0.054	7.336
Asia and Pacific	0.03%	1.72%	0.211	7.969
Europe	0.02%	2.71%	0.216	11.193

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