Measuring network systemic risk contributions: A leave-one-out approach

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November 12, 2018

Abstract

The aim of this paper is to propose a new network measure of systemic risk contributions that combines the pair-wise Granger causality approach with the leave-one-out concept. This measure is based on a conditional Granger causality test and consists of measuring how far the proportion of statistically significant connections in the system breaks down when a given financial institution is excluded. We analyse the performance of our measure of systemic risk by considering a sample of the largest banks worldwide over the 2003-2018 period. We obtain three important results. First, we show that our measure is able to identify a large number of banks classified as global systemically important banks (G-SIBs) by the Financial Stability Board (FSB). Second, we find that our measure is a robust and statistically significant early-warning indicator of downside returns during the last financial crisis. Finally, we investigate the potential determinants of our measure of systemic risk and find similar results to the existing literature. In particular, our empirical results suggest that the size and the business model of banks are significant drivers of systemic risk.

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 would like to thank the Editor Herbert Dawid and the two anonymous referees for their comments and suggestions. We thank the participants of the 6th Workshop in Macro Banking and Finance (University of Sassari & Unicredit Foundation), the Financial Econometrics Conference (Lancaster University Management School), the INFER Workshop on Finance and Fiscal Policy (Bucharest University of Economic Studies), the 6th Applied Macroeconometrics Workshop (MSH Paris Nord), the 2018 Vietnam Symposium in Banking and Finance (Hué College of Economics), the 12th International Workshop of Methods in International Finance Network (Catholic University of Leuven), and the 17ème Journée d'Économétrie (EconomiX, University Paris Nanterre) for their useful feedbacks. We also 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 was amplified by the collapse of Lehman Brothers spread to the global financial market and had a severe impact on the real economy around the world. The size of the negative impact and the related social costs in most countries made new macro-prudential devices more necessary for systemic risk in the financial sector to be stabilised more efficiently. The Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) as regulatory authorities responded to these challenges with a number of reforms, where the main element was the identification of global systemically important financial institutions (G-SIFIs). This allocates G-SIFIs into buckets according to the level of additional loss absorbency they require. A set of principles was also established at country level to allow national authorities to identify domestic systemically important financial institutions (D-SIFIs).

Methodologically, a deep knowledge of the nature of systemic risk is needed for SIFIs to be identified, and suitable tools need to be developed to measure it. The academic literature in this area has evolved over recent years, offering different models or methodologies for evaluating the level of systemic risk for financial institutions. The profusion of different methodologies springs from the range of different sources or facets that systemic events can have, including size, contagion or interconnectedness, lack of substitute financial products, global cross-jurisdictional activity, and the complexity of business models. Indeed Bisias et al. (2012), in their survey of systemic risk analytics, identify 31 quantitative measures of systemic risk in the economics and finance literature, which can be classified in six homogeneous groups as macroeconomic measures like credit-gap indicators; cross-sectional measures, including 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 is in the last of these, network measures that are based on the interconnections between financial institutions. Although this group of measures represents only a small part of the literature, it has always been, and still is, the subject of major studies. From the theoretical side, the literature on network measures of systemic risk is related to financial contagion with major contributions from Allen and Gale (2000), Freixas et al. (2000), Dasgupta (2004), Acemoglu et al. (2015) and Glasserman and Young (2015) among others. The core of these papers is their analysis of the role played by the linkages between financial institutions in amplifying exogenous shocks that hit the system. The analyses generally consider various angles, looking at either the shape of the network and whether it is complete or incomplete, the level of uncertainty prevailing in the financial markets, or 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 categorised in two main groups by whether the input data sets are private or public. The first category of measures uses private data on contractual obligations to measure counterparty connections and establish a counterparty network graph. An illustrative example of such a graph is described in IMF (2009), where the systemic importance of a financial institution is 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 econometric 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), to a combination of both approaches (Härdle et al., 2016), and to 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, which try to evaluate contributions to systemic risk using a Granger-causality network. The seminal paper is Billio et al. (2012), who propose that the systemic risk contribution of a given financial institution can be evaluated by its importance in a network built from pair-wise Granger-causality tests. More precisely, they define a statistic that is equal to the frequency of the statistically significant pair-wise Granger-causality relations, regardless of the direction of causality, in which an institution is involved. Thus higher values for this statistic correspond to more systemic financial institutions and lower values to less systemic ones. This statistic can be further disentangled by focusing on the direction of causality. With empirical applications using monthly returns data for hedge funds, broker/dealers, banks and insurers, the authors show that these statistics help in identifying periods of financial crisis, and have good out-of-sample predictive powers.

Nevertheless, some recent papers give a critical assessment of Granger-causality networks as used by 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 that arise because 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 and also on the indirect connectivities through all the other nodes, or institutions, in the network. Therefore, Granger-causality networks that are based on the direct and indirect effects do not reveal which institutions are the most systemic. Indeed, systemic institutions are central in spreading shocks through the whole system. The consequence on the empirical side is that the pair-wise approach generally leads to networks that are highly dense due to spurious causalities, with a potentially misleading ranking of the systemic importance of financial institutions. This stylised 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. More precisely, the autoregressive equations of the bivariate Granger-causality tests, are extended using controlling variables that correspond to the lagged values of the returns on the other $n-2$ institutions, where n is the total number of institutions in the system. However, with realistic large values of n, a large dimensional VAR model is subject to overfitting with traditional estimation methods such as the least squares approach. Penalised least squares methods can be used to overcome the curse of dimensionality as proposed by Basu et al. (2017), but there is then a no less important challenge in the choice of the penalty parameter. Indeed there are many methods available for calibrating the penalty parameter, such as information criteria or cross-validation, and it is known from the statistical literature that the 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 by addressing these two shortcomings of indirect causalities and the curse of dimensionality. We show that when combined with the leave-one-out (LOO) concept, this approach is still valuable in providing consistent measures of contributions to systemic risk. Formally, for a given financial institution A, we introduce a new measure of systemic risk importance, which evaluates how far the total number of significant Granger-causalities breaks down when this institution is excluded from the system. We control for causalities between the remaining $n-1$ institutions that arise from the indirect effect of financial institution A being excluded, using a conditional Granger-causality test. It may be noted that using 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 that 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 for financial institution A.

Empirical applications are conducted using daily market returns for a sample of 90 large banks from around the world. The data run from 12 September 2003 to 19 February 2018, and include the global financial crisis of 2007-2008. The dataset includes almost every global systemically important bank (G-SIBs) identified by the Financial Stability Board (FSB). The results show that our measure gives a 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 is shown to be a robust and significant early-warning indicator of large losses from a systemic event. The predictive power is larger than that associated with 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 cleaned 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. The 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 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. Like those of Brunnermeier et al. (2012) and Laeven et al. (2016), our results suggest that banks specialising in market-based activities tend to have a higher level of systemic risk than do banks specialising 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 using the LOO approach is not new in the literature on systemic risk measures. Indeed, Zedda and Cannas (2017) employ this methodology to analyse systemic risk and the determinants of contagion in a banking system. Formally, they base their approach on a simulated distribution of the 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 return on assets (ROA) plus the equity-to-assets ratio divided by the standard deviation of ROA. They define an aggregate z-score for the whole system, and the "Minus one bank z-score", which is 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 has some similarities to 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 the best of our knowledge, our paper is the first to mobilise the LOO concept for measuring systemic risk contributions using Granger-causality networks.

The remainder of the article is structured as follows. Section 2 is devoted to a review of the 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 measures of systemic risk contributions based on pair-wise Granger-causality tests. In Section 4, we present the new measure based on the LOO approach, and we assess its reliability using real datasets in Section 5. Section 6 searches for the micro-economic 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 covers contagion induced from direct or indirect linkages. Most of the works[1] on network contagion focus on risk channels issued from direct linkages such as credit exposures or 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 categorised by the dimension of the contagion analysed, such as the density of the network and whether it is complete or incomplete, the level of uncertainty in the markets, or 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 how resilient the system is 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 like in Diamond and Dybvig (1983). In order to protect themselves against liquidity shocks, the timing of which is uncertain, banks hold inter-regional claims on each other. While those cross-holdings of deposits increase the resilience of the network, since a 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 the banks. A fully connected network spreads the liquidity shock across the network and reduces its impact, while an incomplete network that is not fully connected increases the 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, the banks are connected through interbank credit lines because of uncertainty about the location of withdrawals of deposits. As in Allen and Gale (2000), they find that interconnections make the network more resilient to the insolvency of a single bank.

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

Nevertheless, these theoretical predictions should be contrasted with those of Vivier-Lirimont (2006) and Brusco and Castiglionesi (2007), whose results indicate the opposite. Considering network structures like in 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, unlike Allen and Gale (2000), they find that bankruptcies are caused by the moral hazard problem rather than by a liquidity shock. They find that a more connected interbank deposit market means more regions are hit by bankruptcies than when an incompletely connected market is considered. Similar conclusions can be found in Vivier-Lirimont (2006), who analyses the optimal network architecture, where transfers through the interbank market improve the utility of the depositors. He finds that the higher the network density is, the higher is the likelihood of the system collapsing.

Acemoglu et al. (2015) try to reconcile these opposite results by analysing the network as a contagion mechanism in which institutions can be exposed to counterparty risk from the unsecured debt contracts they share among themselves. They observe that the resilience of the network depends on an endogenous threshold for the number of shocks. More precisely, the more interconnected the network is, the less fragile the system will be as long as the magnitude or the number of shocks remains below this threshold. However, the opposite result appears when the magnitude or the number of shocks becomes higher than the threshold, meaning 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 over the years. The debate around the connectivity of the network and its resilience to negative shocks has spread beyond the form of the network as complete or incomplete, and 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 complexity and concentration are important characteristics. They propose a network of 250 banks linked through unsecured claims and subject to funding liquidity shocks. From different simulation 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 through 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 crisis. The first one happens gradually as 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 type of crisis happens instantly, as agents foresee losses and pre-emptively 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 becomes low enough that it falls below a failure threshold, that institution fails and affects its counterparties, which then propagate the initial failure. The authors identify that the two main features of cross-holdings that impact the probability of cascades occurring and the size of them are integration and diversification. Integration corresponds to how much an institution is privately cross-held by other institutions, while diversification represents how much the cross-holdings of a single institution are spread out through the network, and whether they are held by only a few institutions or a large number. Another example is Cabrales et al. (2014), who analyse 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 through the securitisation of mortgage loans sold to other firms. These exchanges allow firms to diversify, but expose them to default by counterparties. They stress two alternatives that allow them to reduce the contagion. The first is to isolate the firms in each component, making a region of the network, and the second is to reduce the number of firms to which a firm is linked. They observe that when the probability distribution of the shocks has fat tails (i.e. a high probability of large shocks), the optimal network is the most segmented one, i.e. characterized by small components. However, when the tails are thin, the best network is a single component with the minimum segmentation in order to maximise risk sharing.

It is worth noting that the analysis of only direct or indirect linkages is not realistic, as in practice banks have many simultaneous direct and indirect linkages. Drawing on this stylised fact, some authors have 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 the overlapping asset portfolios of banks. They find that the effect of an initial shock can be substantial and amplified if the prices of fire-sale assets can change endogenously. The initial failure of one bank leads to the sale of the remaining assets of that bank, and under certain conditions, this can reduce the market prices of those assets and thus spread the initial shock across the network, particularly to 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 make two interesting discoveries. First, rare shocks can have significantly large impacts on the network when they occur, and second, the impact of a shock depends on which node of the network it hits, regardless of its size. Indeed, more central nodes, which are the more interconnected ones, facilitate and amplify the contagion. To take into account 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 whether they use private or public data and by the econometric or statistical methods they mobilise to construct the network and to extract measures of contributions to systemic risk. Drehmann and Tarashev (2013) for instance follow the spirit of theoretical works and use direct and indirect linkages to measure the systemic importance of banks in a network. More precisely, they propose two measures. The first is the participation approach, which quantifies the losses that a bank imposes on its non-bank investors, and the second is the contribution approach, which corresponds to the degree of connectedness of the bank, or its contribution to the contagion of an idiosyncratic shock. Using balance sheet data from 20 international banks, they highlight that interconnectedness is an important feature as it increases the systemic importance of banks, 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 propose various measures of interconnectedness. They focus on major American financial institutions from May 1999 to April 2010 and show that Citigroup has the highest value of connectedness, and more generally the largest commercial banks are the most interconnected. However, their methodology is sensitive 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. Using penalisation methods to reduce the dimensionality of the network, they render the model estimable even when there are a large number of banks. Thus they consider a sample of 96 international banks from the world's top 150 in their empirical applications, and find that there are strong clusters within and between countries.

Other studies focus on the tail risk of firms in building networks. Hautsch et al. (2015), for example, initially propose the "realised 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 in 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 realised systemic risk. Their empirical results from 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 for 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 afterwards, and that the size, leverage and degree of interconnectedness increase the systemic importance of banks. In the same vein, Härdle et al. (2016) combine the tail risk of firms with variance decomposition. They build their network by using the approach of Diebold and Yılmaz (2014), but their adjacency matrix, which has 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, including depositories, insurers, broker-dealers and others, they find that the banking sector supplies more of the pace in risk transmission and the insurance sector supplies less.

Another empirical approach that has gained 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 non-linear 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 has recently been 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 models estimated with penalisation 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 that represent long-run partial correlation connections. Considering 90 US blue-chip companies, 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 containing measures of contributions to systemic risk based on Granger-causality networks.

3 Measuring Systemic Risk via a 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 contributions to systemic risk through Granger-causality networks.

3.1 Granger-Causality Inference

Consider a system of n interconnected financial institutions, and denote by $y_{k,t} \equiv \Delta \log P_{k,t} = \log P_{k,t} - \log P_{k,t-1}$ 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 formalised 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

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

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

The concept of causality carried out by this null hypothesis is strong as it aims to test 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, through causality in specific moments of the conditional distribution such as mean, variance or 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 using the following test statistic

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

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 the absence of Granger-causality in mean, the test statistic $U_{j\to i}$ has an asymptotic chi-square distribution with a degree of freedom equal to M. So, if $U_{j\to i} > \chi^2_{1-\eta}(M)$, one rejects the null hypothesis of no Granger-causality in asset returns from financial institution j to 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 have focused 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 derive both a global measure of systemic risk and an institution-specific measure. 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 statistic of the Granger-causality test in mean from financial institution k to financial institution j, as defined in Eq. (5), and $\chi^2_{1-\eta}(M)$ is 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 (the Out-part of the measure), while the second term measures the number of financial institutions that significantly Granger-causes the institution k (the In-part of the measure). Hence the statistic InOut_k measures the fraction of the total number of financial institutions

[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.

that are involved in a significant connection with the financial institution k. Note that higher values of the statistic InOut_k correspond to a more systemic institution from the viewpoint of interconnectedness and lower values to a less systemic institution.

A central point that motivates our paper, is that the statistic InOut_k can lead to inconsistent rankings of financial institutions for systemic risk because 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. In this simplified financial system, there is transmission in asset returns from financial institution 2 to financial institution 3 and from institution 3 to institution 1.

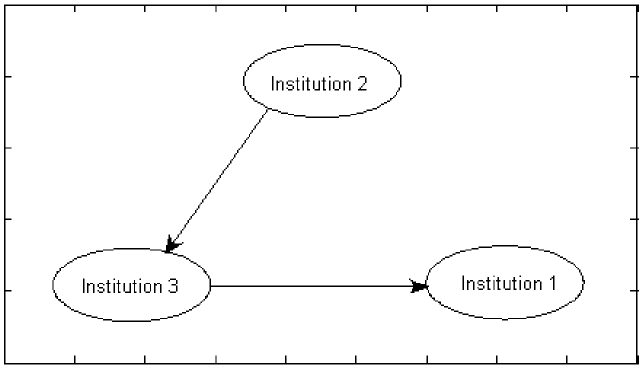

Figure 1: True network for a system of three financial institutions

Statistically, such a financial system can be represented using the following data generating processes of asset returns for our three financial institutions 1, 2 and 3 as follows

$$\begin{cases} y_{2,t} = 0.5y_{2,t-1} + u_{2,t} \\ u_{2,t} = \sigma_{2,t}v_{2,t} \\ \sigma^2_{2,t} = 0.05 + 0.85\sigma^2_{2,t-1} + 0.1u^2_{2,t-1}, \end{cases} \tag{9}$$

$$\begin{cases} y_{3,t} = 0.5y_{3,t-1} + 0.2y_{2,t-1} + u_{3,t} \\ u_{3,t} = \sigma_{3,t}v_{3,t} \\ \sigma^2_{3,t} = 0.05 + 0.85\sigma^2_{3,t-1} + 0.1u^2_{3,t-1}, \end{cases} \tag{10}$$

$$\begin{cases} y_{1,t} = 0.5y_{1,t-1} + 0.2y_{3,t-1} + u_{1,t} \\ u_{1,t} = \sigma_{1,t}v_{1,t} \\ \sigma^2_{1,t} = 0.05 + 0.85\sigma^2_{1,t-1} + 0.1u^2_{1,t-1}, \end{cases} \tag{11}$$

where $y_{1,t}$, $y_{2,t}$ and $y_{3,t}$ are the returns on the assets of the financial institutions 1, 2 and 3, and each $v_{k,t}$, $k = 1, 2, 3$, follows a Student-t distribution with degree of freedom equal to 5. Hence, we assume that each series of asset returns follows an AR(1)-GARCH(1,1) model, and that there is causality in mean from financial institution 2 to financial institution 3, and from financial institution 3 to financial institution 1. Hence with the application of the Granger-causality test in mean, we should detect a significant connection from 2 to 3 and from 3 to 1. Note that these specifications are calibrated to capture important stylised facts in the dynamics of asset returns such as autocorrelation, heteroskedasticity, and fat tails.

Economically, this form of network can arise from indirect contagion through 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. More precisely, institution 2 faces an idiosyncratic shock that impacts its equity negatively, so it sells its assets to maintain its target level of leverage. If the assets are illiquid, fire sales depress prices, and this in turn can impact the equity of financial institution 3 because of its common exposures to those assets. The same phenomenon involving institutions 3 and 1 would take place, with common exposures to other assets setting up this type of network.

Based on this simplified network and using Eq. (8), the true levels of the contribution of each financial institution to the Granger-causality network are thus equal to

$$\mathrm{InOut}_2 = \frac{1}{4} = 0.25, \mathrm{InOut}_3 = \frac{2}{4} = 0.5, \mathrm{InOut}_1 = \frac{1}{4} = 0.25. \tag{12}$$

From this, financial institution number 3 is the most systemic. However, 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 financial institution 2 to financial institution 1, running through financial institution 3.[3] The information that can be extracted from this network is that all three financial institutions are systemically equivalent, because we have

$$\mathrm{InOut}_2 = \frac{2}{4} = 0.5, \mathrm{InOut}_3 = \frac{2}{4} = 0.5, \mathrm{InOut}_1 = \frac{2}{4} = 0.5. \tag{13}$$

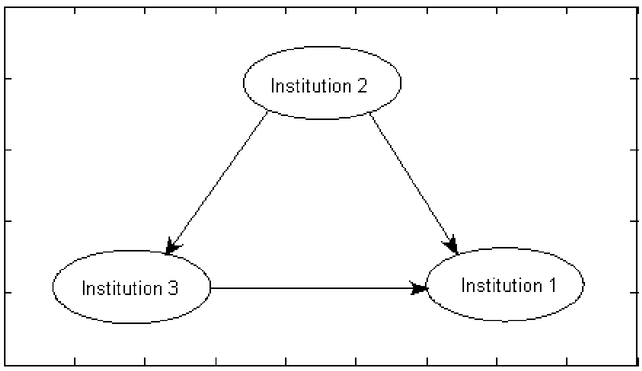

Figure 2: Detected network using Granger-causality tests

Using the data generating processes of Eq. (9) to (11), the following Monte Carlo experiments give more insights about this point. We generate asset returns for the three financial institutions, and run the Granger-causality test in mean from the financial institution 2 to the financial institution 1. As we stress above, although there is no

[3] Note that the probability of this indirect effect being detected is theoretically equal to the power of the Granger-causality test.

connection between 2 and 1, the Granger-causality test in mean should detect an indirect spillover effect from financial institution 2 to 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 $\eta = 5\%$. The 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 Eq. (5) is set to $M = 5$.[4] We observe in Figure 3 that the rejection frequencies of the test are high and increase with the sample size. To summarise, the outcomes from our Monte Carlo experiments show that the ranking of financial institutions using the statistic InOut_k can indeed be misleading because of the detection of spurious causalities in the network.

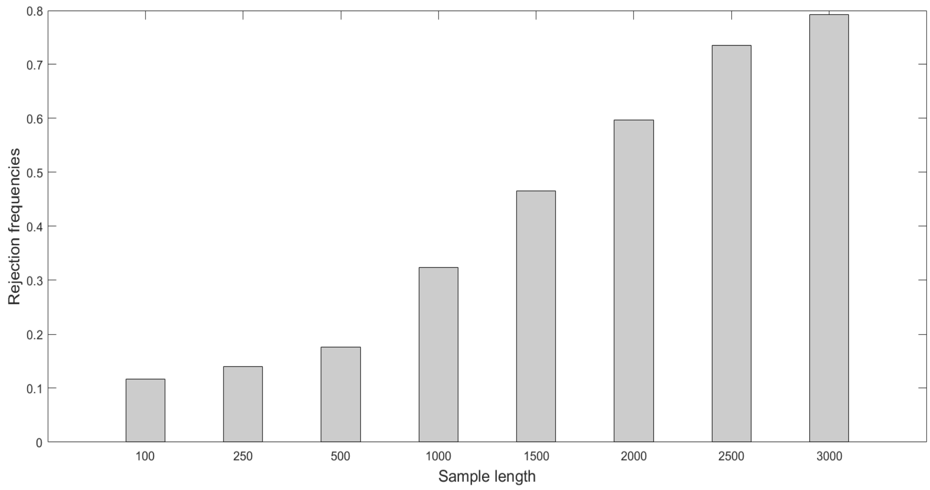

Figure 3: Rejection frequencies of the Granger-causality test from 2 to 1

Note: The null hypothesis corresponds to the absence of Granger causality from bank 2 to bank 1.

A traditional solution for dealing with this is to consider a network based on a *conditional* Granger-causality test. Indeed, the conditional Granger-causality test introduced by Geweke (1984) is able 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 on k is identical to its unconditional version $U_{j\to i}$ in Eq. (5), that is

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

where again T is the sample length, and $\widetilde{\sigma}^2_{i,1}$ 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

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

[4]We make the same exercise for different lag structures by considering $M \in \{1, 2, 3, 4\}$. Results that we obtain are very similar to those reported below with $M = 5$.

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

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

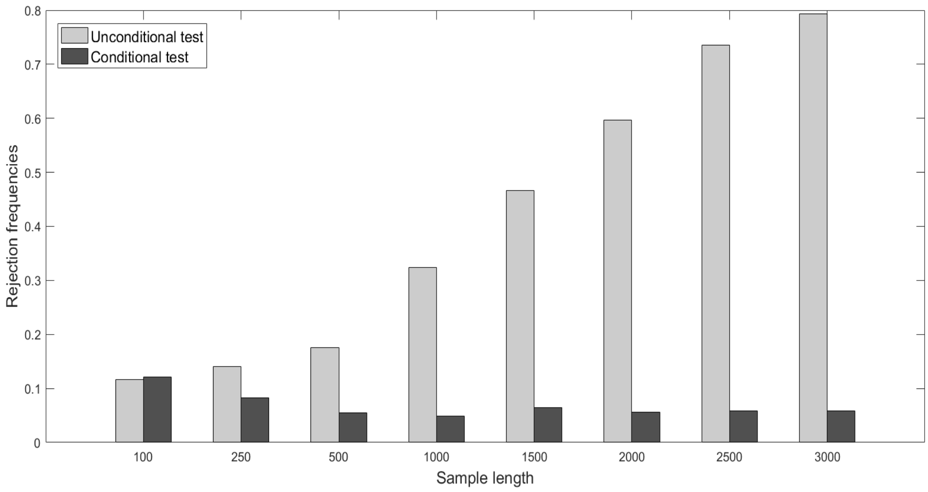

Figure 4: Comparison of conditional and unconditional Granger-causality tests

Note: The null hypothesis corresponds to the absence of Granger causality from bank 2 to bank 1.

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 Eq. (9) to (11). The rejection frequencies (at the nominal risk level $\eta = 5\%$) over $1,000$ simulations of the Granger-causality test from financial institution 2 to institution 1 conditional on 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. So based on the statistic InOut_k, the conditional test would give a consistent ranking of the systemic importance of the three financial institutions, as it is designed to exclude the spurious causality from institution 2 to institution 1 that comes from the indirect contagion.

The conditional test described above is also adapted to manage another form of indirect causality resulting from the joint exposure of financial institutions 1 and 2 to institution 3. The related true network is depicted in Figure 5, where institution 3 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

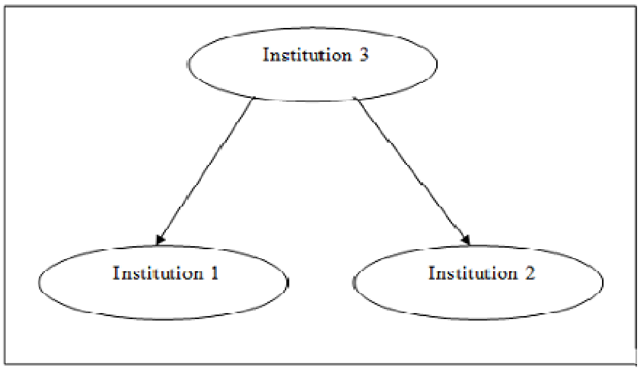

Figure 5: True network for a system of three financial institutions: second scenario

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. Using these data generating processes, rejection frequencies (over 1000 simulations) of the conditional and unconditional Granger-causality tests from financial institution 2 to 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.

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

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

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

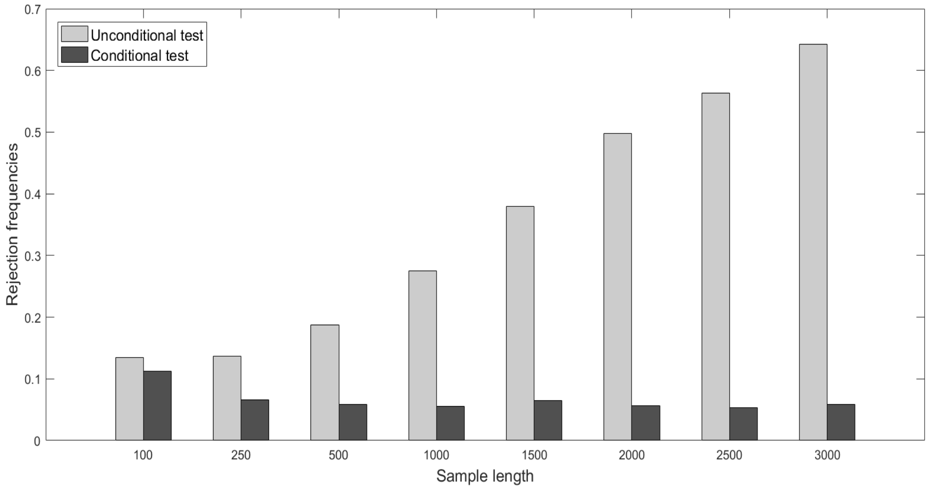

Figure 6: Comparison of conditional and unconditional Granger-causality tests: second scenario

Note: The null hypothesis corresponds to the absence of Granger causality from bank 2 to bank 1.

with $\psi_{k,s}$, $\theta_{k,s}$, $s = 1, ..., M$, $k = 1, ..., n-2$, as 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 analysed by Basu et al. (2017), these issues can be handled within a lasso penalised vector auto-regressive (LVAR) model, which is designed to provide estimates of a large dimensional vector autoregressive model with sparse coefficients. Their empirical applications on a set of large US financial institutions show indeed that the LVAR succeeds in controlling for spurious causalities, and hence helps recover less dense networks than those in the BGLP approach. Note that in their work, a multivariate approach is adopted instead of the pair-wise approach, with a VAR model specified for all firms simultaneously, taking all the interactions in the system into account. 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 modelling.

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 estimate Granger-causality network systemic risk contributions consistently. As will be made clearer later, the LOO methodology allows us to deal with the issue of indirect causalities, without facing the inherent curse of dimensionality that arises 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 statistic which summarises the level of Granger-causality (LGC) in the system, meaning the number of statistically significant Granger-causality relationships among all $n(n-1)$ pairs of financial institutions in the system

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

This statistic can be seen as a global measure of the systemic risk in the system, from the viewpoint of interconnectedness. For a given financial institution k, consider a system of size $n-1$ that includes all the n institutions except the institution number k. We can define the level of Granger-causality in this system in a similar way to Eq. (22), 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 statistic $\mathrm{LGC}_{(-k)}$ measures the number of significant connections in asset returns remaining when the financial institution k is excluded from the system. It may be noted however that this statistic removes direct causalities in the network that come from the financial institution k, but fails to clean indirect causalities between the remaining $n-1$ financial institutions that are due to the financial institution k. To overcome this shortcoming, we re-define the statistic $\mathrm{LGC}_{(-k)}$ as

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

where $U_{j\to i|k}$ is the conditional Granger-causality test as defined in Eq. (14). Observe that using 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, lets us clean all the spurious causalities that exist in the remaining $n-1$ institutions and that arise from the indirect effect of the institution k. 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 k as controlling variables (see equations 15-16).

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

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

This statistic evaluates how far the total number of significant Granger-causalities breaks down when the institution k is excluded from the system, and hence appears as a proxy of its systemic importance. Note that the statistic $\Delta\mathrm{LGC}_k$ takes positive values, and higher values correspond to more systemic institutions and lower values to less systemic ones. Moreover, as it deals with spurious causalities arising from indirect contagion effects, it should lead to consistent ranking of the systemic importance of financial institutions.

To provide some support to the relevance of the LOO approach, we consider the true network depicted in Figure 1 along with the associated data generating processes in Eq. (9) to (11). It may be recalled that in this simplified financial system with three institutions, the most systemic in terms of interconnectedness is the third (3), and the other two (1 and 2) are systemically equivalent. Following 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 ΔLGC_k, $k = 1, 2, 3$. Figure 7 displays the box plots of these measures obtained over $1,000$ simulations.

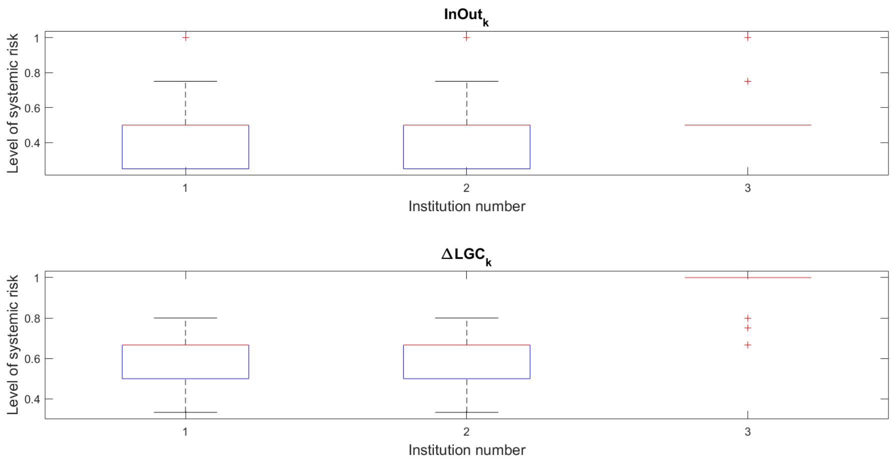

Figure 7: Box plots of alternative measures of systemic risk contributions

The first panel of the figure that displays the measures InOut_k for the three institutions shows that the median values, highlighted in red, are equal, which confirms that this measure leads to inconsistent ranking of the financial institutions. Indeed, the equality of the median values means that the three institutions are systemically equal. In contrast, the box plots of our statistic ΔLGC_k confirm the relevance of the LOO approach. Here, the median values are equal for the institutions 1 and 2. This means that these two institutions are found to be systemically equivalent most frequently across the 1000 simulations. Importantly, the median value for 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 simulation setup considered. The next section gives 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 present the data used to illustrate our new measure and give some summary statistics. Then, we compare the new measure to that of BGLP and highlight the differences between the two measures. Finally, we evaluate its predictive power, which shows how far it can be taken as an early-warning indicator of the fragility of financial institutions in response to a systemic event.

5.1 Data and Summary Statistics

We analyse the performance of our measure using the daily asset returns denominated in local currency of 90 banks from 28 countries around the world. The data are downloaded from Datastream and run from 12 September 2003 to 19 February 2018, with a total of 3766 daily observations. The banks are mostly from developed countries, as 80 are from 21 advanced countries and 10 are from seven emerging countries. The sample of banks considered is the one used by Demirer et al. (2018), except for 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 country and label.

One important feature of our dataset is that it includes almost every G-SIB identified by the Financial Stability Board (FSB). This will allow us to compare the banks that we identify as the most systemic using our new measure with those identified by the FSB. Running from September 2003 to February 2018, our dataset is large enough for sub-samples to be analysed, so we will consider three sub-periods for further analysis: pre-crisis, crisis and post-crisis. We follow Laeven et al. (2016) by setting the beginning of the crisis period as July 2007 and the end of the crisis as June 2009, which corresponds to the recovery of financial markets. Table B2 in Appendix B reports the mean, the standard deviation, the skewness and the kurtosis of the asset returns of the banks regrouped by continent for the full sample and for each sub-sample. As expected, the average returns fell sharply for all regions during the crisis period and became negative everywhere except Africa. The standard deviation also increased during this period, particularly for American and European 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 the Granger-causality network to produce inconsistent rankings of the systemic importance of financial institutions. This is particularly the case for the measure InOut_k of BGLP. We thus introduced a new measure we denoted ΔLGC_k that is based on the LOO concept. The goal of this section is to highlight the differences between our measure and that of BGLP, and to this end, we compute these two measures for our three sub-periods.[5]

Note 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 treated with caution, since with multiple testing there is an increased probability of the null hypothesis, which here is the absence of causality, being rejected just by chance, with an inflation of the overall significance level. Hence we correct both measures for the 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 for this procedure.

Tables 1-3 show the ten most systemic banks identified by the two measures and the ten least systemic for the three sub-periods. For the pre-crisis period (see Table 1),

[5]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 on the innovations or the filtered returns 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	$\Delta\text{LGC}_\text{k}$
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 and the 10 least 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 pre-crisis period 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 and the 10 least 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 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	$\mathrm{InOut_k}$	Bank Name	Country	$\Delta\mathrm{LGC_k}$
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 and the 10 least systemic banks identified by the BGLP measure $\mathrm{InOut_k}$ and our new measure $\Delta\mathrm{LGC_k}$ of systemic risk contributions. Both measures are compared over the post-crisis period from July 2009 to February 2018 with a total of 2253 daily returns.

JPMorgan Chase & Co is identified by our LOO approach as the most systemic bank, with the value of 0.938 for the measure $\Delta\mathrm{LGC}_k$. This means that when this institution is excluded from the system and the impact of spurious causalities is controlled for, the number of significant connections in the system drops by 93.8%. This decline is notable and reflects the importance of this institution in the network. Figure 8 displays the network for the whole system for the pre-crisis period, including all the 90 banks in the sample. The number of significant connections given by the statistic LGC is 1312. The same network excluding JPMorgan Chase & Co is exhibited in Figure 9, with the statistic $\mathrm{LGC}_{(-k)}$ equal to 81. This means that when this institution is excluded from the system, the number of significant connections drops from 1312 to 81, with our measure $\Delta\mathrm{LGC}_k$ taking the value $(1312 - 81)/1312 = 93.8\%$. This result may be contrasted with the one obtained for the least systemic institution, Ping An Bank, for which the statistic $\Delta\mathrm{LGC}_k$ equals 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 the institutions (see Figure 8). Indeed the number of statistically significant connections in the system that excludes Ping An Bank is 1271 and therefore very close to 1312.

The results in Table 1 also indicate that the most systemic banks identified are mostly American for both measures, while the least systemic are from Japan and China for the measure $\Delta\mathrm{LGC}_k$, but from China, Europe and Canada for the measure InOut_k. The differences between the most systemic institutions are thus weak, but when all of the 90 financial institutions are considered, some divergences appear between the two measures of contributions to systemic risk, as illustrated in Figure 10, which displays the scatter plot of the ranks of financial institutions. The most systemic institution is ranked one for both measures, and the least systemic is ranked 90. We observe that although both measures identify American banks as the most systemic during the pre-crisis period, some differences exist for the rest of the sample.[6] Indeed, banks from Asia and the Pacific other than China and India are identified as much more systemic by the InOut_k measure than by the $\Delta\mathrm{LGC}_k$ 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 underlies the measure InOut_k detects many spurious causalities involving many banks from Asia and the Pacific.

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

[6] The overall correlation between the ranks is 0.423.

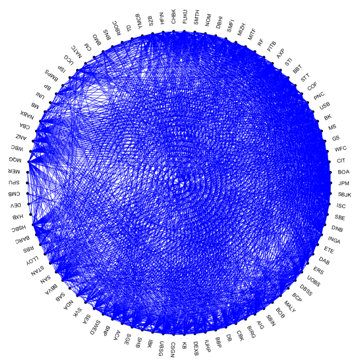

Figure 8: Network for all 90 banks: pre-crisis period

Note: List of labels can be found in Table B1 in Appendix.

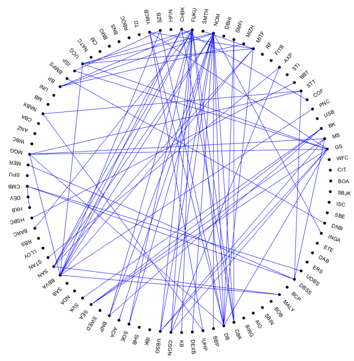

Figure 9: Network for the system excluding JPMorgan Chase & Co: pre-crisis period

Note: List of labels can be found in Table B1 in Appendix.

As the true levels of the contributions to systemic risk are latent, the question may be posed whether our measure is more accurate than that of BGLP. One way to answer this question is to compare both rankings with the one provided by the Financial Stability Board (FSB). Since 2011, this institution has published a ranking each year of the most systemic banks worldwide, denoted as G-SIBs (global systemically important banks), organised in buckets. These buckets differ in the level of additional common equity loss absorbency they require as a percentage of the 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 and make a comparison with our ranking and with that from the BGLP approach over the period 2016-2017. We consider this period as it covers the time-span over which the 2017 FSB ranking is generated. As our sample does not include four Chinese banks from 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) because of a lack of data over the whole sample, 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 of the FSB, while the third column indicates whether each G-SIB is identified as systemic by the $\Delta\mathrm{LGC}_k$ measure and the fourth by the InOut_k measure, with the related rankings from 1 to 26 in parentheses. Our measure identifies 16, or 61.54% of the 26 banks, which is a large proportion, especially as most of those not identified (Mizuho Financial Group, Nordea Bank, Royal Bank of Canada, Royal Bank of Scotland, Standard Chartered, State Street Corporation, and Sumimoto Mitsui Financial Group) are classified by the FSB as the least systemic institutions among the 26 banks and are in the bottom bucket. In contrast, the measure from BGLP only identifies 6 of these G-SIBs, which is a low level of accuracy at 23.08%. Moreover, those not identified come not only from the bottom bucket, but also from the top buckets containing the most systemic banks. One illustrative example is JPMorgan Chase & Co, which is a top systemic institution according to the FSB, but is not identified, while Bank of America, another top systemic institution, is only just present by a small margin as it is identified in 23rd place. These stylised facts are in accordance with the results in Table 3 for the post-crisis period, which show that the most systemic banks identified by the $\Delta\mathrm{LGC}_k$ are mostly from the US, while those identified by the InOut_k measure are mainly from Japan. As the G-SIBs, and especially the most systemic ones, are mostly American banks, our measure appears to be a more reliable indicator of systemic risk.

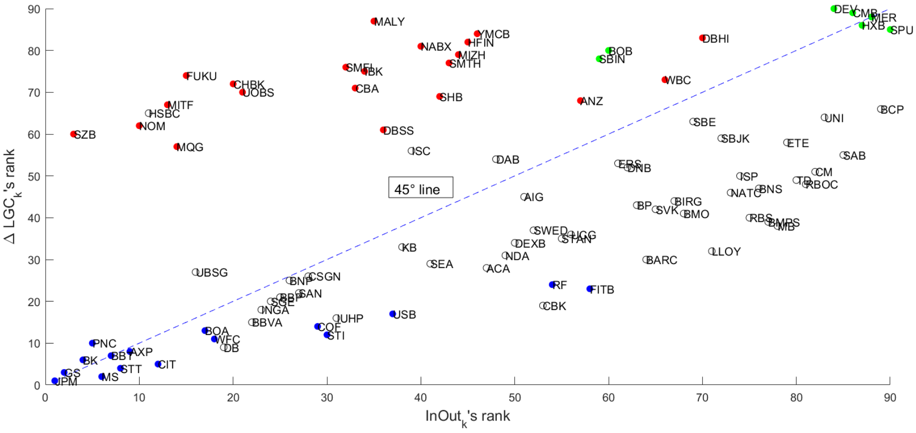

Figure 10: Comparison of the ranks of InOut_k and ΔLGC_k: pre-crisis period

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

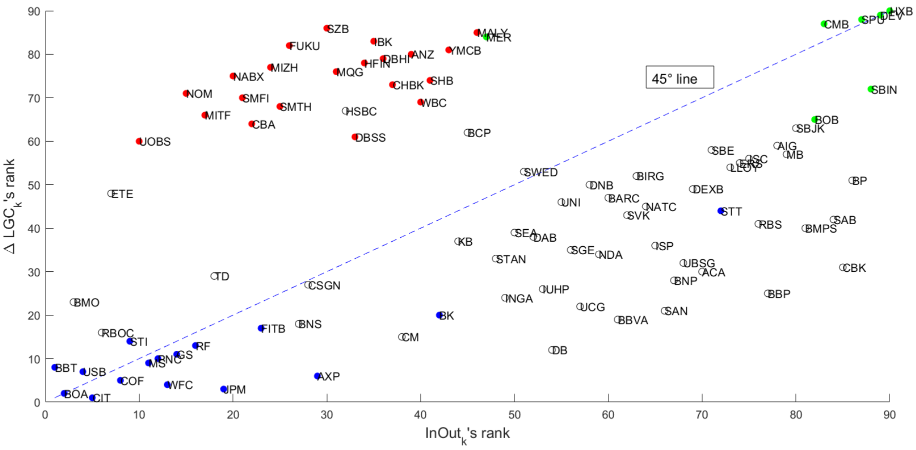

Figure 11: Comparison of the ranks of InOut_k and ΔLGC_k: crisis period

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

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 ranking in parentheses, and the total number identified as a percentage in brackets.

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. In other words, any consistent measure of the systemic risk profile of an institution should be an early-warning indicator of losses in a systemic event. In this section, we check whether this characteristic is fulfilled by our measure ΔLGC_k of systemic risk contributions. More precisely, we focus on the crisis period from July 2007 to June 2009, with a total of $T_c = 522$ daily observations. Over the crisis period, we compute the performance for each bank given by the average of downside returns. For a given financial institution $k = 1, ..., 90$, the performance is given by

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

for $t = 1, ..., T_c$, where $y_{k,t}$ is the return at time t on the asset of bank k, $Z_{k,t}$ is 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 $\delta < 0$ as a threshold. The parameter m is the number of times $Z_{k,t}$ takes the value one over the crisis period, so

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

The performance measure in Eq. (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

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

where $[\text{Perf}_k]$ is the rank in ascending order of the performance of bank k, with the worst performing bank taking the value one, and the best performer ranked 90. The variable $[\Delta\text{LGC}_k]$ is the rank in descending order of our measure ΔLGC_k for the bank k over the pre-crisis period from September 2003 to June 2007, with the most systemic bank taking the value one, and the least systemic ranked 90. So with predictive content, we expect a positive sign for β_4, meaning more systemic institutions in the pre-crisis period have higher realised losses in the crisis period and less systemic institutions have lower losses.

It should be remembered that our institution-level measure of the contribution to systemic risk is built on the weakness of the measure InOut_k of BGLP in ranking institutions, as we argued that the ranking of financial institutions by that 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 that measure separately, the statistics In_k and Out_k, with their ranks in descending order. Therefore, as for the parameter β_4, the other slope parameters should also take positive values with predictive content.[7]

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 nine different specifications. In specifications [1] to [4] we consider each of the alternative measures of systemic risk separately. In specifications [5] to [7] we include our measure of systemic risk and each of the three measures of BGLP. In column [8], we report the results from a specification that includes the four alternative measures of systemic risk. Finally, to take into account a potential multicollinearity problem, we estimate the same specification using a ridge regression approach. As usual in the literature, the tuning parameter is calibrated via cross-validation. Results that we obtain are reported in column [9].

First, specifications [1] to [4] show the slope parameter associated with each measure of systemic risk to be statistically significant at the conventional levels. This means that individually, each measure of systemic risk contributions is significantly related to the losses suffered by the banks from a systemic event. The BGLP measures InOut_k and Out_k and our measure ΔLGC_k appear with the expected sign, so the riskier a bank is in the pre-crisis period, the more severe its losses are during the crisis period. Surprisingly, the measure In_k of BGLP appears with a negative sign, which indicates that banks with a higher level of systemic risk 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 than do the three measures of BGLP, and the values of the adjusted R-squared are always higher. For instance, with $M = 3$, the adjusted R-squared is 31.3% with our measure ΔLGC_k, while it is 28.2%, 7.5% and 3.2% for the BGLP measures Out_k, InOut_k and In_k. Second, we can see from specifications [5] to [7] that the coefficients associated with the three measures of BGLP lose 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, together with additional information which probably comes from our methodology for cleaning indirect spurious causalities. This result is robust when we consider jointly the four measures of systemic risk (see specifications [8] and [9]).

Table 6 presents the same results with $\delta = -5\%$. The 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 on either the estimated parameters or the adjusted R-squared. This is also the case for the parameter δ, which measures the severity of the losses. Figures B3 and B4 in the Appendix represent the performance of each bank for the case $(\delta, M) = (-5\%, 3)$ as measured by the mean of realised losses as a function of the measures of systemic risk contributions InOut_k and ΔLGC_k respectively. We observe that there is almost no correlation between the average realised losses and the measure InOut_k, whereas our new measure ΔLGC_k can predict the average realised losses relatively well.

[7] We consider using the ranks of the variables instead of their true values to avoid possible multicollinearity 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 below -3%

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
					$M=3$				
Constant	32.173***	54.876***	21.014***	19.796***	17.693***	10.725	19.515***	4.961	4.992
	(4.485)	(4.646)	(4.232)	(3.898)	(3.997)	(7.994)	(4.052)	(10.452)	(10.477)
InOut_k	0.293***				0.078			-0.045	-0.044
	(0.088)				(0.090)			(0.119)	(0.132)
In_k		-0.206**				0.130		0.217	0.216
		(0.102)				(0.107)		(0.159)	(0.157)
Out_k			0.538***				0.090	0.303	0.298
			(0.074)				(0.249)	(0.275)	(0.283)
ΔLGC_k				0.565***	0.534***	0.634***	0.481**	0.416*	0.420*
				(0.068)	(0.078)	(0.092)	(0.231)	(0.233)	(0.247)
$\overline{R^2}$	0.075	0.032	0.282	0.311	0.309	0.316	0.305	0.309	0.309
					$M=5$				
Constant	32.607***	54.786***	21.432***	19.907***	19.445***	13.716*	19.725***	7.400	7.027
	(4.587)	(4.606)	(4.194)	(3.889)	(3.955)	(7.494)	(4.023)	(9.584)	(10.268)
InOut_k	0.283***				0.019			-0.123	-0.127
	(0.090)				(0.102)			(0.135)	(0.146)
In_k		-0.204*				0.092		0.216	0.222
		(0.102)				(0.103)		(0.150)	(0.160)
Out_k			0.529***				0.055	0.239	0.236
			(0.074)				(0.224)	(0.251)	(0.269)
ΔLGC_k				0.562***	0.553***	0.607***	0.512**	0.505**	0.515**
				(0.067)	(0.084)	(0.087)	(0.207)	(0.231)	(0.239)
$\overline{R^2}$	0.070	0.031	0.272	0.309	0.301	0.307	0.301	0.300	0.302
					$M=10$				
Constant	35.927***	53.117***	23.941***	20.243***	20.666***	13.345*	21.007***	10.212	10.052
	(4.788)	(4.809)	(4.230)	(3.910)	(4.093)	(7.597)	(3.982)	(9.271)	(9.514)
InOut_k	0.210***				-0.016			-0.167	-0.169
	(0.094)				(0.094)			(0.122)	(0.150)
In_k		-0.167				0.104		0.222	0.225
		(0.108)				(0.105)		(0.155)	(0.159)
Out_k			0.474***				-0.190	-0.027	-0.0241
			(0.080)				(0.229)	(0.242)	(0.244)
ΔLGC_k				0.555***	0.561***	0.602***	0.728***	0.748***	0.747***
				(0.069)	(0.079)	(0.087)	(0.218)	(0.230)	(0.215)
$\overline{R^2}$	0.033	0.017	0.216	0.300	0.292	0.301	0.298	0.298	0.300

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 realised losses for each of the 90 financial institutions in the crisis period of July 2007-June 2009. We approximate the realised losses by the average value of returns below a given threshold $\delta = -3\%$. The regressions differ by the number of predictors considered, from 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 of 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 marked by ***, ** and *.

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

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
					$M = 3$				
Constant	32.122***	54.554***	21.218***	20.252***	17.982***	11.011	19.857***	4.495	4.572
	(4.543)	(5.059)	(4.203)	(3.926)	(3.944)	(7.652)	(4.074)	(9.710)	(10.544)
InOut_k	0.294***				0.084			-0.044	-0.045
	(0.086)				(0.092)			(0.129)	(0.133)
In_k		-0.199*				0.133		0.228	0.227
		(0.104)				(0.099)		(0.148)	(0.158)
Out_k			0.534***				0.127	0.351	0.345
			(0.076)				(0.230)	(0.243)	(0.285)
ΔLGC_k				0.555***	0.521***	0.625***	0.437**	0.367*	0.373
				(0.068)	(0.085)	(0.083)	(0.208)	(0.200)	(0.248)
$\overline{R^2}$	0.076	0.029	0.277	0.300	0.298	0.305	0.294	0.301	0.300
					$M = 5$				
Constant	32.151***	53.971***	22.363***	20.245***	19.365***	12.786*	20.383***	8.774	8.3167
	(4.471)	(5.014)	(4.169)	(3.884)	(3.932)	(7.175)	(4.007)	(9.418)	(10.339)
InOut_k	0.293***				0.037			-0.094	-0.096
	(0.086)				(0.103)			(0.146)	(0.147)
In_k		-0.186*				0.110		0.196	0.202
		(0.103)				(0.095)		(0.147)	(0.161)
Out_k			0.509***				-0.041	0.128	0.126
			(0.078)				(0.233)	(0.257)	(0.271)
ΔLGC_k				0.555***	0.537***	0.609***	0.593***	0.577***	0.585**
				(0.066)	(0.090)	(0.078)	(0.211)	(0.222)	(0.241)
$\overline{R^2}$	0.076	0.024	0.250	0.300	0.293	0.302	0.292	0.289	0.292
					$M = 10$				
Constant	35.254***	52.346***	24.231***	20.642***	20.471***	12.668*	21.367***	9.854	9.673
	(4.801)	(5.242)	(4.296)	(3.897)	(4.089)	(7.162)	(4.042)	(9.005)	(9.578)
InOut_k	0.225***				0.006			-0.148	-0.150
	(0.091)				(0.099)			(0.146)	(0.151)
In_k		-0.150				0.121		0.226	0.228
		(0.110)				(0.097)		(0.150)	(0.160)
Out_k			0.467***				-0.180	-0.020	-0.020
			(0.085)				(0.237)	(0.268)	(0.246)
ΔLGC_k				0.546***	0.544***	0.601***	0.710***	0.726***	0.729***
				(0.068)	(0.086)	(0.076)	(0.211)	(0.215)	(0.217)
$\overline{R^2}$	0.040	0.012	0.210	0.291	0.282	0.294	0.288	0.288	0.290

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 realised losses for each of the 90 financial institutions in the crisis period of July 2007-June 2009. We approximate the realised losses by the average value of returns below a given threshold $\delta = -5\%$. The regressions differ by the number of predictors considered, from 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 of 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 marked by ***, ** and *.

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 do. Since the last financial crisis there has been a lot of debate about the potential channels and drivers of the transmission of financial distress between banks. In particular, some recent studies have investigated whether the size and business models of banks drive their contributions to systemic risk significantly. They have found strong evidence that large and market-oriented financial institutions are more prone to contributing to the build-up of systemic risk in the financial system than their peers are.

Against this background, we check whether we find results in line with the existing literature when we consider our measure of systemic risk as a dependent variable. This issue is particularly interesting in our case as our measure of systemic risk is a measure of the interconnections between financial institutions, and so is more likely to be driven by the size and activities of banks than other more traditional measures of systemic risk such as the marginal expected shortfall (MES), the SRISK or the ΔCoVaR. In consequence, we consider a panel data framework and regress different balance-sheet variables on our measure of systemic risk. We consider annual data over 2004-2017, or more precisely, we consider seven non-overlapping sub-periods: 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15, and 2016-17. For each bank in our sample, we then compute our systemic risk measure for these different sub-periods, using a two-year average for balance sheet data. The 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. As noted above, a number of recent empirical studies have found 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 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 $Size_{k,t-1}$ is the size of the bank. Following Brunnermeier et al. (2012) and Laeven et al. (2016), the right-hand side variable is lagged one period to reduce the 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 so we estimate Eq. (30) using the random effects (RE) estimator.

The results that we obtain are reported in the first column of Table 7. We find a positive and significant relationship between bank size and our measure of systemic risk. As higher values for our statistic 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 subsidies for being "too big to fail", letting 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 that we propose in this paper.

In a second step, we extend our previous findings by investigating whether the business models 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. In this way we distinguish between retail-oriented and market-oriented banks, and then assess the effect of the asset structure of the banks 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 systemic risk, while Brunnermeier et al. (2012) find that banks with higher non-interest income tend to make a higher contribution to systemic risk than traditional banks do.

Our results are reported in columns [2] and [3] of Table 7. Similarly to Laeven et al. (2016), column [2] shows that the relationship between the loans-to-assets ratio and our measure of systemic risk is negative and statistically significant. This suggests that traditional intermediation activities tend to reduce the contribution of banks to systemic risk as lending-based activities make banks less exposed to common shocks. In contrast to this, the results reported in column [3] show a positive and significant relationship between the share of non-interest income in total income and our measure of systemic risk. This result is consistent with the view that banks with more market-based activities are more likely to contribute to systemic risk. 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 the profitability of banks on systemic risk. We proxy 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. One argument is that higher profitability may shield banks from the risk of defaulting, and so it should be associated with a lower contribution to systemic risk, but the counter-argument is that higher profitability could be the result of the bank engaging in risky side activities such as market-based investment and trading activities. Furthermore, our previous results suggest that profits from non-lending activities significantly drive our measure of systemic risk. As a consequence, higher profitability could induce a larger contribution to systemic risk. As we can see in column [4] of Table 7, the estimated coefficient associated with ROE comes out positive and statistically significant, confirming that the profitability of a bank increases its contribution to 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)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
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, our results suggest strong evidence that bank size is one of the key drivers of systemic risk. This result is not surprising if we look at 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 specialisation of banks, their business model, and also their profitability, are significant drivers of systemic risk. Our results give particular support to the argument 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 for quantifying the risk contribution of financial institutions to the financial system, and then identifying the global systemically important banks or G-SIBs. Some of these measures focus on one fundamental aspect of systemic risk, which is the connectedness of financial firms, as the linkages between banks can act as a channel for contagion during a crisis. However, measuring interconnectedness in relatively large and complex financial systems is empirically challenging, especially as it is of critical importance that linkages between firms and contagion in the financial system can stem from both direct and indirect exposures to counterparties.

However, to the best of our knowledge, there are few measures in the existing literature on systemic risk that explicitly try to take the existence of indirect contagion effects into account. In their seminal paper, Billio et al. (2012) propose evaluating the contribution of a given financial institution to systemic risk 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 have 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 addressing this shortcoming of the pair-wise approach by estimating a large dimensional VAR model that includes all firms simultaneously and so take into consideration all the interactions in the system. An inherent computational difficulty with this type of modelling is the curse of dimensionality, since the number of parameters grows quickly with the size of the system.

Against this background, the aim of this paper is to propose an alternative measure for the contribution to systemic risk that overcomes these two shortcomings. It formally manages indirect causalities between firms in the network and breaks the curse of dimensionality. To do this, 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 how far the proportion of statistically significant connections in the system breaks down when a given financial institution is excluded, controlling for the indirect effects of that institution. This means the systemic risk contribution of that institution is high when the proportion is large.

We use daily asset returns for a sample of the world's largest banks from 12 September 2003 to 19 February 2018 to assess the reliability of our systemic risk measure in different ways. First, we rank the systemic importance of each bank in our sample using our measure of systemic risk and that developed by Billio et al. (2012). The results that we obtain show substantial differences between the two rankings. More importantly, when we compare both the 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) is. Our measure identifies 16 of the 26 G-SIBs in our sample, or 61.54%, while the measure of Billio et al. (2012) identifies six, or 23.08%. Second, we assess the predictive power of our measure of systemic risk 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 that associated with the measure of Billio et al. (2012). These findings reinforce the idea that a pair-wise Granger causality approach is more reliable when the effects of indirect causalities are cleaned out in a meaningful way.

Finally, as is usual in the literature on systemic risk, we empirically investigate the potential drivers of the contribution of banks to systemic risk. 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 the banks. Our results suggest that systemic risk increases with bank size. This result clearly indicates that the largest banks tend to contribute more to systemic risk. We also find that the degree of specialisation in non-traditional banking activities is an important driver of systemic risk, and indeed our results indicate that the systemic risk contribution is higher for banks with more market-based activities. Supporting this, we find a negative relationship between specialisation in lending-based activities and our measure of systemic risk. Furthermore, we find that the profitability of a bank significantly increases its contribution to 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. More specifically, our leave-one-out (LOO) metrics for measuring contributions to systemic risk 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, which 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 those, would be rejected. However, in reality, not all false hypotheses will be rejected and some of those that are rejected will be rejected mistakenly. This issue is of great interest because it can mislead authors so that they arrive at the wrong conclusions. To solve this problem, the number of false rejections should be reduced and as many correct rejections as possible should be made. The literature provides many methods for controlling for the problem of multiplicity in statistical inference, and the two main alternative controlling methods are the Family Wise Error Rate (FWE) and the False Discovery Rate (FDR).

The FWE is defined as the probability of at least one of the true null hypotheses being rejected. The FWE is controlled by requiring its value to be lower than or equal to the significance level α, at least asymptotically. Different methodologies have been developed for controlling FWE and the most widely used is the Bonferroni method. There are two main reasons for its popularity. First, it is really simple as it consists only of comparing 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, loses power as the number of hypotheses increases. Indeed the critical values become very small, making it difficult to reject clearly even one hypothesis. Say for example that $(n-1)(n-2)$ hypotheses are tested for each institution 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-value to the threshold 0.05/7832, and obviously some false null hypotheses will not be rejected because of the very low significance level. Some less conservative methods have been developed in the literature (Šidák, 1967; Holm, 1979; Hommel, 1988; Hochberg, 1988), but they have failed to improve much as they are still conservative. Thus the traditional approach is to control the FWE when the number of hypotheses tested 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 the 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, the error control can be based on the False Discovery Proportion (FDP) defined as FDP = F/R if R > 0, and 0 otherwise. In this way the FDR is finally the expected value of the FDP. The most popular method for controlling the FDR is the linear step-up procedure from Benjamini and Hochberg (1995), which 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 $\gamma_i = \gamma i/M$, and with γ the level of control. If such $i^\star$ exists, reject the $i^\star$ 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.[8] From this result, it is obvious that if the true value of M_0 is known, a more powerful 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 hypotheses in the linear step-up procedure. This leads to their two-stage linear step-up procedure which works as follows:

- Use the linear step-up procedure at level $\gamma' = \gamma/(1+\gamma)$. Let R be the number of hypotheses rejected. 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 $\gamma^\star = \gamma' M/\widehat{M}_0$.

We use this two-stage linear step-up procedure for both measures InOut_k and ΔLGC_k, 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) than that of 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 than the alternative FDR procedures under various forms of p-value dependences.

It is worth mentioning that with both types of methodology, FWE and FDR, there is a class of controlling methods that is based on resampling procedures. To control for the FWE, White (2000) for example 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 the measures used in this paper, we cannot use such an approach. For each institution, $(n-1)\times(n-2) = 7832$ hypotheses are tested for our LOO measure, and $n \times (n-1) = 8010$ for the BGLP measure.

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

Appendix B: Additional Tables and Figures

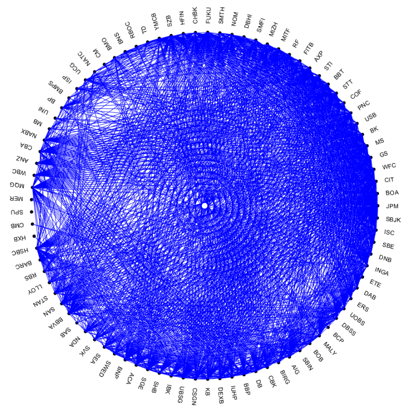

Figure B1: Network for the system excluding Ping An Bank: pre-crisis period

Note: List of labels can be found in Table B1 in Appendix.

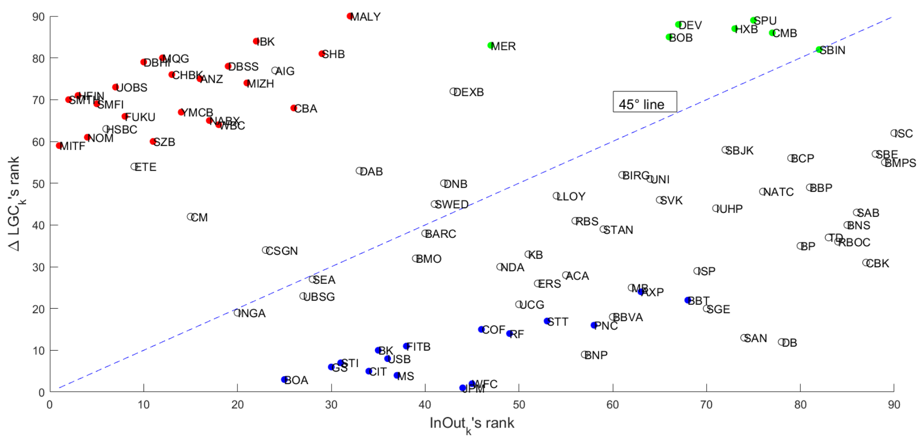

Figure B2: Comparison of the ranks of InOut_k and ΔLGC_k: post-crisis period

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

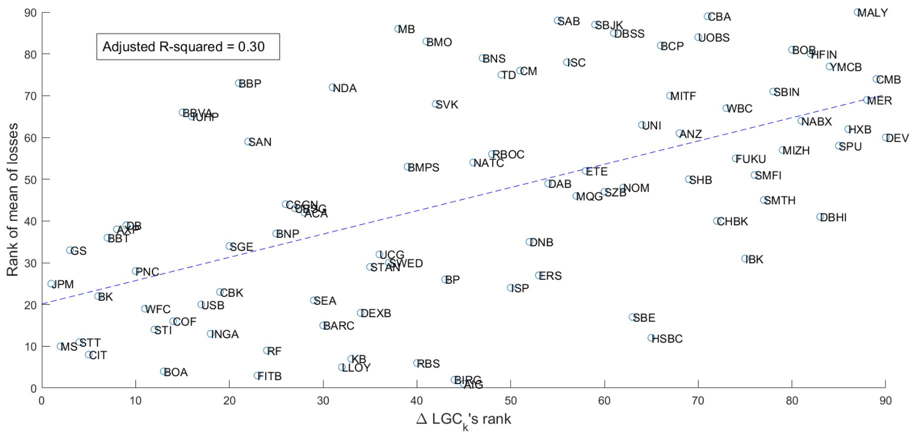

Figure B3: Systemic risk contributions ΔLGC_k and mean of realized losses: $\delta = -5\%$

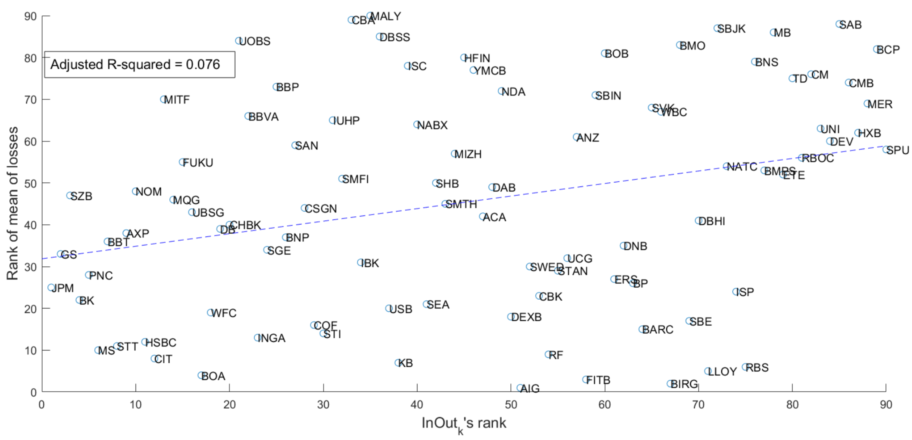

Figure B4: Systemic risk contributions InOut_k and mean of realized losses: $\delta = -5\%$

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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