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Nestedness and systemic risk in financial networks[☆]

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ABSTRACT

In this paper, we explore the relationship between node nestedness contribution and network stability in financial networks. We rely on data from the Brazilian interbank market. For each bank in the network, we computed the individual nestedness contribution (INC), along with two measures of systemic risk: systemic impact (SI) and systemic vulnerability (SV). The INC is computed considering the different roles played by the banks: lender and borrower. We found that borrowing banks with a higher INC would cause more damage to the network if they were hit by a shock — i.e, they have a higher SI. Moreover, lending banks with a higher INC are more vulnerable to shocks on the network.

1. Introduction

Nestedness is a hierarchical structure commonly observed in complex networks. In a perfectly nested network, the neighbors of a node also interact with the nodes with a higher topological measure — usually, the degree. The nodes with many (few) counterparties are called *generalists* (*specialists*). Specialists interact mostly with generalists, and interactions among specialists are unusual (Bascompte et al., 2003).

A simple illustration of a perfectly nested network is depicted in Fig. 1. We portray a network of banks, labeled as B1, …, B6. A red square means that the bank in the corresponding column is connected to the bank in the corresponding row, in the sense that both extended loans to at least one firm in common. Looking at the columns (rows), banks have a degree equal to or greater than that of the banks located at the right (below). The connections of a given bank are also connected to the banks with a higher or equal degree. For instance, banks 1 and 2 are connected to bank 5, and they are also connected to banks above (or to the left at) bank 5. The more generalist (specialist) banks correspond to the columns located on the left (right) of the figure.

Nestedness is closely related to some network topological properties.[1] Some studies (Jonhson et al., 2013; Abramson et al., 2011) confirmed that nestedness is significantly correlated with disassortativity. Lee et al. (2016) point out that nestedness is

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[1] Those who are unfamiliar with the main concepts of network science may refer, for instance, to Barabasi (2016).

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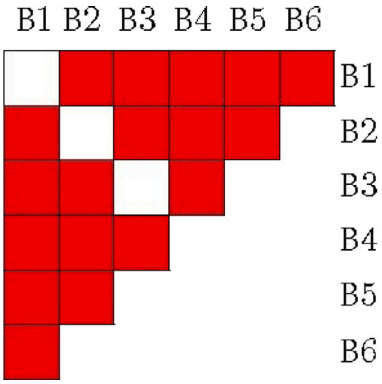

Fig. 1. Example of a perfectly nested bank network. The connections of a given bank compose a subset of the connections of the banks with a higher or equal degree.

a generalization of the core–periphery structure. Payrató-Borras et al. (2019) propose that the most heterogeneous networks in terms of degree distribution are also the most nested ones. Moreover, nestedness also correlates with properties not captured by the topological structure of the network. Nestedness minimizes competition and allows for the coexistence of a higher number of species in ecological networks (Bastolla et al., 2009). Bustos et al. (2012) show nestedness in industrial ecosystems is quite stable, and hence it predicts the appearance and disappearance of individual industries in each location. The nestedness of world trade networks plays an important role in predicting countries' growth trajectories (Tacchella et al., 2012; Cristelli et al., 2017). Finally, nestedness is used to assess the performance of network reconstruction methods, as is done by Ramadiah et al. (2020) in their study on the Japanese bank-firm credit network.

Saavedra et al. (2011) follow a slightly different approach from the studies discussed in the previous paragraph. They focus on how the nodes' contribution to the network nestedness – rather than the nestedness of the whole network itself, as the above-mentioned studies – is related to network properties. Assessing an ensemble of flowering plant/insect pollinator networks and a network of designer and contractor firms in the New York City garment industry, they computed the nodes' contribution to the nestedness of the network by randomizing the nodes' connection (more details in Section 3.1). Next, they calculated the difference between the persistence of the network – defined as the fraction of remaining nodes at the end of the simulation – with and without the removal of a given node. They reached two main conclusions. First, the removal of a strong contributor to network nestedness tends to decrease overall network persistence more than the removal of a weak contributor. Second, strong contributors to nestedness are the nodes most vulnerable to extinction.

The purpose of this paper is to explore the relationship between node nestedness contribution and network stability in financial networks.[2] Using quarterly information from March 2012 through December 2015 of the Brazilian interbank (IB) market, we apply the methodology developed by Saavedra et al. (2011) to compute the individual nestedness contribution (INC) of banks. The INC of a given node is computed by comparing the nestedness of the network when the interactions of this node are randomized. Keeping the same number of connections, the original links are deleted, and new connections are created. The average nestedness of the randomized network is computed by performing such randomization as many times as possible (1,000 times, to be precise). The INC of the node is given by comparing the average nestedness of the randomized network to that of the original network. If the average nestedness increases (decreases) when the node links are randomized, its INC is positive (negative).

We innovate in this study by computing the INC according to the role played by the bank in the IB network — borrower or lender. To obtain the lending INC of a given bank, we randomize only its outgoing links – the loans granted by the bank – and keep its incoming links – the loans received by the bank – fixed. The borrowing INC is computed similarly through the opposite operation.

After computing the INC of the nodes, we assess the correlation between INC and two systemic risk measures presented in Alexandre et al. (2021): the systemic impact (SI) and the systemic vulnerability (SV) of the banks. While the former refers to the loss caused by a shock in the bank to the whole system, the latter measures the loss suffered by the bank in case of a shock in the system. In order to compute both SI and SV, we consider different levels of shock. Note that, according to Saavedra et al. (2011) findings, we expect to find a positive relationship between the INC and both SI and SV.

There are two meaningful correlations assessed in our study, in the sense that they involve variables associated with the same role played by the banks in the IB network (borrower or lender): the correlation between the lending INC and SV and the correlation between the borrowing INC and SI. Both are positive. Thus, borrowing banks that contribute the most to the nestedness of the network are those that would cause more damage to the network if they were hit by a shock. Moreover, lending banks with higher

[2] Despite nested networks having been discovered (Patterson and Atmar, 1986) and mainly studied in ecology (Bascompte and Jordano, 2013), nestedness has also been reported in financial (König et al., 2014), as well as in other economic networks (De Benedictis and Tajoli, 2011; Saavedra et al., 2009; Tacchella et al., 2012).

Table 1
Summary statistics of the IB network.

Quarter-year	N. of banks	Density	Avg. weighted degree[a]	Avg. net worth[a]
01–2012	128	0.0843	2747.6	3516.2
02–2012	128	0.0850	2940.7	3598.1
03–2012	130	0.0825	3142.7	3620.7
04–2012	130	0.0802	3257.2	3690.7
01–2013	130	0.0823	3604.7	3609.1
02–2013	128	0.0837	3401.2	3610.6
03–2013	127	0.0796	3474.4	3728.4
04–2013	127	0.0777	3557.1	3840.9
01–2014	130	0.0773	3551.3	3724.5
02–2014	130	0.0773	3433.9	3830.6
03–2014	130	0.0781	3756.4	3908.8
04–2014	129	0.0732	3970.7	3878.8
01–2015	129	0.0757	3966.3	3943.7
02–2015	130	0.0743	3819.8	4071.2
03–2015	128	0.0781	4023.9	4127.6
04–2015	126	0.0792	4111.5	4181.9

[a] In BRL million.

INC are the most vulnerable to shocks on the network. Therefore, considering these two correlations, the findings of Saavedra et al. (2011) are corroborated by this study. These results can be explained in light of the determinants of the INC and the systemic relevance of banks in IB networks.

We extend the analysis performed by Saavedra et al. (2011) in at least three ways. First, this is the first study to apply the methodology developed in Saavedra et al. (2011) to financial networks. Second, we assess the relationship between nestedness contribution and network stability considering partial shocks. In Saavedra et al. (2011), shocks are complete — i.e., nodes are removed. Here, we also consider the case in which nodes lost a fraction of their resources. Third, we disentangle the INC according to the role played by the node. Specifically, we compute the lending INC and the borrowing INC of the banks. Finally, this study is related to the literature on the role of topological features in identifying systemically important banks (Alexandre et al., 2021; Martinez-Jaramillo et al., 2014; Kuzubas et al., 2014; Ghanbari et al., 2018).

This paper proceeds as follows. Sections 2 and 3 discuss, respectively, the data set and methodological issues. In Section 4, we present the results concerning the correlation between INC and systemic risk. Finally, concluding remarks are presented in Section 5.

2. The data set

Using several unique Brazilian databases that comprise supervisory and accounting data, we extract quarterly information from March 2012 through December 2015 (16 periods) and build the bank-bank (IB) network.

The IB network comprises all types of unsecured financial instruments registered in the Central Bank of Brazil (BCB). Credit, capital, foreign exchange operations, and money markets are among the main types of financial instruments. Different custodian institutions register and control these operations: Cetip[3] (private securities), the BCB's Credit Risk Bureau System – SCR[4] (credit-based operations), and the BM&FBOVESPA[5] (swaps and options operations).

We compute the net financial exposures taking into account financial conglomerates or individual financial institutions (FIs) that do not belong to conglomerates (classified as "b1", "b2", or "b4" in the BCB's classification system[6]), removing intra-conglomerate exposures. As the shock to be assessed takes the form of a loss of a given fraction of the bank's equity, we exclude institutions with negative equity. FIs' equity was retrieved from https://www3.bcb.gov.br/ifdata. Some statistics of the IB network are presented in Table 1.

[3] Cetip is a depositary of mainly private fixed income, state and city public securities, and other securities. As a central securities depositary, Cetip processes the issue, redemption, and custody of securities, as well as, when applicable, the payment of interest and other events related to them. The institutions eligible to participate in Cetip include commercial banks, multiple banks, savings banks, investment banks, development banks, brokerage companies, securities distribution companies, goods and future contracts brokerage companies, leasing companies, institutional investors, non-bank financial companies (including investment funds and private pension companies) and foreign investors.

[4] SCR is a very thorough data set that records every single credit operation within the Brazilian financial system worth 200BRL or above. Up to June 30th, 2016, this lower limit was 1,000BRL. Therefore, all the data we assess have been retrieved under this rule. SCR details, among other things, the identification of the bank, the client, the loan's time to maturity and the portion of the loan that is overdue, modality of loan, credit origin (earmarked or non-earmarked), interest rate, and risk classification of the operation and the client.

[5] BM&FBOVESPA is a privately-owned company that was created in 2008 through the integration of the Sao Paulo Stock Exchange (Bolsa de Valores de Sao Paulo) and the Brazilian Mercantile & Futures Exchange (Bolsa de Mercadorias e Futuros). As Brazil's main intermediary for capital market transactions, the company develops, implements, and provides systems for trading equities, equity derivatives, fixed-income securities, federal government bonds, financial derivatives, spot FX, and agricultural commodities. On March 30th, 2017, BM&FBOVESPA and Cetip merged into a new company named B3.

[6] See https://www.bcb.gov.br/content/estabilidadefinanceira/scr/scr.data/metodologia.pdf.

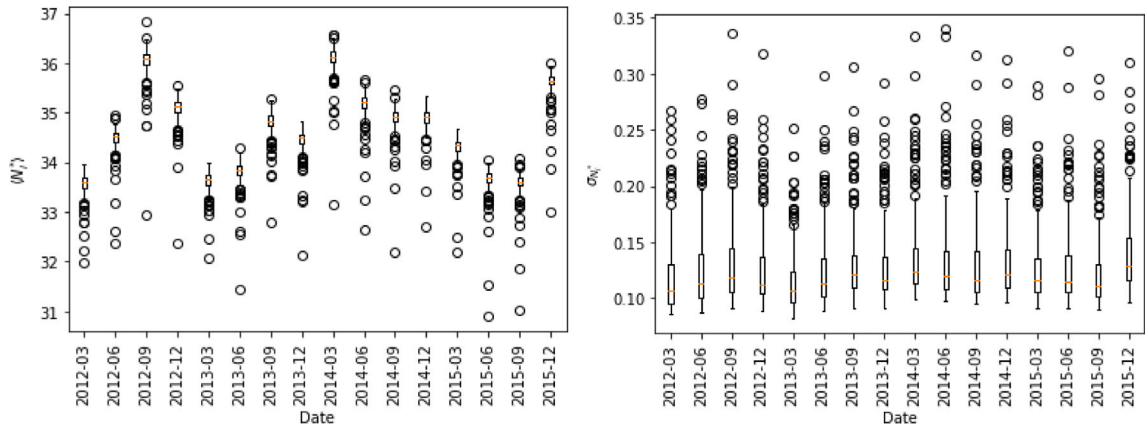

Fig. 2. Boxplots at different dates for $\langle N_i^* \rangle$ and $\sigma_{N_i^*}$.

3. Methodology

3.1. Measuring nestedness and INC

In this paper, the measure used to quantify nestedness is the Nestedness metric based on Overlap and Decreasing Fill (NODF) (Almeida-Neto et al., 2008; Ramadiah et al., 2020).[7] The NODF of the network, N, is defined by the following equation:

$$N = \frac{\sum_{i<j}^{C} M_{ij} + \sum_{i<j}^{R} M_{ij}}{\left[\frac{C(C-1)}{2}\right] + \left[\frac{R(R-1)}{2}\right]}. \tag{1}$$

In Eq. (1) above, C (R) is the number of nodes of the type displayed in columns (rows). Note that these numbers can differ in bivariate networks but will necessarily be equal in univariate networks. For every pair of nodes i and j, $M_{ij} = 0$ if $k_i = k_j$, and $M_{ij} = n_{ij}/min(k_i, k_j)$ otherwise, where k_i is the number of interactions of node i, and n_{ij} is the number of interactions in common between i and j. Thus, this is the number of nested interconnections (of both rows and columns) as a fraction of the total number of interconnections. N varies between 0 and 1, where 1 designates a perfectly nested network.

The INC is quantified following the methodology developed by Saavedra et al. (2011). The INC of node i is given by the following equation:

$$c_i = \frac{(N - \langle N_i^* \rangle)}{\sigma_{N_i^*}}, \tag{2}$$

where N is the network's observed nestedness (NODF), $\langle N_i^* \rangle$ is the average nestedness across a set of random replicates within which the interactions of node i have been randomized, and $\sigma_{N_i^*}$ is the standard deviation of N_i^*. Fig. 2 depicts the dispersion of these two variables at different dates.

We randomize the interactions of a node following the null model specified in Bascompte et al. (2003). Similar to Saavedra et al. (2011), we generate 1,000 random replicates. The randomization of the interactions of a given node i works as follows: we cancel some link between i and another node, and then we connect i with another node with which i does not have a connection. Node i is connected to another node j with probability[8]

$$p_{ij} = \frac{1}{2}\left(\frac{k_i}{C} + \frac{k_j}{R}\right), \tag{3}$$

supposing i is a node of the type displayed in columns (if i is a row-type node, k_i and k_j are divided by R and C, respectively, in Eq. (3)). Thus, according to Eq. (3), the rewiring is not random: nodes with a higher degree (as a fraction of the maximum degree) are more likely to be connected. We innovate in the computation of the INC by considering the different roles a node can play in a network. In bivariate networks, nodes play only one role. For instance, in a bank-firm credit network, banks are always lenders and firms, borrowers. However, in univariate, directed networks, our innovation can be quite useful. For example, in IB networks, all nodes are of the same type (banks), but a given node i can be a lender, a borrower, or both. We will compute the lending INC (INC_L) and the borrowing INC (INC_B). The former is obtained by randomizing only its outgoing links, which represent loans granted by i, and keeping its incoming links – loans received by i – fixed. The latter is computed similarly through the opposite operation.

[7] There is not a consensus on how nestedness should properly be quantified. For this reason, there are other metrics to measure nestedness being used, such as the *spectral radius* (Staniczenko et al., 2013). For more details, see, for instance, Payrató-Borràs et al. (2020) and Mariani et al. (2019), Section 3.1.

[8] See Saavedra et al. (2011), esp. Figure 1 and Methods, for details.

3.2. Systemic risk

Saavedra et al. (2011) show the nodes with higher INC are those whose removal leads to a decrease in network persistence – defined as the fraction of remaining nodes at the end of the simulation after the removal of a given node –, as well as are the more vulnerable to extinction. That is, shocks in strong contributors cause more damage to the whole network, and shocks in the network affect mostly the strong contributors. To test this hypothesis, we compute the *systemic impact* and *systemic vulnerability* – SI and SV, respectively (Alexandre et al., 2021) – for the banks participating in the Brazilian IB market. We take into consideration various levels of the initial shock.

Both SI and SV are computed following the *differential DebtRank* methodology (Bardoscia et al., 2015).[9] The exposure network of the IB market is represented by $\mathbf{A} \in N \times N$, where N is the number of banks and A_{ij} is the asset invested by *i* in *j*. At period 0, we impose an exogenous shock on FI *j*, reducing its equity by a fraction of ζ. It will cause a subsequent loss $L_{ij}(1)$ to its creditors, indexed by *i*, equal to $\mathbf{A}_{ij}\zeta$. At period 2, *j*'s creditors will propagate this loss to their creditors in a similar fashion, and so on. Formally, we have

$$L_{ij}(t) = min\left(A_{ij}, L_{ij}(t-1) + \mathbf{A}_{ij}\frac{[L_j(t-1) - L_j(t-2)]}{E_j}\right), \tag{4}$$

$$L_i(t) = min\left(E_i, L_i(t-1) + \sum_j \mathbf{A}_{ij}\frac{[L_j(t-1) - L_j(t-2)]}{E_j}\right), \tag{5}$$

in which $t \geq 0$, $L_i(t)$ is the aggregate loss suffered by *i* at *t*, and E_j is financial institution (FI) *j*'s equity. Thus, when an FI *j* suffers an additional loss equal to a fraction ζ of its equity, it will impose a loss to its creditors corresponding to ζ times their exposures towards *j*. Observe that equity positions and the exposure network are time-invariant, i.e., they are taken as exogenous. The propagation considers stress differentials rather than stress absolute values (hence the methodology's name) to avoid double-counting.

Observe L_{ij} cannot be greater than A_{ij}. It means that *j* cannot impose to *i* a loss greater than *i*'s exposures towards *j*. When $L_{ij} = A_{ij}$, *j* stops imposing losses on *i*. Moreover, L_i cannot be greater than E_i, i.e., *i*'s losses cannot be greater than its equity. When $L_i = E_i$, *i* stops propagating losses to other FIs.

The system converges after a sufficiently large number of periods $T \gg 1$. Then we have the final matrix of losses $\mathbf{L}^{j,\zeta} \in N \times 1$, where $L_j^{i,\zeta}$ is the total loss suffered by agent *j* after an initial shock of size ζ on agent *i*. After repeating this process for the other FIs, we compute our two measures of SR. The *systemic impact* (SI) of bank *i* is defined as

$$SI_{i\zeta} = \frac{\sum_j \left[L_j^{i,\zeta} - L_j^{i,\zeta}(0)\right]}{\sum_j E_j}, \tag{6}$$

where $L_j^{i,\zeta}(0) = \zeta E_j$ if $j = i$ and 0 otherwise. The *systemic vulnerability* (SV) is represented by the following equation:

$$SV_{i\zeta} = \frac{1}{N}\sum_j \frac{L_i^{j,\zeta} - L_i^{j,\zeta}(0)}{E_i}. \tag{7}$$

Therefore, $SI_{i\zeta}$ measures the fraction of the aggregate FIs' equity which is lost as a consequence of an initial shock of size ζ at FI *i*'s equity. On the other hand, $SV_{i\zeta}$ refers to the average *i*'s equity loss when the other FIs are reduced by ζ.

As we are interested only in the losses caused by the contagion, we remove the initial shock from the computation of the SR measures. Observe we also compute $SI_{i\zeta}$ for the FI that suffered the initial shock. Due to network cyclicality, a shock propagated by a given FI can hit it back. For the same reason, we include the loss imposed by an FI on itself in the calculation of $SV_{i\zeta}$.

4. Nestedness and systemic risk

Both SI and SV are computed for each node. We vary the level of the initial shock ζ within the interval [0.1,1] with step 0.1. Finally, we compute the correlation between INC (INC_B and INC_L) and systemic risk (SV and SI).

Like the INC_B, the systemic impact is a measure exclusive to borrowing banks. A shock on a bank that is not a borrower will not cause any impact, as it has no creditors to default on. Thus, by definition, non-borrowing banks have a null systemic impact, and banks with non-null systemic impact are necessarily borrowing banks. Similarly, both the INC_L and the systemic vulnerability are exclusive to lending banks. If a bank is not a lender, no other bank can default on it. Hence, the vulnerability of non-lending banks is null, and banks with non-null systemic vulnerability are necessarily lending banks. There are correlations between INC_B and SV and between INC_L and SI because there is an overlap between the different roles – lenders and borrowers – played by the banks in the IB network.[10] The INC_B of a given bank is explained by the features associated with its role as a borrowing bank, while its SV is associated with its role as a lending bank. Therefore, discussing the relationship between INC_B and SV can be misleading. The same can be stated about the relationship between INC_L and SI. Thus, we will compute these two more meaningful correlations, in the sense that both variables are associated with the same role played by the bank in the IB network (lender or borrower): (i) the correlation between INC_B and SI, and (ii) the correlation between INC_L and SV.

[9] The rest of this subsection strictly follows Alexandre et al. (2021).

[10] In our data set, 96% of the lending banks are also borrowers, while 94% of borrowing banks are also lenders.

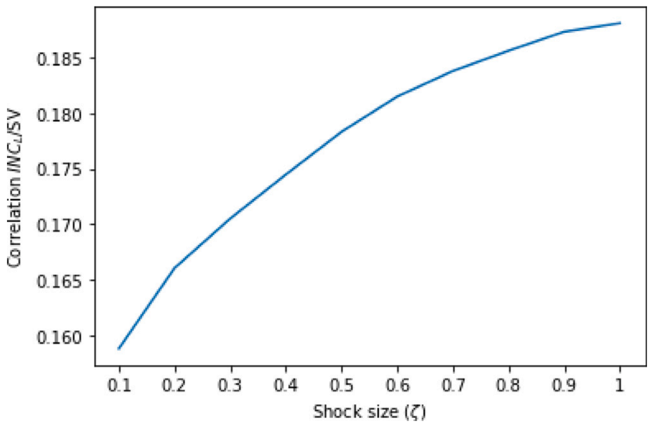

Fig. 3. Correlation between INC_L and SV. The correlation is statistically different from zero for all levels of ζ (p-value $< 10^{-12}$).

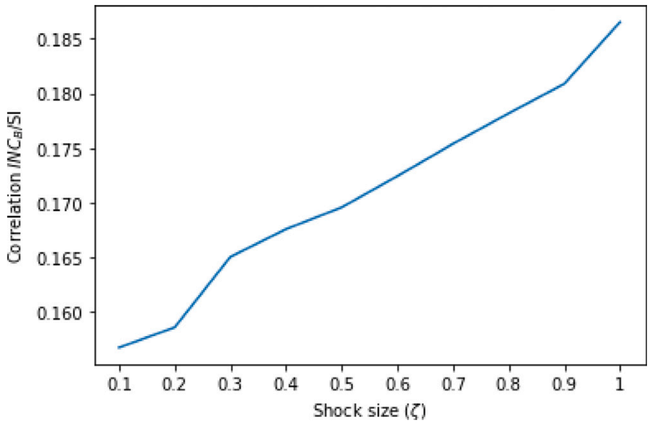

Fig. 4. Correlation between INC_B and SI. The correlation is statistically different from zero for all levels of ζ (p-value $< 10^{-12}$).

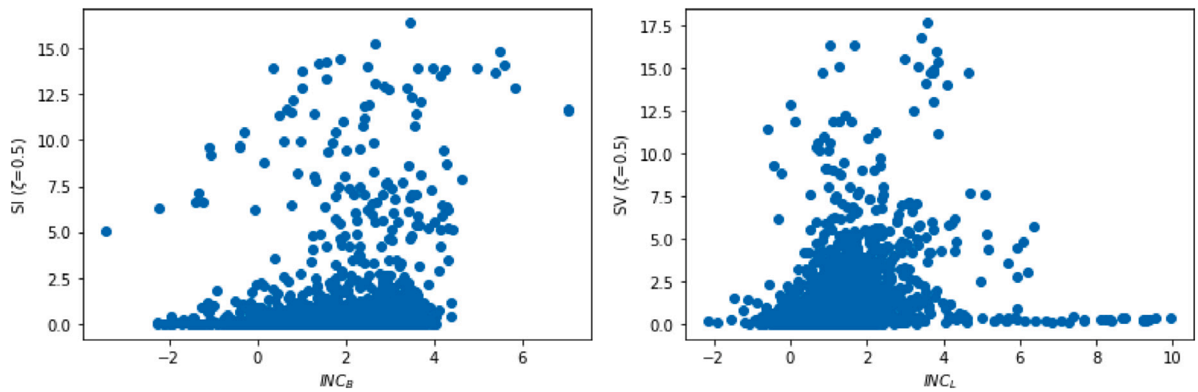

Fig. 5. Scatter plot between INC_B and SI (left) and between INC_L and SV (right) for ζ=0.5.

We find that INC_L and node vulnerability are positively correlated (Fig. 3). We observe the same correlation between INC_B and systemic impact, as can be seen in Fig. 4. The scatter plots in Fig. 5 show these correlations in a more disaggregated manner. In both cases, the absolute value of the correlation increases with the size of the initial shock. This non-linearity may be mainly due to the non-linearity of the two measures of systemic risk in relation to the size of the shock, rather than a non-linearity in the correlation itself. In response to an increase of $x\%$ in the size of the initial shock, systemic risk will increase at a rate greater than this.

4.1. Interpreting the results

The two correlations computed in this study are positive, corroborating the findings of Saavedra et al. (2011). Thus, the lending banks that contribute the most to the nestedness of the whole network are also the more vulnerable to shocks on the IB network, and the borrowing banks that contribute the most to the nestedness of the whole network are those that would cause more damage to the entire network if hit by a negative shock.

These results can be explained in light of the determinants of the INC and the systemic relevance of banks in IB networks. Concerning the correlation between INC_B and SI, Alexandre et al. (2023) found that the INC of borrowers in the IB network is mainly driven (positively) by the weighted in-degree and (negatively) by the weighted out-degree. These variables correspond to the IB liabilities and assets, respectively. Moreover, according to Alexandre et al. (2021), the correlation between the IB liabilities (assets) and systemic impact is positive (negative). Thus, borrowing banks with large (small) IB liabilities (assets) have a higher contribution to the nestedness of the IB network and also a higher systemic impact on it. Regarding the relationship between INC_L and SV, the former is mainly driven by the (weighted and unweighted) out-degree (Alexandre et al., 2023). At the same time, these variables are positively related to systemic vulnerability (Alexandre et al., 2021). Therefore, banks with large out-degrees are more vulnerable to shocks in the IB market and, at the same time, contribute more to the nestedness of the IB network.[11]

5. Final considerations

In this study, we assessed the correlation between nestedness and systemic risk in the Brazilian IB market. Considering the nestedness of the network as measured by the NODF, we calculated the individual nestedness contribution (INC) of the banks, which is a measure of the bank contribution to the network nestedness. The INC was computed separately for the different roles played by banks in IB markets, lender and borrower.

We assessed the relationship between INC and systemic risk. We computed the correlation between (i) the borrowing INC and the systemic impact (SI) – the loss caused in the network by a shock on the node, and (ii) the lending INC and systemic vulnerability (SV) – the loss suffered by the node due to a shock in the network. While the variables involved in (i) are exclusive to borrowing banks, the variables in (ii) are exclusive to lending banks. Both correlations are positive. Thus, borrowing banks that contribute the most to the nestedness of the network are those that would cause more damage to the network if they were hit by a shock. Moreover, lending banks with higher INC are the most vulnerable to shocks on the network. Furthermore, the absolute value of these correlations increases with the size of the initial shock.

This paper contributes to the literature on the determinants of the systemic relevance of FIs. Many studies (Alexandre et al., 2021; Martinez-Jaramillo et al., 2014; Kuzubas et al., 2014; Ghanbari et al., 2018) show that topological features are at least as important as financial variables in driving the systemic importance of FIs. This paper reinforces the importance of topological features in predicting the systemic relevance of FIs. We show that a topological variable – the INC – is correlated not only to the systemic impact but also to the systemic vulnerability of a given FI. Shocks on borrowing banks with higher INC would cause a higher loss in the whole system. Moreover, shocks in the system would cause more damage to lending banks with a greater INC. Thus, the inclusion of the INC as a potential explanatory variable would increase the performance of models aiming at predicting the systemic relevance of FIs. Moreover, the sign of the correlation between INC and both dimensions of FI's systemic relevance is the same. This is not always the case for important topological drivers of FI's systemic importance. For instance, Alexandre et al. (2021) show that PageRank is the main driver of banks' systemic impact and is positively correlated to this dimension. However, the correlation between PageRank and banks' systemic vulnerability is negative. In turn, the INC is positively correlated to both systemic impact and systemic vulnerability.

The methodology proposed in this paper provides policymakers with an easier-to-compute measure of FIs' systemic relevance. The INC requires only information on the connections between the banks to be computed. On the other hand, the DebtRank also requires information on the weight of these connections (e.g., the value of the loans) and the banks' financial statements. A natural follow-up study of this paper would investigate the INC as a driver of the systemic importance of the banks in a model including other explanatory variables.

CRediT authorship contribution statement

Michel Alexandre: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Felipe Jordão Xavier:** Methodology, Supervision. **Thiago Christiano Silva:** Data curation, Supervision. **Francisco A. Rodrigues:** Formal analysis, Methodology, Supervision.

[11] As an additional exercise, we computed the correlation between the total INC – the sum of INC_L and INC_B – and the measures of systemic risk. Only the systemic impact correlates positively to the total INC. It means that SV and SI are negatively correlated. In fact, the correlation between SV and SI in our data set ranges between −0.10 and −0.16, depending on the size of the initial shock. It leads to a stable scenario in case of shocks in the Brazilian IB market. The banks most likely to damage the system if they suffer losses (high SI) are less likely to get hit by losses suffered by other banks (low SV). A strong positive correlation between SI and SV could be interpreted as an unstable or explosive scenario, as those banks are more likely to cause losses to the system if they are hit by negative (exogenous or endogenous) shocks and are also the banks most likely to be hit by such shocks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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