Assessing Contagion Risk in the Maltese Financial Sector: A Network Model Approach

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1. Introduction

Interconnectedness between financial institutions is a source of systemic risk. The IMF defines systemic risk as "the risk of widespread disruption to the provision of financial services that is caused by an impairment of all or parts of the financial system, which can cause serious negative consequences for the real economy" (IMF, 2013 p.4). Systemic risk arises from linkages between financial institutions and can amplify the effects of an adverse shock significantly. To quantify, by looking at the effects of 33 systemic banking crises worldwide, Hoggarth et al (2002) estimate that systemic effects can cause an additional cumulative loss in output equal to circa 15-20% of annual GDP in times of crisis. With this in mind, it comes as no surprise that systemic risk has become a central focus for Central Banks, supervisory authorities and researchers interested in financial stability.

As outlined by Caccioli et al in their 2014 paper, "systemic risk" or the transmission of shocks from one financial institution to another occurs through three main channels:

1. Losses from counterparty exposures, where one entity is directly linked to a failing institution due to direct lending. If the borrowing institution fails, the lender suffers a direct hit to the balance sheet as famously discussed by Allen and Gale (2000).
2. Inability to roll-over debt and the unavailability of short-term financing. This type of financing tends to dry up in times of financial distress as in the case study presented by Anand et al. (2012).
3. Portfolio devaluations due to common asset holding, whereby distress in one financial institution can lead to a fire sale of assets which depresses the asset value and therefore causes a loss in the portfolio value of other institutions (Gorton and Huang 2004; Cifuentes et al. 2005; Neir et al. 2007).

These transmission channels make institutions interconnected and susceptible to the same shocks.

While the risks from high levels of interconnectedness are now undisputed, there is little consensus on how to measure the strength of these linkages or estimate the magnitude of the losses they cause should the risk materialize. Addressing these two issues is crucial in order to create adequate policies to mitigate these risks within the regulatory framework.

The principal aim of this paper is to contribute to the literature in this field by focusing on the first channel of systemic risk, i.e. contagion arising from direct exposures to the failing institution and takes the analysis a step further by considering losses due to indirect exposures. To this end, a simple model has been constructed to assess the size of both direct and indirect effects following the default of a financial institution within the framework. While the methodology closely mirrors other works in this field, the novelty lies in the unique data set being used to test the model empirically.

Using data provided by the Malta Financial Services Authority (MFSA) it was possible to estimate the model and carry out a number of simulations on a network made up of three different types of institutions: banks, insurance undertakings and mutual funds which are linked together through a number of bi-lateral exposures. This rich data set covers granular exposures for 39 financial institutions which together account for over 66% of financial sector assets in Malta.

The flexibility embedded within the model allows simulations of the default of a particular institution or a group of institutions. Although the results of such simulations are subject to significant simplifications, they give some interesting insights which could help inform policy makers and supervisors. Moreover, the model has been updated for two years of data (2017 and 2019), thus providing insights into how interlinkages have evolved over time.

The results suggest that contagion risk within the Maltese financial sector is broadly contained at the current juncture, with no system-wide cascades being observed. Nevertheless, simulated failures on certain institutions indicate elements of material losses that would be generated on the financial sector. A more holistic approach in estimating such risks is required, which incorporates a network of indirect links (through overlapping portfolios).

The results from the simulations are transformed into indicators that measure *systemic relevance* and *systemic fragility* together with more traditional metrics such as *degree* and *betweenness centrality*.[1] These network metrics increase the usability of the network model for risk oversight purpose, allowing identification of institutions which pose the highest risk on financial stability. This model can also be used as a complementary tool for system-wide stress tests, providing a more comprehensive assessment of contagion risk within the financial system.

The rest of the paper is structured as follows. Chapter 2 gives a brief overview of the relevant literature, followed by a description of the methodology in Chapter 3. An overview of the dataset is given in Chapter 4, prior to giving a detailed description of the network and the relevant metrics. Chapter 5 outlines the simulations carried out as well as the results. The final chapter concludes with a discussion of the implications of the results and the limitations of this model along with suggestions for further research.

2. Literature Review

2.1 Interconnectedness and Financial Stability

Following the establishment of the European Systemic Risk Board (ESRB) in 2010 and its subsequent recommendations to the EU Member states to adopt a macroprudential framework aimed at contributing "to the safeguard of the stability of the financial system as a whole" (ESRB, 2011, p.1), a significant amount of research began to emerge related to understanding interlinkages between financial institutions both in academic and policy fora.

Given that interlinkages between financial institutions can be rather complex, traditional economic models were often found to be inadequate in capturing the true nature of financial systems (Caccioli, 2018). For this reason, economists began drawing on methodologies from other

[1] Degree assigns an importance score based on the number of links held by each node; betweenness centrality measures the number of times a node lies on the shortest path between other nodes (Disney, 2020).

fields, such as physics and epidemiology. Several economists began to draw parallels between complex networks such as those in IT or biology and the financial sector. This saw the advent of the application of network models in finance.

Network models can be broadly described as a collection of nodes[2], typically representing banks or financial entities, which are connected by edges[3] between nodes that symbolise the links between the entities. They can take complex or simple forms and allow for granular modelling of individual connections.

Allen and Gale (2000) are often cited as the pioneers of network modelling in finance. They considered contagion impacts through direct linkages between banks under various network structures. Analysing a scenario whereby agents have unpredictable liquidity preferences as described by Diamond and Dybvig (1983), they argue that banks opt to insure against potential liquidity shocks by engaging in interbank transactions. While mitigating the liquidity risks, these transactions create a new web of links between institutions.

Their central argument is that complete networks (whereby all institutions engage in interbank transactions) are more stable than incomplete ones. This is because in the case of losses to one bank, the shock is distributed among all the other entities across the system rather than absorbed by a few players. To demonstrate this, they apply a uniform shock to two separate networks, one where institutions are all perfectly connected and an alternate network where connections are sporadic. They prove that, for the same set of parameters, if all the banks are equally connected to each other in what is called a "perfect network", the system is more resilient.

Drawing from the study of how epidemics spread, Gai et al. (2007) developed a model of contagion in financial networks to assess the fragility of the financial system. Adding to the work of Allen and Gale, they considered various characteristics of the interbank network such as capital buffers, the degree of connectivity, and the liquidity of the market for failed banking assets. Even when accounting for these additional factors, their results support the notion that greater connectivity reduces the likelihood of widespread default. Contrasting evidence was put forward by Blume et al. (2011). The authors also relied on techniques used in epidemiology to model financial sector contagion. However, they found that as the number of entities linked to a bank grows, the likelihood of a systemic collapse increases. Similarly, Vivier-Lirimont (2006) argued that for a network to be stable, it has to have either what he defines as a "Small World property" which implies that banks must only be linked in a short distance, or, as highlighted by Allen and Gale, be perfectly complete. Anything in between destabilizes the system.

These papers are merely a few from a vast array of recent works dedicated to understanding direct links between financial institutions. While an exhaustive review of these works is beyond the scope of this study, it is worth noting that overall results suggest that when the network is diversified enough, the system is quite

[2] Each node corresponds to an institution or macro sector. The size of the node depends on the number of linkages with other nodes within the network (degree centrality).

[3] Edges represent the linkages between one institution and another, they are represented as arrows with the source being the asset holder and the thickness capturing the size of the gross exposure.

stable. However, when these dynamics change and contagion does occur, the effects could be catastrophic. The nature of these networks was best described by Andrew Haldane (2009) who defined the highly interconnected financial networks as "robust-yet-fragile".

2.2 Empirical Work

The limited external availability of granular data on asset-liability networks render empirical work in this area, outside central banks and supervisory authorities, less common. However, given the increasing reporting requirements being placed on financial institutions, alternative data sources are being made available which enable empirical work in this field. To date, most empirical papers use balance sheet information to estimate bilateral credit relationships for different groups of banks. Typically, individual exposures are estimated using maximum entropy and subsequently, the stability of the financial network is tested by simulating the collapse of an individual player (Mistrulli, 2011). Upper and Worms (2004) use this approach in their analysis for the German banking system and estimate that the failure of a single bank could lead to the breakdown of up to 15% of the banking system in terms of assets. Degryse and Nguyen (2007) evaluate the risk of a cascade of failures in the interbank market for Belgium, where contrastingly, they find evidence of considerable resilience with even the worst-case scenario causing a total contraction of approximately 5% of total assets. Wells (2004) find similar results for the United Kingdom. However, sensitivity tests of their results indicate that assumptions considered influence results significantly.

Focusing on more qualitative aspects, Cocco et al. (2005) utilise Portuguese interbank lending data to understand the importance of relationships in banks' decisions when borrowing from other banks. More recently, Battiston et al. (2012) analysed a new and unique dataset on the Federal Reserve System emergency loans program to global financial institutions during 2008–2010. They found that around 20 institutions which received most of the emergency funding are the ones that held strong interlinkages and become systemically important at the peak of the crisis. This gives a clear indication of institutions being that although not "too-big-to-fail" are "too-connected-to-fail".

One shortcoming of the aforementioned works is that they rely on estimation techniques to map the bi-lateral exposures between institutions since granular data is rarely available outside central banks and supervisory authorities. In fact, as argued by Glasserman and Young (2016), the unavailability of data has been one of the main restricting factors in this strand of research. Espinoza-Vega and Sole (2010) were among the first to try to overcome this limitation by utilizing data from cross-country bilateral exposures at end-December 2007, published in the BIS International Consolidated Banking Statistics database. Nonetheless, the nature of the data still lacked the desired granularity.

Following the 2008 crisis, several new restrictions were imposed on banks to limit contagion effects. One such restriction was related to large exposure limits which resulted in quarterly data reporting requirements on large exposures for monitoring purposes to the Single Supervisory Mechanism (SSM). This new data source allowed authors Covi, Gorpe and Kok (2019) to model a network of almost 200 consolidated banking groups in terms of debt, equity, derivative and off-balance sheet exposures larger than 10% of a bank's eligible capital. Given the more granular nature of their dataset, the authors also accounted for heterogeneity amongst banks by calibrating different key parameters for each bank. Using this model, they identify threshold values which shift the system from a "less vulnerable state" to a "highly vulnerable state". Despite offering far more detailed results, reliance on large exposures data implies that several smaller exposures where, by definition, omitted from the network. These exposures, though not large in their own merit, could jointly impact the vulnerability of the system – diffusing shocks or amplifying them. Further to this, the network is limited to banks only, omitting any contagion which may occur as a result of links with other non-bank financial intermediaries.

With this background in mind, this paper contributes to existing literature in four ways. Firstly, by utilizing supervisory data which is reported on a granular basis, the model represents actual bi-lateral exposures in terms of loans, deposits, equity and debt securities – thus encompassing more types of interlinkages than previous studies. Secondly, by incorporating key insurance undertakings and investment funds within the model, a more holistic picture of the financial sector landscape is given. Third, by incorporating macro sectors to represent exposures with domestic households and non-financial corporates, the central government, and the rest of the world, the model allows for a diverse range of simulations apart from the default of individual entities. Finally, updating this complex set-up for two years allows an assessment of how interconnectedness within the sector has evolved over time.

3. Dataset

One of the unique features of this paper is that it uses a highly granular dataset sourced from supervisory data for June 2017 and June 2019.

Table 1 Sub-sector coverage (% total assets)

	June 2017	June 2019
Banks	100%	100%
Domestic Investment Funds	16%	9%
Domestic insurance undertakings	37%	33%

The data is organized into three square matrices, representing loans/deposits[4], equity and debt securities respectively. Data to populate each of the matrices was collated using several cross-mapping procedures, with banking data obtained from the MFSA Banking Rule No. 6 (Br06) Schedules, investment funds data from the Central Bank of Malta Investment Funds Statistical Return and insurance undertakings data from the Solvency II Quantitative Reporting Templates. Security-by-security reporting was fundamental in being able to identify direct exposures through holdings of debt and equity. Data for inter-bank exposures was sourced from large exposures reporting and supplemented with additional information obtained directly from license holders where necessary.

[4] Loans to and deposits placed (assets) are grouped as per reporting requirements.

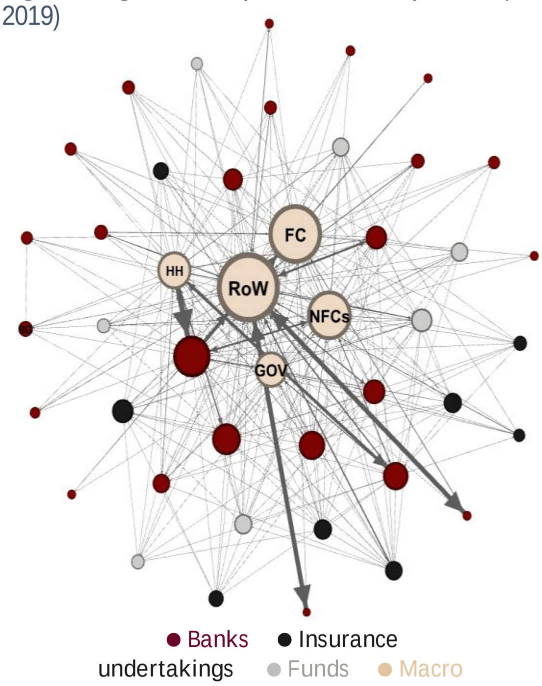
The dataset was constructed for the two years; in both instances the dataset included all banks licensed by the MFSA. Given that the network is designed to map financial stability implications of institutions with ties to the domestic economy, only the domestically relevant insurance undertakings and investment funds were included. While the institutions remained largely the same over the three-year period, some minor changes to the sample were made, mostly due to changes in reporting requirements. Table 1 details the sample coverage vis-à-vis the total assets of the respective industries for both years. While the coverage in terms of total assets for investment funds is low, the funds omitted from the sector do not have domestic investors nor hold domestic assets.

4. Network Topology

By mapping the dataset of bi-lateral exposures it is possible to identify the extent of interlinkages across each institution. In this regard, a high-level map of the interlinkage size and direction provides a wide picture of connectivity within the financial services sector (see Figure 1).

The representation is based on a Fruchterman-Reingold algorithm (Fruchterman and Reingold 1991), having the positioning of the nodes reflecting the importance of the entities within the network such that the more a node is located towards the centre of the map, the stronger the connections with the other nodes are. The edge weight indicates the size of the exposure. The map is directed with the source being the asset holder, this means that an edge from *institution i* pointing towards *institution j* represents an asset for *institution i* and a liability for *institution j.*

Figure 1 High level map of bi-lateral exposures (June 2019)



The network reflects certain known specificities of the domestic financial sector. The core[5] domestic banks lie at the heart of the sector, with most international banks being represented as peripheral nodes within the network. The strongest links within the network are towards the rest of the world by the two international bank branches which largely dominate the direction of international transactions within the banking industry. Both domestic investment funds as well as domestic insurance undertakings have fewer links with other institutions, thus represented by nodes positioned at the periphery of the

[5] At the time of writing six banks were classified by local supervisory authorities as "core domestic banks" for financial stability purposes. These banks have the strongest ties with the domestic economy. A further five banks were classified as "domestic" while the remaining banks were classified as international due to their limited links with the domestic economy.

map. All the nodes are linked to the macro sectors which represent households (HH), non-financial corporates (NFCs), the government (GOV) and other financial corporations (FC).

While these main characteristics remained unchanged between the 2017 and 2019 datasets, it is interesting to note that the average degree (the number of links) of interlinkages for banks declined significantly between the two years.

Table 2 Average degree of interlinkages

	June 2017	June 2019
Domestic Banks	35	20
International Banks	12	6
Domestic Investment Funds	12	13
Domestic Insurance undertakings	14	14

While the decrease in the number of links might suggest lower risk of contagion, upon closer inspection it transpires that although the number of links between institutions has indeed declined, the size (edge weight) of the exposures increased significantly. In fact, the average weighted degree, which accounts for the size of the exposures, for domestic and international banks increased by 147% and 78% respectively. These developments make it even more important to investigate the potential impact of the failure of one institution on those which have links to it.

5. The Model

The model builds on its predecessors, particularly on Espinosa-Vega and Sole (2010) and Covi, Gorpe and Kok (2019). Given the diverse nature of the institutions included in the network, ranging from banks, insurance undertakings, and investment funds, the complexity of the model lies in identifying channels which would come into play following the default of any of these institutions. For this reason, each institution within the network, say *institution i*, is represented using a simplified balance sheet, given by the following identity:

$$\sum_j \sum_k x_{ij}^k + \sum_j Q_{ij} + a_i = \sum_j x_{ji} + c_i + b_i \quad (1)$$

Where x_{ij}^k represents *institution i*'s credit assets of type 'k' vis-à-vis *institution j* (the liability holder in this case), Q_{ij} represents the value of the equity holding *institution i* has in *institution j* and a_i represents all other assets held by *institution i*. On the liabilities side, x_{ji} refers to *institution j*'s assets held in *institution i* (thus the obligations of *institution i* towards *institution j*), c_i refers to *institution i*'s book value of capital while b_i encompasses all other liabilities.

5.1 Default Simulation Mechanism

A sequential default mechanism is adopted in order to quantify the losses generated in the financial system following the default of a specific institution. The failure of an institution is assumed to perturb the network through three channels impacting credit, funding and equity respectively.

(i) The credit channel

The default of *institution j* will result in losses for those institutions which provided credit, either in the form of loans or debts. Given that these are senior claims, creditors can expect to recover at least part of their exposure. The proportional loss given default represents the percentage that creditors will lose from their original credit exposure as a result of the default. This parameter is calibrated at an institution level.

The losses for *institution i* resulting from the default of *institution j* arising from credit exposures can be expressed as follows:

$$\sum_k \vartheta_j x_{ij}^k \text{, where } \vartheta_j \in [0,1] \quad (2)$$

In (2), x_{ij}^k are the credit exposures in terms of loans and debt securities *institution i* had to *institution j* and ϑ_j is the loss given default parameter calibrated for *institution j*. This loss is absorbed by the capital of *institution i*, denoted as c_i, while the amount recovered, expressed as:

$$\sum_k (1-\vartheta_j) x_{ij}^k \quad (3)$$

is absorbed by *institution i*'s other assets, a_i.

(ii) The funding channel

Simultaneously, institutions which had funding exposures to the defaulting entity will need to replace this funding at short notice. The ability of an institution to do so depends on the general 'willingness to lend' (ρ_i) of other parties to the institution in need of funding. Should the institution fail to replace the entire amount, the funding shortfall would need to be counterbalanced through the sale of assets. Given the necessity to replace funding immediately or because of market distress, these assets may have to be sold at a discount.

The funding shortfall for *institution i* following the failure of *institution j*, is reflected by a reduction on the liabilities, which can be given by:

$$(1-\rho_i) x_{ji} \text{, where } \rho_i \in [0,1] \quad (4)$$

This reduction in liabilities will be compensated through a reduction on the assets side, with assets being sold at a discount (δ_i):

$$a_i - (1-\rho_i)(1+\delta_i) x_{ji} \text{, where } \delta_i \in [0,1] \quad (5)$$

Given the above, the reduction on the assets side is larger than that on the liabilities side, implying a reduction in the capital of *institution i*.

(iii) The equity channel

The equity channel is the most complex, as it incorporates an element of feedback. The default of *institution j* will trigger two changes in terms of equity. Firstly, we assume that the value of defaulting institution's share capital is reduced to zero which implies a direct loss to institutions that held shares in *institution j* as part of their portfolio. The failure will also result in second round losses, which are an indirect loss for those institutions which, although not directly exposed to *institution j*, are exposed to the other institutions taking a direct hit. These losses are absorbed by the capital of each institution This process goes on until equity values converge to that level where all losses (both the direct and the 'second round' losses) are fully absorbed.

$$\sum_j Q'_{ij} \text{ where } Q'_{ij} = f(c'_j, q_{ij}) \quad (6)$$

Basing on the assumption of a static balance sheet, the value of the equity held in the portfolio of *institution i*, once the new equilibrium is reached, will reflect the reduction in capital suffered by each institution following the initial default. This is captured by the new level of capital c'_j, i.e. the excess of assets over liabilities once all losses have been incurred. The quantity of shares *institution i* holds in *institution j*, q_{ij}, is assumed to remain unchanged. This implies the assumption that institutions do not engage in fire sales following distress of one player.

5.2 Identifying sequential defaults

At the new equilibrium, the balance sheet of *institution i*, following any losses incurred due to the failure of *institution j*, can be expressed as follows:

$$\sum_j \sum_k x_{ij}^k - \sum_k \vartheta_j x_{ij}^k + \sum_j \mathrm{Q}'_{ij} + a'_i = \sum_j x_{ji} - (1-\rho_i) x_{ji} + c'_i + b_i \tag{7}$$

The balancing figure is the value of capital, c'_i can be expressed as the excess of assets over liabilities. *Institution i* is considered to go into distress when the book value of its capital falls below a certain threshold given by c_i^d. Expressing (7) in terms of book value of capital, the solvency condition is given by:

$$\sum_j \sum_k x_{ij}^k - \sum_k \vartheta_j x_{ij}^k + \sum_j \mathrm{Q}'_{ij} + a'_i - \sum_j x_{ji} + (1-\rho_i) x_{ji} - b_i \geq c_i^d \tag{8}$$

This condition is checked following each round of equity losses. If, at any point in the simulation, the condition is not satisfied for one or more institutions in the network, they are assumed to go into distress and the simulation starts again, assuming their default. The new equilibrium is reached once no more sequential defaults occur and all the losses have been absorbed.

5.3 Parameter calibration and distress thresholds

To partially capture the heterogeneity between the institutions within the network, the three key parameters used in the simulation are calibrated at an institution level. The approach closely mirrors that proposed for banks by Covi, Gorpe and Kok (2019), which was adapted to suit the different reporting requirements and business models of investment funds and insurance undertakings.

(i) Loss given default (LGD)

This parameter determines what proportion of the credit exposure is lost when an institution fails. It is calculated for banks and insurance undertakings as the ratio of net to gross credit exposures to financial institutions. In this way the amount of unsecured exposures, which is least likely to be repaid in cases of default, is captured. For investment funds credit exposures to other institutions are minimal and typically limited to bond holdings. For this reason, it was not possible to calibrate specific LGDs but rather a fixed LGD of 45%[6] was adopted for this category.

[6] This was selected in line with that of the foundation internal ratings-based (F-IRB) approach under Basel III whereby senior claims on sovereigns, banks, securities firms and other financial institutions, that are not secured by recognised collateral, will be assigned a 45% LGD. (BIS, 2019a)

(ii) Funding shortfall rate

The funding shortfall relates to the reluctance to lend to an institution in need of funding, with the parameter taking a value between 0 and 1. For the scope of this analysis it is assumed that institutions will be unable to replace short-term funding should the lending counterparty fail. Given the longer timeframe, long-term funding is assumed to be replaced in its entirety. The funding shortfall rate is thus calculated as the proportion of short-term liabilities (less than three months) to total liabilities. The same approach is applied across the three categories of institutions.

(iii) Fire-sale discount rate

Counterbalancing the funding shortfall is the fire-sale of assets. Given the urgency of the sale, assets are assumed to be sold at a lower price, with the reduction in the sale price being captured by the fire-sale discount rate. Security-by-security reporting allows for the calibration of this parameter based on the portfolio composition for each institution.

The portfolio is categorized by asset type and issuer. Haircuts are then applied to each category following the guidelines (EU) 2019/1033 of the European Central Bank of 10 May 2019. This approached is used for banks, insurance undertakings and investment funds within the model. For banks the haircuts are applied to unencumbered assets only (as reported in the asset encumbrance template FINREP F.32.01).

(iv) Distress thresholds

The distress threshold represents the level of loss an institution can sustain. Institutions incurring losses above this level are considered within the model to be in distress. The distress threshold is defined for each category of institutions that are considered within the network. For banks, the threshold is defined as the basic capital requirement, that is 8% of risk weighted assets (RWA) under Basel III (BIS, 2019b). Similarly, the default threshold for insurance companies is set depending on the solvency capital requirement as outlined by the European Union's Solvency II Directive.

For mutual funds, the requirements are less onerous and thus the solvency condition for this sub-set of entities within the model only requires funds to have positive equity. Within this simple set-up, a mutual fund is considered solvent for as long as the sum of the market value of its portfolio and other asset holdings exceeds its liabilities.

5.4 Contagion indicators

Apart from the traditional graph metrics such as betweenness and degree, the simulations allow for the construction of more sophisticated measures of interconnectedness. Three specific metrics have been constructed for this purpose.

(i) Systemic relevance index (SRI)

Following the simulation of the failure of each institution, it is possible to quantify the losses incurred by every other institution in the network. The losses are measured as a proportion of the initial book value of each respective institution. The systemic relevance index (SRI) is a count of the number of institutions which suffer a loss greater than 5% of their book value following the failure of the player for which the index is being calculated. For instance, if *institution j* has a systemic relevance index of

5, it would imply that as a result of the simulation of the failure of *institution j*, five other institutions in the network suffer a loss greater than 5% of their book value. The SRI for *institution j* can thus be expressed as:

$$SRI_j = \sum_{i \neq j} V_{ji} \text{ ,}$$

$$\text{where } V_{ji} = \begin{cases} 1 & \frac{L_{ji}}{c_i} \geq 5\% \\ 0 & otherwise \end{cases}$$

(9)

The losses arising to *institution i* from the failure of *institution j* are given by L_{ji} and the initial capital (book value) of *institution i* is captured by c_i. It follows that if there are N institutions in the network, the highest SRI for any institution is N-1.

(ii) Systemic vulnerability index (SVI)

The second metric captures the vulnerability of each institution. As with the SRI index, the losses are measured as a proportion of the initial book value. The systemic vulnerability index (SVI) is a count of the number of instances when the institution for which the index is being calculated suffers a loss greater than 5% of its book value following the failure of another institution. Thus, if *institution j* has a systemic vulnerability index of 5, it follows that *institution j* suffers losses greater than 5% of its book value following the simulated failure of five other institutions. The SVI for *institution j* is given by:

$$SVI_j = \sum_{i \neq j} V_{ij} \text{ ,}$$

$$\text{where } V_{ij} = \begin{cases} 1 & \frac{L_{ij}}{c_j} \geq 5\% \\ 0 & otherwise \end{cases}$$

(10)

In this case, L_{ij} captures the losses arising to *institution j* from the failure of *institution i* and they are measured as a proportion of the initial capital (book value) of *institution j*, c_j. As with the SRI, if there are N institutions in the network, the highest SVI for any institution is N-1.

(iii) Loss amplification factor (LAF)

An institution may be systemically relevant both due to the direct losses it generates in other institutions, but also through second round effects. This follows from the presumption that although an institution might not be "too-big-to-fail", it might instead be "too-connected-to-fail". In order to identify whether any indirect links are driving the systemic relevance of an institution, the loss amplification factor (LAF) is measured. For *institution j*, the LAF is simply a ratio of the total losses incurred by all institutions in the network to the sum of the direct losses to the same institutions generated by the failure of *institution j*:

$$LAF_j = \frac{\sum_{i \neq j} L_{ji}}{\sum_{i \neq j} L_{ji}^D}$$

(11)

An LAF of 1 would imply that there are no indirect effects, the losses in the system are simply limited to those arising from direct exposures. On the other hand, an LAF exceeding a value of 2 would suggest that the indirect losses are greater than the direct losses generated by the failure of a particular entity.

6. Results

The default of each institution was simulated, and the results reinforce the key characteristics of the local financial sector.

The domestic banks were found to have the highest systemic relevance. The failure of one node was found to cause losses greater than 5% of equity in most institutions included in the analysis. In fact, this failure was the only one to result in significant distress in other institutions (i.e. falling below capital requirements). Reassuringly, this systemically relevant node suffered relatively small losses (below 5% of its book value) following the failure of other institutions in the network.

As anticipated international banks have little systemic relevance. Similarly, the failure of the investment funds and insurance undertakings included in the model would have far less impact when compared to the domestic banks.

Figure 2: Systemic Relevance Index (SRI)

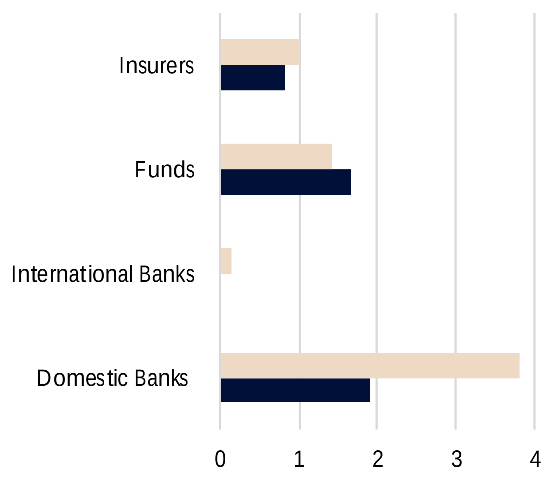
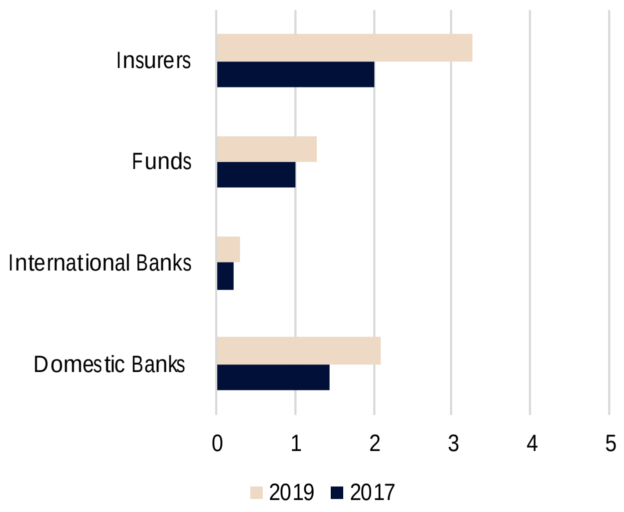


Figure 3: Systemic Vulnerability Index (SVI)



Insurance undertakings rank highest in terms of vulnerability, due to their links with both banks and investment funds in terms of deposits and equity holdings respectively. Moreover, the vulnerabilities also capture their ownership links with certain domestic institutions.

When comparing the results for 2019 with those obtained using 2017 data, it is interesting to note the significant increase in systemic relevance of core domestic banks as well as the overall rise in vulnerability. This reiterates the concept that although the number of links between institutions has decreased, the remaining linkages are larger which thus may cause more significant disruptions.

Nonetheless, the absence of system-wide cascades in both rounds of simulations supports the notion that contagion risk within the financial sector remains subdued.

Direct linkages appear to be the most relevant with low amplification factors being recorded across the sample.

Table 3 Average amplification factor

	June 2017	June 2019
Domestic Banks	1.09	1.20
International Banks	1.01	1.01
Domestic Investment Funds	1.15	1.06
Domestic Insurance undertakings	1.10	1.03

Once again, the failure of domestic banks has the largest effect, with an additional 20% of losses being generated through an indirect impact from equity holdings.

While evidence points towards low loss amplification, these results are to be interpreted with caution since the model fails to include overlapping portfolio effects whereby the failure of an institution may result in a fire-sale thus lowering the price of other assets. Further to this, additional consideration should be given to potential runs or herding reactions which the market may have should one of the key players fail. With these factors in mind, the results presented in this section may be viewed as a lower benchmark value of the actual losses to be incurred, should a failure of an institution occur.

7. Conclusion

The results from the simulations as well as the key metrics calculated from the network representation in Section 3, uphold the notion that the network is robust to institution defaults when considering contagion effects through direct exposures and second round effects. Nonetheless, when comparing the results for June-2017 and June-2019, the number of linkages has diminished while the amplification factor is on the rise. This suggests that the financial sector is moving towards a more centralised network, suggesting lower diversification and a higher possibility of contagion.

While these findings have interesting implications for supervisors and policy makers, they are to be interpreted with caution due to the simplifications underlying the model. Firstly, the current model is purely mechanistic and does not take into account behavioural considerations. As outlined by Gai et al (2011) this may be one of the main reasons as to why network models have failed to gain traction in mainstream economics, especially given that these dynamics are thought to be of importance during times of distress. Caccioli et al (2014) attempted to include some market reactions by extending their model to cater for portfolio rebalancing by financial institutions. They found that portfolio rebalancing can exacerbate contagion. This result has been attributed to additional downward pressure resulting from additional sales which further depress prices (Thurner et al., 2012).

In addition, the model presented in this paper is limited to direct exposures between entities; however, following the failure of an institution other players may face a portfolio devaluation due to common asset holdings. In brief, distress in one financial institution can lead to a fire-sale of assets which depresses the asset value and therefore causes a loss in the portfolio value of other institutions. (Gorton and Huang 2004; Cifuentes et al. 2005; Neir et al. 2007). By mapping any portfolio overlap and adding a common asset channel to the network dynamics, a more realistic measure of contagion risk can be obtained. This seems to be the way forward in this type of analysis, as outlined by Poledna and co-authors (2018) in their analysis of the Mexican system.

In essence, the estimates of contagion presented in this paper can be viewed as a "lower bound" of contagion, and actual effects are likely to be stronger. Nonetheless, the model presented, as well as the key indicators used, serve as a tool for stress testing by macroprudential supervisors, a step in the right direction towards a more comprehensive view of systemic risk.

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