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Financial networks, bank efficiency and risk-taking☆

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ABSTRACT

Networks with a core–periphery topology are found in many financial systems across different jurisdictions. Though the theoretical and structural aspects of core–periphery networks are clear, the consequences that core–periphery structures bring for banking efficiency stand as an open question. We address this gap in the literature by providing insights as to how the structure of financial networks can affect bank efficiency. We find that core–periphery structures are cost efficient for banks, which is a characteristic that encourages the participation of banks in financial networks. On the downside, we also show that core–periphery structures are risk-taking inefficient, because they imply higher systemic risk levels in the financial system. In this way, regulators should be aware of the excessive risk inefficiency that arises in the financial system due to individual decisions made by banks in the network.

1. Introduction

Bank efficiency has been on the top of the research agenda in the past decades (Berger et al., 2009; Duygun et al., 2013; Tabak et al., 2013). Though it has been extensively studied in the literature, little is known on the role financial networks play in promoting bank efficiency. Considering that banks interconnect through a diversity of complex financial operations in modern financial networks, it is imperative that banks understand where they stand inside the network and also how the financial network can influence their day-to-day operations. In this work, we address this gap in the literature by providing an empirical study on how financial networks and their structure can affect bank efficiency.

We study the Brazilian financial network that comprises more than 120 unsecured and secured financial instruments between banking institutions. We consider the most representative financial instruments in terms of trading volume, which are: interfinancial deposits, repos with federal securities, onlending, credit assignment and loans. In this way, our financial network encompasses the notion of interbank market, but is not limited to the classical operations that banks often perform in this market, which are mainly to deal with liquidity issues due to unexpected cash outflows or regulatory restrictions associated with reserve requirements. In the next paragraphs, we discuss some operations that banks may perform in the financial network with the goal of minimizing costs or of obtaining profit, thus affecting their overall efficiency.

In the Brazilian jurisdiction, though the compulsory deposit requirements are employed mainly as a macroprudential tool by the central bank, banks can obtain reductions on their deposit requirements by channeling their credit to the financial operations on mortgage loans, rural credit, and microfinance. In addition, banks can still enjoy this incentive by outsourcing these types of financial operations to other banks whose activities are specialized towards those financial operations. In this way, they avoid the costs of creating an internal framework to enter these markets that are not related to their business lines, in which they do not enjoy comparative advantage. Thus, banks may decide that outsourcing these obligations to specialized counterparties via the financial network is optimal in terms of cost minimization and hence profit maximization.

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In credit assignment, banks sell part of their investment portfolios to other counterparties to raise funds and fulfill liquidity issues. Banks can group together and use these financial instruments to obtain mutual benefits with cost savings and increased profits. For instance, banks that are competitive in lending to the non-financial sector and do not have the same ability as fundraisers can borrow funds from banks with excess of liquidity, thus obtaining the necessary fund to supply credit to the non-financial sector. In light of this association, both banks would be acting in their business lines that they possibly enjoy comparative advantage and would therefore have increased credit portfolios. In any case, banks would establish these operations at the cost of having to incur or transfer to counterparties substantial risks.

Financial bills are a fixed income instrument with minimum maturity of two years that allows fundraising term extension for banks. Since they are long-term financial operations that are non-redeemable, they provide means for reducing the liquidity shortage vulnerability of the issuer. Furthermore, banks have incentives to obtain funds using these financial instruments because they are exempt from additional reserve requirements. Consequently, they reduce liquidity maintenance costs and hence improve their cost and profit management over the raised funds.

The hypothesis that financial network and its structure can affect bank efficiency is also shared across jurisdictions. For instance, Iori et al. (2008) report changes in the network structure of the Italian interbank market during the pre-crisis period, in which banks gradually increase the number of banks from which they borrow funds while at the same time they are willing to supply credit to a smaller number of banks. The authors attribute this behavioral change to the liquidity shortage that non-large banks were facing due to the increase of credit demand by the non-financial sector. In other macroeconomic conditions, such as in the introduction of the Euro currency, Italian banks seemed to prefer lending liquidity to the European market rather than to the non-financial sector. In a related work, Monticini and Ravazzolo (2014) find that frictions in the interbank market, such as a consequence of liquidity crises, permit banks to obtain positive intraday interest rate spreads, leading to economic gains due to arbitrage. These works corroborate our claim that banks, besides adjusting liquidity and regulatory constraints, can make use of connections in the financial networks to improve their efficiency levels.

Banks engage in financial networks in diverse ways. For instance, large banks normally have better investment opportunities outside the financial network and may not have incentives to lend to non-large banks. Thus, they may demand a large spread to maintain financial operations with non-large banks in case they decide to forgo external options and accept opportunities in the interbank market. Creditor banks can also charge an extra spread in case the debtor is in stressed positions or during operations that occur at the end of the day, period at which banks have little room to adjust to their daily reserve requirements at the Central Bank. In turn, non-large banks with excess of liquidity may prefer to lend in the financial network given the low risk levels associated with these operations.

Considering the broad range of financial operations that the Brazilian data set captures and the evidence found so far in the literature, it is then reasonable to assume that banks use, among other factors, other counterparty banks that are participants in the financial networks as input resources to improve efficiency. In this respect, this paper explores the role that the network structure brings to bank efficiency. To the best of our knowledge, there is virtually no research linking network theory to bank efficiency.

One of the trends that has been documented in the banking literature is the emergence of core–periphery networks in several financial systems. Core–periphery structures present two perceptible mesoscale structures: the core and the periphery. Core members intermediate financial operations between members of the periphery and are also strongly connected to other core members. In contrast, periphery members can only establish a few connections with core members and not among similar peers. Reports in the literature converge to the fact that the core–periphery structure is the usual network structure found in financial networks. Among the evidences, we can highlight the financial networks in the UK (Langfield et al., 2014), the Netherlands (in 't Veld and van Lelyveld, 2014), Germany Craig and von Peter (2014), among others. Though the theoretical and structural aspects of core–periphery networks are clear, the consequences that core–periphery structures bring for the banking efficiency stand as an open question that we investigate in this work.

Lux (2015) supplies a theoretical model that attempts to explain the recurrent emergence of core–periphery in financial networks. He claims that the core–periphery structure is a natural consequence of a banking system with heterogeneous balance sheet size as we historically find in industrialized economies. Lux (2015) also shows that non-observability of the full network structure along with the existence of relationship lending are ingredients that reinforce the existence of core–periphery structures.

Our hypothesis is that it is costly for banks to engage in operations with different counterparties in the financial network due to, among other factors, monitoring costs. It is expected that large banks with large amounts of cash surplus will engage in financial operations with many counterparties as they would benefit from diversification. In addition, banks may need to transact with more counterparties because a single one may not be able to fulfill their needs. In both cases, banks will engage in financial operations with many counterparties as long as the marginal benefits of diversification are higher than the associated marginal costs of these transactions. Given that real financial networks have strong bank size heterogeneity distributions with the presence of few large banks and several small banks, we should therefore expect the emergence of a core–periphery topology in these networks. The core would be composed of a small fraction of banks – mainly large banks – that has many counterparties and the periphery would comprise banks with a small number of interconnections. Our first hypothesis to be tested is then:

Hypothesis 1. The core–periphery structure contributes to better efficiency levels of banks.

We can test efficiency from two different perspectives: cost and profit efficiencies. Banks can engage in financial operations in the financial network to manage their costs or to boost their profits. Traditionally, the literature has focused on the cost efficiency side of banks. The main goal of banks, however, is to maximize profits, which may be achieved not only by minimizing costs but also by maximizing revenues as well. The computation of profit efficiency thus supplies bank management with more information than just the cost efficiency evaluation. Our results will provide some insights on whether the financial network topology (core–periphery structure) has an effect on cost or profit efficiency. Our main hypothesis can then be split into two:

Hypothesis 1a. The core–periphery structure contributes to better cost efficiency levels of banks.

Hypothesis 1b. The core–periphery structure contributes to better profit efficiency levels of banks.

In this work, we also explore how the network structure affects the risk-taking efficiency levels of banks. In this respect, we expect that the participation of banks in interbank funding and investment decisions is a factor that explain not only bank cost and profit efficiency but also more importantly the risk-taking efficiency. We consider as risk-taking efficient those banks that lend or borrow in the financial network and thus increase their output production without increasing their risk-taking levels. In this case, the interpretation is how banks can produce services and outputs given the inputs they have and perform well with lower risk-taking levels. Banks in the frontier are banks that produce more services, given the inputs they use, and have lower risk-taking levels, and therefore are financially sound.[1] In this sense, our model may also subside bank supervision in that it permits the identification of banks that assume excessive risk-taking with regard to their counterparts.

An important feature of core–periphery structures is that they imply in higher systemic risk. Concerning bank liquidity issues, Lee (2013) performs a comparative analysis between different types of financial network structures and finds that core–periphery structures with deficit core banks give rise to the highest levels of systemic liquidity shortage. In addition, core–periphery structures can also be seen as a particular type of scale-free networks, in which each network core corresponds to a hub. In network theory, for the same level of bank capitalization, the scale-free network is known to be the network structure with the highest contagion speed (Silva and Zhao, 2016), which is another evidence favoring risk buildup and spread potentialities.

Banks engage in financial operations not only to maximize profits but also to minimize assumed risks. Banks may find better opportunities in the interbank network as their counterparties normally have lower risks than other segments, such as the non-financial sector. We expect that, as banks engage in interbank operations, they also change their risk profiles. At the same time, while it may be individually advantageous to banks to engage in connections in financial networks from the risk viewpoint, the resulting global network structure – which is constructed by the decisions of all of the economic agents at once and, according to empirical evidence, has a core–periphery structure – implies higher systemic risk levels and hence higher social costs in case of materialized risks. Therefore, we also test the relation between how compliant the network is to a perfect core–periphery structure and the risk-taking efficiency profile of banks:

Hypothesis 2. The core–periphery structure reduces the risk-taking efficiency levels of banks.

We employ Battesi and Coelli (1995)'s model to estimate the cost, profit and risk-taking efficiency levels of banks. We control for the different roles that a bank may play inside a network using strictly local and mixed network measures (Silva and Zhao, 2016). We discriminate between core and peripheral members using the closeness network measurement as proxy, which assumes larger values the closer a bank is to other banks in the network. Thus, the coreness property of a member is stronger the larger its closeness measure is. We also discriminate between banks that act mainly as investors or borrowers in the financial network using the in- and out-strength network measurements, which extract the bank-level total borrowing and lending amounts inside the network, respectively.

To give us a sense of the importance of the financial network for banks in their overall funding portfolios (external and internal financing), we also control for the interbank funding to total funding ratio. We also control for bank size to absorb the differences in the banks' lending and borrowing potentialities. We also interact bank size with the network measurements to verify the role bank size plays as an attenuator or amplifier of bank efficiency levels. Finally, we also control for other bank features such as capitalization, asset quality and ownership to absorb bank particularities and decisions that are external to the network.

We find evidence to support hypothesis H1a in the Brazilian financial network. We verify that banks absorb the effects of the network structure in heterogenous manners. In this respect, we find that non-large banks have sharper reductions in their efficiency levels the more the network topology distances from a perfectly compliant core–periphery structure when compared to large banks. In contrast, we cannot accept H1b since the results show that the core–periphery network topology is not one of the drivers for explaining profit inefficiency of banks. In relation to the risk-taking perspective, we find evidence to support hypothesis H2. In sum, the core–periphery structure implies cost efficiency with the drawback of being risk-taking inefficient.

Regarding the bank role in the network, we conclude that banks in the core, though more cost efficient, are less profit and risk-taking efficient. Conversely, banks in the periphery are less cost efficient, but more profit and risk-taking efficient. We also find evidence showing that banks that lend and borrow more in volume from the financial network have, on average, better risk-taking efficiency. Therefore, even though it may be individually better for banks to participate in the financial network, the resulting network structure that emerges implies in risk-taking inefficiency for banks.

A major concern regarding the results is the possibility of potential endogeneity, which may bias our results. We expect that core–periphery topology to have an impact on bank efficiency. Since the topology is a global measure, a single bank cannot change the topology to a large extent by simply modifying its financial operations with counterparties. Moreover, a bank normally does not have information about the network topology as a whole due to incomplete information. Therefore, it is fair to assume that most banks cannot individually change the network topology. In this respect, the endogeneity problem due to mutual causality is reduced. We also address the endogeneity issue by performing robustness test by regressing bank inefficiency levels on one- and two-lagged measures of interconnectivity. We find that the results are robust and qualitatively the same.

The paper proceeds as follows. Section 2 presents the estimation methodology and the interconnectivity measures. Section 3 provides information about the data set. Section 4 presents the empirical results and discussions. Finally, Section 5 concludes the paper.

2. Methodology

In this section, we specify the empirical model and the variables we employ to estimate the efficiency of Brazilian banks. We also define the network measures that we employ as proxies for capturing the bank interconnectivity and network topology, in special the core–periphery structure.

2.1. Measuring efficiency

The most common approaches to estimating efficiency are non-parametric and parametric techniques. Non-parametric techniques generally focus on technological optimization rather than economic optimization (Sun et al., 2013). In this paper, we are interested in the economic optimization and some of its interconnectivity determinants. Thus, we apply the well-known parametric method Stochastic Frontier Analysis (SFA) proposed simultaneously by Aigner et al. (1977) and Meeusen and Van den Broeck (1977).

The literature usually employs two different economic efficiency concepts to measure efficiency of financial institutions: the cost and profit efficiency. The cost efficiency is the most used

[1] We can also look at risk-taking efficient those banks that present a lower risk-taking level per return unit.

efficiency criterion in the literature. In particular, considering that banks produce the same output under the same conditions, cost efficiency measures how close to the minimum cost a bank is, in which this minimum cost is determined by banks with the "best practices" in the sample (Berger et al., 2009).

In contrast, though not widely employed in the literature, profit efficiency is considered more informative than cost efficiency. Some researchers argue that cost efficiency offer only a partial vision of banks, because it overlooks revenues (Maudos et al., 2002). The profit maximization strategy that is conducted by banks comprises two complementary components: (1) minimization of costs in producing goods and services and (2) maximization of revenues. Therefore, while cost efficiency only looks at only the first component, profit efficiency is a more comprehensive measure in the sense that it analyzes both components simultaneously.

In this work, we also explore the risk-taking efficiency dimension. In this respect, we expect that the use of interbank funding and the relative importance of banks within the network are factors that explain not only bank cost and profit efficiency but also more importantly their risk-taking efficiency. Therefore, efficient banks should be lending or borrowing in the financial network and increasing their output production without increasing their risk-taking. A bank is considered more risk-taking efficient than another one if it incurs in less risks to produce the same amount of outputs with a given quantity of inputs. Therefore, the model enable us to identify banks that present excessive risk-taking with regard to their counterparts, which is relevant question for bank supervision. Risk-taking efficiency has already been employed in the literature to evaluate competition of banks. For instance, Fang et al. (2011) and Tabak et al. (2012) find that banks that are more risk-taking efficient have advantages over banks that take excessive risk in providing the same kind of outputs with the same kind of inputs.

In order to investigate the impact of the network topology on bank inefficiency, we employ Battesi and Coelli (1995)'s stochastic frontier model, which estimates both the efficiency degree and the coefficients of the exogenous variables. This specification avoids the bias of the usual two-step approach, in which efficiency is assumed to be half-normally distributed in the first step, while it is assumed to be normally distributed and dependent on the explanatory variables during the second step.

We estimate inefficiency levels using the translog functional form for the cost, profit and risk-taking functions. We evaluate the inefficiency level of the cost function as follows:

$$\begin{aligned}\ln\left(\frac{C}{w_2 z}\right)_{it} = {} & \beta_0+\sum_{j=1}^{3}\beta_j \ln\left(\frac{y_j}{z}\right)_{it}+\frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk}\ln\left(\frac{y_j}{z}\right)_{it}\ln\left(\frac{y_k}{z}\right)_{it} \\ & +\alpha_1\ln\left(\frac{w_1}{w_2}\right)_{it}+\frac{1}{2}\alpha_{11}\ln\left(\frac{w_1}{w_2}\right)_{it}\ln\left(\frac{w_1}{w_2}\right)_{it} \\ & +\sum_{k=1}^{3}\theta_j\ln\left(\frac{y_j}{z}\right)_{it}\ln\left(\frac{w_1}{w_2}\right)_{it}+\text{year dummies}_t \\ & -u_{it}+v_{it}, \end{aligned} \quad (1)$$

in which i and t are indices for banks and time, respectively. The indices $j, k \in \{1, 2, 3\}$ are three output variables and $\beta_{jk} \equiv \beta_{kj}$. The dependent variable C represents the bank's total costs. The three outputs (y) are:

- total loans net of non-performing loans;
- total liquid assets; and
- total deposits.

We use two input prices (w):

- w_1: interest expenses to total deposits ratio as a proxy for the price of funding; and
- w_2: total non-interest expense to total assets ratio as a proxy for the price of capital.

In addition, we employ a single fixed input (z): total earning assets. Note that we normalize the cost function by the bank's total earning assets (z) to reduce the heteroscedasticity and to allow banks of any size to have comparable residual terms from which the inefficiency levels are estimated. The normalization by the price of capital (w_2) ensures price homogeneity and should be interpreted as the price of both physical and human capital. The term v_{it} is a random error that incorporates both measurement error and luck and u_{it} term is associated with a bank's inefficiency level. We also include time dummies to account for changes in technology or in the economic and regulatory environments.

Following Battese and Coelli (1995), the inefficiency effect u_{it} is specified as:

$$u_{it} = \delta_0 + \delta_{it}^{(1)} x_{it} + \delta_{it}^{(2)} b_{it} + \delta_t^{(3)} g_t + m_{it} \quad (2)$$

in which the random variable m_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-(\delta_0 + \delta_{it}^{(1)} x_{it} + \delta_{it}^{(2)} b_{it} + \delta_t^{(3)} g_t)$. The vector x_{it} represents the explanatory variables for bank inefficiency and the vectors b_{it} and g_t indicate bank-level and global network topology measures.

Eqs. (1) and (2) are estimated simultaneously by the maximum likelihood method using the implementation presented by Belotti et al. (2013). The profit and risk-taking efficiency frontiers are estimated similarly using the econometric model in (1), but with different dependent variables.

When computing the profit inefficiency, we use the same model specification as in (1) except for the following modifications. First, the profit variable P can assume negative values, so we cannot directly apply the natural logarithm onto it. To overcome this issue, we follow Bos and Koetter (2011) who introduce an additional independent variable: the Negative Performance Indicator (NPI). We compute NPI as follows:

$$NPI = \begin{cases} 1, & \text{if } P > 0 \\ |P|, & \text{if } P \leq 0 \end{cases}. \quad (3)$$

Secondly, we use the following dependent variable $\overline{P}$ to evaluate the profit inefficiency in (1):

$$\overline{P} = \begin{cases} P, & \text{if } P > 0 \\ 1, & \text{if } P \leq 0 \end{cases}. \quad (4)$$

To estimate the risk-taking inefficiency, we also use the same functional form as in (1) but with the following modifications. We now use the Z-score measure as the dependent variable for the risk-taking inefficiency. Z-score is a proxy for risk-taking that has been widely employed in many studies that evaluate bank risk-taking behavior.[2] We compute the Z-score as:

$$Z - \text{score} = \frac{\overline{RoA} + \overline{\text{Capital Ratio}}}{\sigma_{RoA}}, \quad (5)$$

in which $\overline{RoA}$ is the average return on assets, $\overline{\text{Capital Ratio}}$ is the average equity-to-assets ratio, and σ_{RoA} is the standard deviation of the return on assets. The Z-score of a bank measures the number

[2] See, for instance, Mercieca et al. (2007), Laeven and Levine (2009), Houston et al. (2010) and Demirguç-Kunt and Huizinga (2013).

of standard deviations that its $\overline{RoA}$ has to decrease so that it becomes insolvent. In other words, Z-score is inversely proportional to the bank's probability of default. The Z-score also incurs in the same problem of the log transformation because it can assume negative values. In this way, we also apply Bos and Koetter (2011)'s variable transformation as defined in (3) and (4).

2.2. Network measures for capturing bank interconnectivity and network topology

We represent the financial network as a graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$, in which $\mathcal{V}$ is the set of vertices $\mathcal{E}$ is the set of edges. The cardinality of $\mathcal{V}$, $V = |\mathcal{V}|$, represents the number of vertices or banks in the network. The matrix $\mathbf{A}$ expresses the gross exposure or assets matrix (weighted adjacency matrix), in which the (i, j)th entry corresponds to the assets of the bank i towards j. We define the set of edges $\mathcal{E}$ by the following filter over $\mathbf{A}$: $\mathcal{E} = \{\mathbf{A}_{ij} > 0 : (i, j) \in \mathcal{V}^2\}$. In our analysis, there is no netting between i and j.[3] As such, if an arbitrary pair of banks owe to each other, then $\mathbf{A}$ will present two directed independent edges linking each other in opposite directions. An interesting property of maintaining the gross exposures in the network is that, if a bank defaults, its debtors remain liable for their debts.

We adapt complex network measures to characterize bank interconnections and extract the network topology of the Brazilian financial network. In special, we choose network measurements that extract information in three complementary perspectives (Silva and Zhao, 2012, 2015):

- *Strictly local measures*: these measures only use network-based characteristics from the bank. They are always vertex-level indices. We select the out- and in-strength measures in this category.
- *Mixed measures*: besides using strictly local information, these measures also use topological information from its direct and indirect neighborhoods. They are always vertex-level indices. We use the closeness measure in this category.
- *Global measures*: we compute these network measurements using the entire network structure. They are always network-level measures. We use the assortativity measure in this category.

We select those network measurements in such a way that their cross-correlations are small.[4] Using these network measurements, we expect to capture topological network characteristics that range from local to global aspects. We now introduce these network measurements with an emphasis on their economic meaning in the context of interbank networks.

2.2.1. Out- and in-strength: strictly local measures

The strength of a vertex $i \in \mathcal{V}$, indicated by s_i, represents the total sum of weighted connections of i towards its neighbors. When we deal with weighted networks, such as the Brazilian financial network, the notion of strength can be further decomposed into the in-strength, $s_i^{(\text{in})}$, and out-strength, $s_i^{(\text{out})}$, such that the identity $s_i = s_i^{(\text{in})} + s_i^{(\text{out})}$ holds. The feasible values of s_i corresponds to the continuous interval $[0, \infty)$.

The out- and in-strength of vertex $i \in \mathcal{V}$ are defined as:

$$s_i^{(\text{out})} = \sum_{j \in \mathcal{V}} \mathbf{A}_{ij}, \tag{6}$$

$$s_i^{(\text{in})} = \sum_{j \in \mathcal{V}} \mathbf{A}_{ji}. \tag{7}$$

In a network of exposures, the out-strength represents the amount of money that a bank has invested in that market, providing a measure of total exposure or dependence of that entity to a specific market segment. Note that as the out-strength of an institution increases, *ceteris paribus*, it is more likely that it will be more and more susceptible to impacts due to its potential higher vulnerability in that market. In contrast, the in-strength symbolizes the amount of money a bank has borrowed from players of that market segment.

2.2.2. Closeness: mixed measure

We compute the closeness of vertex i, ϵ_i, in accordance with the following expression (Latora and Marchiori, 2001):

$$\epsilon_i = \frac{1}{V-1} \sum_{\substack{j \in \mathcal{V} \\ j \neq i}} \frac{1}{p_{ij}}, \tag{8}$$

in which p_{ij} represents the shortest path length starting from i and ending at j. We evaluate the shortest paths using the directed graph. The closeness of i is the sum of the reciprocal of all of the shortest path lengths starting from i. For central vertices, the average shortest path distance is expected to be small, resulting in a large closeness index. Opposed to that, for peripheral vertices, we expect shortest paths to the remainder of the network to be relatively large, yielding a small closeness value.

Latora and Marchiori (2002) relate the concept of closeness to the propagation speed in complex networks, in the sense that propagate speed measures how well information propagates throughout the network. In this way, banks with a large closeness indices are strong diffusers or receipts of operations in the financial network both at global and local scales. These types of banks have facility in obtaining funding from other players in the market, as they play a central role in the network.

2.2.3. Assortativity: global measure

Assortativity is a network-level measure that, in a structural sense, quantifies the tendency of nodes to link with similar nodes in a network. The assortativity coefficient r is computed as the Pearson's correlation of degrees of nodes in each connected pair. In the financial network, the degree corresponds to the number of lending and borrowing financial operations the banks have in the network. Thus, it gives us a sense of the portfolio diversification. Positive values of r indicate that network links generally have nodes in their endpoints with similar degrees, while negative values indicate endpoints with different degrees (Newman, 2003). In general $r \in [-1, 1]$. When $r = 1$, the network has perfect assortative mixing patterns, while it is completely disassortative in the case $r = -1$. Considering that i_u and k_u represent the degrees of the corresponding vertices at the origin and destination, respectively, of the uth edge of a non-empty graph and that l is the number of links in the interbank network, we compute the assortativity r as follows (Newman, 2002):

$$r = \frac{l^{-1}\sum_{u \in \mathcal{E}} i_u k_u - \left[\frac{l^{-1}}{2}\sum_{u \in \mathcal{E}}(i_u + k_u)\right]^2}{\frac{l^{-1}}{2}\sum_{u \in \mathcal{E}}(i_u^2 + k_u^2) - \left[\frac{l^{-1}}{2}\sum_{u \in \mathcal{E}}(i_u + k_u)\right]^2}. \tag{9}$$

[3] We do not net out pairwise liabilities so as to maintain consistency with the Brazilian law, because financial compensation is not always legally enforceable.

[4] Network measurements are known to be highly correlated to each other. So we choose them carefully to minimize this problem.

Table 1
Total amount traded and the respective share in the Brazilian financial network as of December 2014.

	Repo Gov. Sec.	Interfinancial deposits	Credit	Credit assignment	Financial bills	Others
Total (R$ bi)	109.60	38.65	13.91	14.08	21.68	7.47
Share (%)	53.36	18.82	6.77	6.85	10.56	3.64

Silva et al. (2016) show that the Brazilian financial network presents a strong disassortative mixing pattern.[5] They also show that large banks are mostly located at the network core, while the periphery regions mainly correspond to banks that are non-large and assume the role of either borrowers or lenders, but generally not both.

In an ideal core–periphery structure, recall that core members intermediate financial operations between members of the periphery and are also strongly connected to other core members. In contrast, periphery members can only establish a few connections with core members and not among similar peers. In this way, non-compliance errors in the perfect core–periphery network model would occur, for instance, when periphery members interconnect to each another.

In this respect, Silva et al. (2016) provides evidence that the network assortativity is a good proxy to measure how compliant the network is to a perfect core–periphery network topology, given that the network has a core–periphery structure and that the network core is small.[6] For that, they show that the network assortativity closely relates to the error measure that Craig and von Peter (2014)'s methodology output to check how compliant a network is with an ideal core–periphery structure.

3. Data

In this paper, we use a unique Brazilian database with supervisory and accounting data.[7] From this database, we take quarterly information on unsecured and secured exposures in the Brazilian financial network. Our sample is an unbalanced panel that includes 92 banks over the period from 2008 to 2014, totaling 2.113 observations. There is a total of 123 financial instruments that are traded in the Brazilian financial network during the analyzed period.

Table 1 reports the total amount traded and the respective share in the Brazilian financial network as of December 2014. We discriminate the amounts by six different financial instruments: Selic (repos), interfinancial deposits, credit, credit assignment, financial bills, and others. Operations classified as Selic are secured transactions involving federal government bonds and represent the largest share in the Brazilian financial network. Banks mainly perform these operations to adjust their liquidity positions in the market. In contrast, banks may use interfinancial deposits, credit, credit assignment, financial bills, among others, to minimize costs or maximize profits as discussed in Section 1. We see that these financial instruments account for a representative share in the market.

Banks that perform mortgage loans, rural credit, and microfinance operations enjoy reductions on their capital requirements. Therefore, they can benefit from this incentive by realizing interfinancial deposits channeled at these credit modalities with their counterparty banks. Banks can employ this strategy whenever these credit modalities do not belong to their main business lines. In this case, they would perform operations of directed interfinancial deposits with these counterparties banks, which are specialized in those credit modalities, to fulfill their regulatory constraints. In this configuration, each bank would still be operating in the segment that it enjoys comparative advantage, thus possibly leading them to cost minimization or profit maximization.

As proxy for bank cost, we use total expenses and for profit, we use profits before tax. We proxy risk-taking by using the *Z*-score. As explanatory variables, we include bank interconnectivity and network topology measures as defined in Section 2.2 and control variables to fit bank inefficiency as described in (2). Next, we define these control variables.

First, we include the equity to assets ratio (*ETA*) to assess for the influence of shareholders capital on the ability of banks to optimize their resources and maximize their profits. We use the non-performing loans to total loans ratio (*NPL*) as a proxy for bank asset quality. We expect that banks that have assets of bad quality will have lower efficiency, due to higher expected losses. It is well established in the literature that bank size matters to measure efficiency.[8] Thus, we include the logarithm of total assets as a proxy for bank size (*Size*) in (2). We also include the bank-level variable total interbank debt to total funding ratio (*ETF*) to control for the representativeness of the interbank network in terms of the banks' total funding. We evaluate this measure by the ratio between the total funding that a bank obtains inside the financial network to its total external and internal funding. We add two different dummies for ownership (foreign and state-owned) to assess the differences of inefficiency across different bank ownership types. As mentioned before, we incorporate year dummies to avoid any bias that may arise due to changes in bank performance due to technological progress or changes in the economic and regulatory environments.

We include strictly local and mixed network measurements as control variables to explain the role of individual bank-level characteristics and to control for different roles banks play inside the interbank network. In this respect, these controls allow us to discriminate between banks that are members of the network core or periphery, or those that are mainly investors or borrowers from the financial network. We use the in- and out-strength (strictly local measures) to discriminate between banks that are investors and borrowers. When the in-strength assumes large values, banks are active borrowers in the financial network. Similarly, when the out-strength is large, banks significantly invest in the network. We use the closeness (mixed measure) to discern between core and peripheral members. We expect members of the core to have large closeness values, because they intermediate several financial operations. In contrast, we expect peripheral members to have small

[5] The strong disassortativeness is not a peculiar characteristic of the Brazilian financial network. We have several works from other countries reporting the same finding for their domestic networks: the US (Soramäki et al., 2007), Mexico (Martinez-Jaramillo et al., 2014), Italy (Iori et al., 2008), the Netherlands (in 't Veld and van Lelyveld, 2014), Turkey (Kuzubaş et al., 2014), among others.

[6] The constraint that the network must have a core–periphery structure is crucial for the validity of the assortativity as a proxy for estimating the core–periphery structure compliance. To see that, Piraveenan et al. (2010) show that it is possible to construct disassortative networks that do not have core–periphery structures. The constraint on the network core relates to the fact that, the larger the network core is, the worse the assortativity as proxy becomes. This fact happens because members of the core have similar degree and must be strongly interconnected. Therefore, they are locally assortative. By constraining on a small-sized core, the error embedded in the assortativity as a proxy of the core–periphery compliance reduces.

[7] The collection and manipulation of the data were conducted exclusively by the staff of the Central Bank of Brazil.

[8] For instance, see Maudos et al. (2002), Berger et al. (2009) and Maudos et al. (2005).

Table 2
Summary statistics.
The in- and out-strength have the same statistical descriptors. In this way, we report them as the unified variable "strength."

Variables	Mean	Std. Dev.	Min.	Max.
Cost and Profit (in R$ million) and Z-score				
Total profits	278.06	1139.81	−8326.25	14,220.40
Total costs	2103.39	6916.50	1.09	65,746.18
Z-score	3.26	1.09	−1.43	6.46
Output quantities (in R$ million)				
Total loans (y_1)	21,930.10	74,684.04	0.00	652,770.87
Total deposits (y_2)	19,062.35	64,328.60	1.97	487,446.67
Liquid assets (y_3)	8311.10	23,624.79	0.01	175,046.05
Fixed input (in R$ million)				
Earning assets (z)	30,241.20	96,791.40	0.28	777,687.92
Input prices				
Price of funding (w_1)	0.09	0.10	0.01	1.73
Price of capital (w_2)	2.40	3.79	−0.38	32.61
Control variables				
Leverage (*ETA*)	0.17	0.10	0.02	0.82
Asset quality (*NPL*)	0.04	0.06	0.00	1.00
Log(assets) (*Size*)	22.07	2.11	17.19	27.67
Interbank debt to total funding (*ETF*)	0.19	0.53	0	22.65
Network measurements				
Strength (in R$ billion)	1.50	0.64	0.55	2.40
Closeness	0.04	0.01	0.03	0.07
Assortativity	−0.33	0.04	−0.39	−0.25

Table 3
Panel regressions on the relative importance of network topology in determining cost inefficiency of banks.
Model 1: benchmark with no network measurement. Models 2–4: with contemporaneous, one lagged, two lagged network measurements that capture strictly local, mixed, and global network characteristics. We interact every network measurement with bank size.
Standard errors in parentheses; ***, **, * stand for 1%, 5% and 10% significance levels, respectively.

Variables	Cost inefficiency (u_t)							
	Model 1		Model 2		Model 3		Model 4	
	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.
$\text{ETA}_{i,t}$	30.300**	(11.840)	11.170***	(2.347)	4.246***	(0.469)	9.598***	(2.133)
$\text{NPL}_{i,t}$	0.413**	(0.173)	0.126***	(0.030)	0.055***	(0.008)	0.115***	(0.029)
$\text{ETF}_{i,t}$	−2.804*	(1.671)	0.279	(0.334)	0.043	(0.141)	0.068	(0.374)
$\text{Foreign}_{i,t}$	3.515**	(1.525)	1.050***	(0.268)	0.318***	(0.065)	0.837***	(0.234)
$\text{State}-\text{owned}_{i,t}$	4.492**	(1.897)	2.164***	(0.452)	2.103***	(0.471)	1.752***	(0.364)
$\text{Size}_{i,t}$	−0.839**	(0.372)	−2.201***	(0.548)				
Disassort_t			−84.330***	(30.220)				
$\text{Closeness}_{i,t}$			−24.450***	(7.880)				
$\text{In}-\text{strength}_{i,t}$			0.170	(0.232)				
$\text{Disassort}_t \cdot \text{Size}_{i,t}$			3.805***	(1.429)				
$\text{Closeness}_{i,t} \cdot \text{Size}_{i,t}$			1.308***	(0.373)				
$\text{In}-\text{strength}_{i,t} \cdot \text{Size}_{i,t}$			0.002	(0.012)				
Size_{t-1}					−0.798***	(0.135)		
Disassort_{t-1}					−29.610***	(9.200)		
$\text{Closeness}_{i,t-1}$					−12.940***	(2.650)		
$\text{In}-\text{strength}_{t-1}$					0.091	(0.069)		
$\text{Disassort}_{t-1} \cdot \text{Size}_{i,t-1}$					1.249***	(0.423)		
$\text{Closeness}_{i,t-1} \cdot \text{Size}_{i,t-1}$					0.652***	(0.118)		
$\text{In}-\text{strength}_{i,t-1} \cdot \text{Size}_{i,t-1}$					−0.001	(0.004)		
$\text{Size}_{i,t-2}$							−1.978***	(0.553)
Disassort_{t-2}							−66.980**	(30.620)
$\text{Closeness}_{i,t-2}$							−24.650***	(7.556)
$\text{In}-\text{strength}_{i,t-2}$							−0.035	(0.237)
$\text{Disassort}_{t-2} \cdot \text{Size}_{i,t-2}$							2.731*	(1.414)
$\text{Closeness}_{i,t-2} \cdot \text{Size}_{i,t-2}$							1.188***	(0.347)
$\text{In}-\text{strength}_{i,t-2} \cdot \text{Size}_{i,t-2}$							0.013	(0.013)
Constant	5.827	(3.850)	39.460***	(10.130)	15.810***	(2.859)	37.300***	(10.600)
Observations	2113		2113		2020		1929	
Number of banks	92		92		92		92	
Log likelihood	−704		−638		−615		−585	

Table 4
Panel regressions on the relative importance of network topology in determining profit inefficiency of banks.
Model 1: benchmark with no network measurement. Models 2–4: with contemporaneous, one lagged, two lagged network measurements that capture strictly local, mixed, and global network characteristics. We interact every network measurement with bank size.
Standard errors in parentheses; ***, **, * stand for 1%, 5% and 10% significance levels, respectively.

Variables	Profit inefficiency (u_t)							
	Model 1		Model 2		Model 3		Model 4	
	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.
$\text{ETA}_{i,t}$	−7.763***	(1.192)	−7.037***	(1.056)	−7.070***	(1.138)	−6.905***	(1.159)
$\text{NPL}_{i,t}$	−0.025***	(0.009)	−0.020**	(0.008)	−0.022**	(0.009)	−0.021**	(0.008)
$\text{ETF}_{i,t}$	0.261	(0.328)	0.212	(0.314)	0.060	(0.324)	0.213	(0.294)
$\text{Foreign}_{i,t}$	0.288***	(0.104)	0.174*	(0.096)	0.259**	(0.101)	0.228**	(0.098)
$\text{State}-\text{owned}_{i,t}$	−0.864***	(0.241)	−0.895***	(0.231)	−0.801***	(0.223)	−0.768***	(0.228)
$\text{Size}_{i,t}$	−0.030	(0.028)	0.627**	(0.256)				
Disassort_t			27.940	(18.190)				
$\text{Closeness}_{i,t}$			16.280***	(5.763)				
$\text{In}-\text{strength}_{i,t}$			−0.320***	(0.123)				
$\text{Out}-\text{strength}_{i,t}$			0.142	(0.142)				
$\text{Disassort}_t \cdot \text{Size}_{i,t}$			−1.425*	(0.833)				
$\text{Closeness}_{i,t} \cdot \text{Size}_{i,t}$			−0.782***	(0.251)				
$\text{In}-\text{strength}_{i,t} \cdot \text{Size}_{i,t}$			0.014**	(0.006)				
$\text{Out}-\text{strength}_{i,t} \cdot \text{Size}_{i,t}$			−0.007	(0.007)				
Size_{t-1}					0.599**	(0.276)		
Disassort_{t-1}					15.540	(18.920)		
$\text{Closeness}_{i,t-1}$					18.120***	(6.151)		
$\text{In}-\text{strength}_{t-1}$					−0.224*	(0.124)		
$\text{Out}-\text{strength}_{t-1}$					0.337*	(0.176)		
$\text{Disassort}_{t-1} \cdot \text{Size}_{i,t-1}$					−1.401*	(0.830)		
$\text{Closeness}_{i,t-1} \cdot \text{Size}_{i,t-1}$					−0.754***	(0.261)		
$\text{In}-\text{strength}_{i,t-1} \cdot \text{Size}_{i,t-1}$					0.013**	(0.006)		
$\text{Out}-\text{strength}_{i,t-1} \cdot \text{Size}_{i,t-1}$					−0.016*	(0.008)		
$\text{Size}_{i,t-2}$							0.572**	(0.286)
Disassort_{t-2}							8.533	(19.350)
$\text{Closeness}_{i,t-2}$							15.360**	(6.012)
$\text{In}-\text{strength}_{i,t-2}$							−0.173	(0.122)
$\text{Out}-\text{strength}_{i,t-2}$							0.426**	(0.188)
$\text{Disassort}_{t-2} \cdot \text{Size}_{i,t-2}$							−0.073	(0.864)
$\text{Closeness}_{i,t-2} \cdot \text{Size}_{i,t-2}$							−0.608**	(0.251)
$\text{In}-\text{strength}_{i,t-2} \cdot \text{Size}_{i,t-2}$							0.005	(0.006)
$\text{Out}-\text{strength}_{i,t-2} \cdot \text{Size}_{i,t-2}$							−0.020**	(0.009)
Constant	2.457***	(0.677)	−9.938*	(5.618)	−11.690*	(6.166)	−11.740*	(6.387)
Observations	2113		2113		2020		1929	
Number of banks	92		92		92		92	
Log likelihood	−2995		−2976		−2840		−2688	

closeness values because they do not intermediate financial operations.

As our main variable of interest, we use the assortativity measure as a global measure to capture how well the network topology fits into a core–periphery model. This variable will be useful to draw conclusions about our hypotheses.

In addition, since we expect that the relation between network measurements and bank efficiency to be strongly dependent on the bank size, we also interact the network measurements with the size of banks.

We estimate (2) using the logarithm of the explanatory variables plus one, except for the dummies. Table 2 presents the descriptive statistics of the variables for both (1) and (2). Note that the assortativity remains negative in the entire studied period. In this way, for clarity, we use the disassortativity that is the absolute value of the assortativity measure with no loss of generality. Given that the network has a core–periphery structure, it complies more to an ideal core–periphery model the more disassortative it is.

4. Empirical results

In this section, we use the functional forms of cost, profit, and risk-taking inefficiency levels discussed in Section 2.1, Battesi and Coelli (1995)'s specification to evaluate these inefficiency levels, and Belotti et al. (2013)'s methodology to solve the econometric system. Tables 3–5 report the results of the panel regressions for cost, profit and risk-taking inefficiency levels, respectively, on the discussed network measurements and control variables. Our main goal is in determining whether network topology, in particular core–periphery structures, affects bank efficiency. For robustness, we report the results using contemporaneous, one-lagged, and two-lagged explanatory variables.

When designing the panel specifications, we use the in- and out-strength network measurements as controls when explaining profit and risk-taking inefficiency levels. However, we only employ the in-strength (funding amount) as control when explaining cost inefficiency. In this configuration, we do not use the out-strength (investment amount) because it relates closely to bank decisions concerning profit maximization and risk management.

We find that the coefficient of the NPL variable, which proxies the assets quality of banks, is statistically significant and positive in the cost and risk-taking inefficiency models. This observation suggests that an increase in the NPL is positively associated to bank cost and risk-taking inefficiency. In this way, banks that have assets with higher quality tend to be more efficient in terms of cost and risk-taking. Contrasting to that, we see a negative and statistically significant coefficient for NPL for profit inefficiency of banks. As such, banks that retain assets with higher quality tend to be more inefficient in the profit dimension. We may relate this finding to the fact that banks demand higher returns and hence

Table 5
Panel regressions on the relative importance of network topology in determining risk-taking inefficiency of banks.
Model 1: benchmark with no network measurement. Models 2–4: with contemporaneous, one lagged, two lagged network measurements that capture strictly local, mixed, and global network characteristics. We interact every network measurement with bank size.
Standard errors in parentheses; ***, **, * stand for 1%, 5% and 10% significance levels, respectively.

Variables	Risk-taking inefficiency (u_t)							
	Model 1		Model 2		Model 3		Model 4	
	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.
$\text{NPL}_{i,t}$	0.115***	(0.026)	0.099***	(0.020)	0.115***	(0.027)	0.133***	(0.036)
$\text{ETF}_{i,t}$	−3.281***	(0.522)	−3.204***	(0.544)	−3.024***	(0.583)	−3.196***	(0.646)
$\text{Foreign}_{i,t}$	0.322***	(0.109)	0.175	(0.107)	0.194*	(0.114)	0.171	(0.126)
$\text{State}-\text{owned}_{i,t}$	−3.600**	(1.554)	−3.840***	(1.408)	−3.187***	(1.337)	−3.782**	(1.920)
$\text{Size}_{i,t}$	−0.294***	(0.040)	0.707**	(0.349)				
Disassort_{t}			82.020***	(24.020)				
$\text{Closeness}_{i,t}$			34.540***	(8.274)				
$\text{In}-\text{strength}_{i,t}$			−0.383**	(0.178)				
$\text{Out}-\text{strength}_{i,t}$			−0.178**	(0.090)				
$\text{Disassort}_{t}\cdot\text{Size}_{i,t}$			−3.360***	(1.133)				
$\text{Closeness}_{i,t}\cdot\text{Size}_{i,t}$			−1.762***	(0.387)				
$\text{In}-\text{strength}_{i,t}\cdot\text{Size}_{i,t}$			0.022**	(0.009)				
$\text{Out}-\text{strength}_{i,t}\cdot\text{Size}_{i,t}$			0.008*	(0.004)				
Size_{t-1}					0.663*	(0.389)		
Disassort_{t-1}					83.540***	(27.180)		
$\text{Closeness}_{i,t-1}$					38.980***	(9.243)		
$\text{In}-\text{strength}_{t-1}$					−0.302	(0.187)		
$\text{Out}-\text{strength}_{t-1}$					−0.186	(0.142)		
$\text{Disassort}_{t-1}\cdot\text{Size}_{i,t-1}$					−3.078**	(1.271)		
$\text{Closeness}_{i,t-1}\cdot\text{Size}_{i,t-1}$					−1.858***	(0.429)		
$\text{In}-\text{strength}_{i,t-1}\cdot\text{Size}_{i,t-1}$					0.018*	(0.010)		
$\text{Out}-\text{strength}_{i,t-1}\cdot\text{Size}_{i,t-1}$					0.009	(0.007)		
$\text{Size}_{i,t-2}$							0.517	(0.452)
Disassort_{t-2}							75.260**	(31.630)
$\text{Closeness}_{i,t-2}$							39.170***	(10.300)
$\text{In}-\text{strength}_{i,t-2}$							−0.284	(0.212)
$\text{Out}-\text{strength}_{i,t-2}$							−0.122	(0.162)
$\text{Disassort}_{t-2}\cdot\text{Size}_{i,t-2}$							−2.468*	(1.480)
$\text{Closeness}_{i,t-2}\cdot\text{Size}_{i,t-2}$							−1.846***	(0.477)
$\text{In}-\text{strength}_{i,t-2}\cdot\text{Size}_{i,t-2}$							0.017	(0.011)
$\text{Out}-\text{strength}_{i,t-2}\cdot\text{Size}_{i,t-2}$							0.006	(0.008)
Constant	8.327***	(0.801)	−16.960**	(7.319)	−18.540**	(8.272)	−16.950*	(9.599)
Observations	2113		2113		2020		1929	
Number of banks	92		92		92		92	
Log likelihood	−3204		−3155		−2981		−2842	

higher profits when they accept assets with low quality in financial transactions. The results suggest that the returns demanded are higher enough to cover the extra cost that bank incur to deal with lower asset quality, such as in renegotiation and loss recovery expenses.

Furthermore, in line with Tabak et al. (2012) and Tabak et al. (2013), we find that large banks have lower inefficiency levels on cost than non-large banks. This fact can explain, at least partially, the recent wave of mergers and acquisitions that have happened in the Brazilian banking system. These findings corroborate the existence of economies of scale.

The equity to asset ratio (*ETA*) is statistically significant and positively associated to the cost inefficiency. In contrast, it is significant and negatively related to profit inefficiency. These results indicate that a bank has higher cost to keep a higher equity to assets ratio. However, these costs can be compensated in some way and the bank can achieve higher profit efficiency.

Bank ownership seems to matter to explain bank inefficiency. We find that, though state-owned banks are more cost inefficient, they are more profit and risk-taking efficient. In contrast, we see that foreign banks are more inefficient in the three studied dimensions: cost, profit, and risk-taking. State-owned banks mostly concentrate their main financial operations with large banks, which in turn often offer low return rates at the cost of low risk levels. This is one of the reasons that may explain the reason state-owned banks are usually more cost inefficient.

Our main interest is on the disassortativity coefficient that explains how the network topology fits into a core–periphery model. We see that as the network gets more disassortative, banks become on average less cost inefficient. We verify that the effect of this particular network topology is very strong due to the large negative and statistically significant coefficient for the disassortativity measure. Therefore, we see that a global aspect of the network, the network topology that is determined by the collection of bank-level decisions, has an important role in determining how cost efficient banks in the individual level are. This finding confirms our hypothesis H1a.

We see that the core–periphery network topology is not one of the drivers for explaining profit inefficiency of banks. This observation suggests that profit efficiency of banks is not related to global aspects of the network topology; instead, it relates more closely to bank-level decisions on how to manage their assets and liabilities to maximize revenues, while minimizing costs. Consequently, we cannot accept hypothesis H1b.

In relation to the risk-taking dimension, we obtain a statistically significant and positive disassortativity coefficient. Therefore, as the network topology complies more to a perfect core–periphery structure, banks become, on average, more risk-taking inefficient. Note that we use the *Z*-score when measuring risk-taking efficiency, which holds intimate relation to bank solvency issues. Our finding complements that of Lee (2013) on the bank liquidity spectrum. In this sense, he performs a comparative analysis between different types of network structures and finds that the core–periphery structure that has a deficit core bank (illiquid) gives rise to the highest level of systemic liquidity shortage. In this way, the core–periphery model naturally implies greater risks both in the solvency and liquidity dimensions that banks must assume. Therefore, we find evidence in favor of hypothesis H2. In sum, the core–periphery structure implies cost efficiency with the drawback of being risk-taking inefficient.

We also see that the interbank debt to total funding (*ETF*) is statistically significant and negatively related to risk-taking inefficiency of banks. We can conceive *ETF* as measuring the dependency of banks on the financial network to obtain funds. In this respect, our finding suggests that obtaining funds in the financial network can increase risk-taking efficiency of banks. Therefore, from the bank-level viewpoint, banks individually have incentives to engage in the financial network, because they increase their risk-taking efficiency.

Though the increase of the *ETF* variable contributes to reducing banks' risk-taking inefficiency, the financial network structure leads to larger systemic risk levels, because of the natural riskiness embedded within a core–periphery structure. On one side, banks have incentives to engage and get exposed to in the financial network to obtain cost and risk-taking efficiency. On the other side, the collectiveness of the banks' decisions that in turn creates a core–periphery structure may not be good for the financial system.

With regard to the network measurements that act as controls, we see that the closeness is statistically significant and negatively related to cost inefficiency. Recall that the closeness proxies the bank centrality in the network in the sense of how active banks are in intermediating financial operations. Banks in the network core intermediate many more operations than those that are located at the peripheries. We see that banks in the core seem on average to have less cost inefficiency. Contrasting to that finding, bank centrality seems to reinforce profit and risk-taking inefficiency. In this way, we conclude that banks in the core, though more cost efficient, are less profit and risk-taking efficient. Conversely, banks in the periphery are less cost efficient, but more profit and risk-taking efficient.

Looking at the interactions of the assortativity and the closeness indices with bank sizes, we see that core banks have attenuated risk-taking inefficiency. Therefore, banks in the core may have even more incentives than banks in the periphery to participate in the financial network, because that behavior results in better risk-taking and cost efficiency.

We see that the in-strength coefficient is statistically significant and negatively relates to profit inefficiency. In this way, we find that getting funds in the financial network can contribute to better profit and risk-taking efficiency levels. A possible explanation for the negative sign of the in-strength coefficient relates to the difficulty banks may face in obtaining other funding sources that are comparatively more advantageous. In view of this scenario, banks may still decide to borrow from the financial network even in the case they find better investment opportunities in the non-financial sector whose returns make up for the higher assumed funding cost.

We also verify that the in- and out-strength negatively relates to risk-taking inefficiency. Thus, banks that heavily invest and borrow from the financial network have, on average, better risk-taking efficiency levels. Though individually may be better for banks to participate in the financial network, the tradeoff is a network structure with a more accentuated core–periphery structure. This particular topology, in contrast, counterweights that individual gain in efficiency of banks by positively contributing to risk-taking inefficiency.

A concern regarding the results is the possibility of potential endogeneity may bias our results. It is possible that banks that have efficiency problems try to circumvent this issue using the strategy of be more interconnected at the financial network. We address the endogeneity issue by re-evaluating all of our models with one lag and two lags of the explanatory variables as Tables 3–5 show. We can see that all of the results are maintained in both cases.

5. Conclusion

Financial intermediaries decide the use of a mix of inputs, such as labor and capital (and funds), to generate outputs, such as financial services. Some banks are more efficient than others in producing these outputs – either by producing at lower costs or by generating higher profits. Financial intermediaries also decide whether they will interconnect to other financial institutions in interbank activities. These interbank links are used to help these financial intermediaries improve their liquidity. However, these activities may have an impact on bank efficiency – either cost or profit – as they can be seen as alternative investments or funding opportunities that financial intermediaries have at their disposal.

Financial intermediaries have to evaluate the cost–benefit of performing interbank operations. On the one hand, if the financial intermediary enters in financial operations with more borrowers, it has increasing information costs to analyze the financial health of its counterparty borrowers. On the other hand, it can diversify its investments and becomes less exposed to credit risk. Therefore, one should expect that large banks engage in operations with many counterparties, while small banks establish operations with few counterparties. The size heterogeneity and the marginal benefits that banks obtain by engaging in the financial network lead to the emergence of core–periphery structures that in turn contribute to a more efficient financial system.

To the best of our knowledge, this is the first paper that relates network measures from interbank activities, in particular how compliant is the financial network to a core–periphery structure, to banking efficiency. We show that the core–periphery structure contributes to better cost efficiency levels of banks. However, we do not find evidence that core–periphery structures imply a better profit efficient financial system.

It is very important to highlight that core–periphery structures are known as carrying more systemic risk. Our paper also contributes to the literature by explicitly showing that core–periphery structure also lead to more inefficient risk-taking in financial systems. We use the *Z*-score when measuring risk-taking efficiency, which holds intimate relation to bank solvency issues. Our finding complements that of Lee (2013) on the bank liquidity spectrum.

Putting together these findings, we see that the resulting network topology encourages banks to maintain operations in the financial network due to cost efficiency. On the other side, this particular network topology that emerges from the decisions made by all of the banks generate a more risk-taking inefficiency configuration for banks. Due to that, regulators should be aware of the risk inefficiency that arises in the financial system due to individual decisions made by banks in the network.

Our results support the idea that financial regulation could consider network topology in the analysis of the building up of financial imbalances. The design of proper incentives mechanisms to cope with systemic risk should also consider the trade-offs between higher efficiency and risk-taking.

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