ISSN 1518-3548

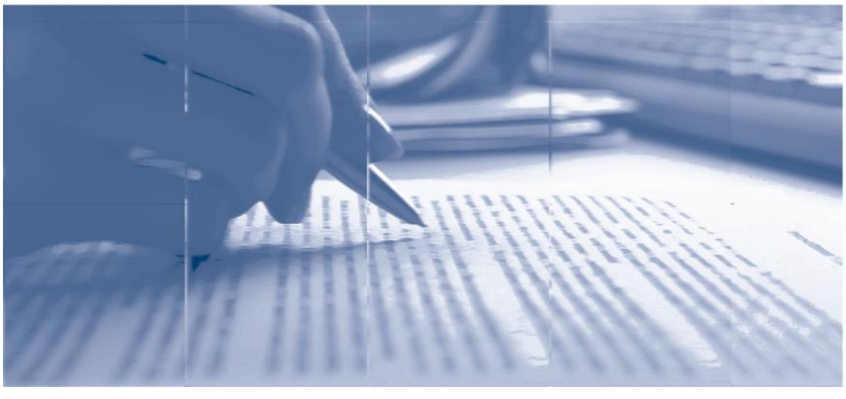
BANCO CENTRAL DO BRASIL

Do Interconnections Matter for Bank Efficiency?

Solange Maria Guerra,
Benjamin Miranda Tabak and
Rodrigo Cesar de Castro Miranda

December, 2014

Working Papers



374

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	n. 374	December	2014	p. 1-35

Working Paper Series

Edited by Research Department (Depep) – E-mail: workingpaper@bcb.gov.br

Editor: Francisco Marcos Rodrigues Figueiredo – E-mail: francisco-marcos.figueiredo@bcb.gov.br
Editorial Assistant: Jane Sofia Moita – E-mail: jane.sofia@bcb.gov.br
Head of Research Department: Eduardo José Araújo Lima – E-mail: eduardo.lima@bcb.gov.br

The Banco Central do Brasil Working Papers are all evaluated in double blind referee process.

Authorized by Carlos Hamilton Vasconcelos Araújo, Deputy Governor for Economic Policy.

General Control of Publications

Banco Central do Brasil

Comun/Dipiv/Coivi

SBS – Quadra 3 – Bloco B – Edifício-Sede – 14º andar

Caixa Postal 8.670

70074-900 Brasília – DF – Brazil

Phones: +55 (61) 3414-3710 and 3414-3565

Fax: +55 (61) 3414-1898

E-mail: editor@bcb.gov.br

Citizen Service Division

Banco Central do Brasil

Deati/Diate

SBS – Quadra 3 – Bloco B – Edifício-Sede – 2º subsolo

70074-900 Brasília – DF – Brazil

Toll Free: 0800 9792345

Fax: +55 (61) 3414-2553

Internet: <http//www.bcb.gov.br/?CONTACTUS>

Do interconnections matter for bank efficiency?*

Solange Maria Guerra†
Benjamin Miranda Tabak‡
Rodrigo Cesar de Castro Miranda§

Abstract

The Working Papers should not be reported as representing the views of Banco Central do Brasil. The views expressed in the papers are those of the authors and do not necessarily reflect those of Banco Central do Brasil.

This paper addresses the issue of how individual bank interconnectivity and the interbank network topology impact on Brazilian banking efficiency between 2007 and 2013. We use several network measures to analyze the effects of bank interconnections on cost, profit and risk-taking efficiency. The results suggest that interconnections matter for bank efficiency. We find that interconnectivity can increase cost and risk-taking inefficiency levels. We also find that the density of the network topology can reduce profit and risk-taking inefficiency levels.

Key Words: Efficiency, Network, Inter-connectivity, Interbank Market.

JEL Classification: G21, G28.

*Benjamin M. Tabak gratefully acknowledges financial support from CNPQ Foundation.
†Research Department, Banco Central do Brasil. Email: solange.guerra@bcb.gov.br.
‡Senado Federal and Universidade Católica de Brasília. Email: benjaminm.tabak@gmail.com.
§Banco Central do Brasil and Universidade de Brasília. Email: rodrigo.miranda@bcb.gov.br.

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]). The degree of bank efficiency is important to assess as it may influence risk taking, systemic risk, banking spreads and the soundness of the financial system (Tabak et al. [2013]). On the other hand, since the recent financial crisis there is an ongoing discussion on how banks are interconnected and how these interconnections may pose systemic risk.

This paper analyzes whether connectivity in the interbank market, measured using complex network tools, has an impact on bank efficiency. We focus on Brazilian banks due to data availability. We analyze the effect on efficiency of specific features of bank interconnections, such as centrality and dominance measures. We study the effects of bank individual network characteristics and also the effects of the network topology on bank efficiency. Since Allen and Gale [2000] it is widely recognized that bank topology matters for systemic risk (see also Cajueiro and Tabak [2008] and Lenzu and Tedeschi [2012]). We show that banking network topology also matters for bank efficiency, which can be a conduit for systemic banking risk.

The use of network theory to understanding the relationship in financial market is not new. De Masi et al. [2010] and De Masi and Gallegati [2012] use network theory to help understand better the network structure of loans from bank to firms in Italy and Japan. Fujiwara et al. [2009] model credit network fragility and describe changes in time in the topology of loans network between banks and large firms in Japan. However, this is the first paper that relates network measures from interbank activities to banking efficiency.

Interbank markets may affect efficiency through different channels. The main funding source for banks is provided by deposits, which generally incur in low funding costs. Interbank funding sources can be seen as an additional important funding source. It can be used to manage banks liquidity needs over time and to increase resources that are available to invest in profitable opportunities. Interbank funding can increase or reduce bank cost and profit efficiency. It depends on the cost and for what goal banks use this source of funding.

The use of interbank funding implies that banks may be connected through a network of financial claims. The recent financial crisis has shown that this network topology is relevant in evaluating systemic risks as a shock to a specific bank may affect its neighbors, which may lead to a domino contagion effect. Several papers have shown that these networks can help explain why banks have a special role in the economy and they have to be supervised to deal with the emergence of systemic risk (Cajueiro and Tabak [2008]).

Interbank networks and their specific characteristics can have a major impact on the banking sector (Allen and Gale [2000]). As such the network topology, such as how dense the network is, can affect bank cost and profit efficiency. If the network is concentrated in specific banks, then these banks may have too-interconnected-to-fail or too-big-to-fail characteristics, which affects their funding costs and investment opportunities, which in its turn affect their efficiency. In this case it should also affect overall bank efficiency. Individual bank characteristics in the network should also be related to bank efficiency. If a bank is highly connected in the network then it can diversify its borrowing and should suffer less from negative shocks to interbank lending as it can spread its funding risks. On the other hand, if the bank spreads its lending in the interbank market it can also diversify its investments, which should have an implication on its associated risk and bankruptcy risks.

We can estimate efficiency of financial institutions using parametric or non-parametric approaches. We opted for parametric approach, stochastic frontier, since we are interested in modeling cost and profit efficiency and evaluating how these network topology and interbank measures affect this efficiency. We follow the Sealey and Lindley [1977] intermediation approach, which treats banks as intermediaries that collects funds from savers and transforms those funds into earning assets, such as loans.

Overall, we also implement a translog risk-taking model to evaluate banks risk taking efficiency. We expect that the use of interbank funding and the relative importance of banks within the network should explain not only bank cost and profit efficiency but more importantly its risk-taking efficiency. Therefore, efficient banks should be lending/borrowing in interbank markets and increasing their output production without increasing their risk-taking. Furthermore, with the model it is possible to pinpoint banks that are taking excessive risk-taking with regards to their counterparts, which is relevant for bank supervision.

This paper contributes to the bank efficiency literature by exploring the role of inter-connectivity on efficiency. To the best of our knowledge there is virtually no research on the impact of connectivity on efficiency. We employ methods from network theory to develop inter-connectivity measures to evaluate their impact on bank efficiency. Banks that are highly interconnected can have access to several sources of external finance and as such could potentially benefit and have lower funding costs, which would increase their efficiency if compared to banks that have low inter-connectivity.

We also calculate the power law of the banking interbank network and test whether the density of the network can explains inefficiency levels (see Gabaix [2009] and Li and Zhuang [2010] for power law usage in finance and banking). We find that power law exponents can explain inefficiency levels.

We also contribute using a new approach to bank efficiency. If a bank is seen as too interconnected to fail it may incur in lower costs in the interbank market. Thus, we should expect that interconnectivity help explain bank inefficiency through the cost channel. Possibly, there is also a profit channel, since a reduction or an increase in costs could impact on bank profitability. In both cases, banks that are highly interconnected could be seen as special banks with implicit guarantees. These implicit guarantees could impact on banks efficiency. These banks seen as special could also incur in more risk to produce the same products than other banks. Therefore, it is possible that risk-taking also impact on bank efficiency.

We investigate this possibility using as dependent variable in our model the individual bank risk-taking measure known as the Z-Score (Laeven and Levine [2009] and Boyd and Runkle [1993]). We then use a translog function to model the Z-Score. 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. 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. Overall, our results suggest that individual bank interconnections matter for cost and risk-taking efficiency. We find that higher inter-connectivity can increase bank inefficiency. Also banking network topology helps explain bank inefficiency levels.

A concern regarding the results is the possibility of potential endogeneity may bias our results. We expect that bank interconnections impact on bank efficiency. However, it is possible that the causality occurs in the opposite direction. Banks that are more efficient can incur in lower costs and have higher profits. Hence, they possible face excess of liquidity. To deal with this situation they can offer funding to banks with a deficit of liquidity by means of the interbank market. Consequently, they became more interconnected. We address this endogeneity issue regressing bank inefficiency levels on one-lag measures of interconnectivity. The results are virtually the same obtained when endogeneity problem is not considered.

The remainder of the paper is structured as follows. Section 2 presents the methodology, the inter-connectivity measures and the sample, whereas section 3 presents the empirical results. Section 4 concludes the paper.

2 Methodology and Data

In this section, we specify the model as well as the variables we used to estimates the efficiency for Brazilian banks. We also present the definition of network measures used as a proxies for bank's inter-connectivity.

2.1 Measuring efficiency

The most common approaches to estimate efficiency are nonparametric and parametric techniques. Nonparametric techniques generally focus on technological optimization rather than economic optimization (Sun et al. [2013]). In this paper, we are interest in the economic optimization and some of its inter-connectivity determinants. Thus, we apply the well known parametric technic Stochastic Frontier Analysis (SFA) proposed simultaneously by Aigner et al. [1977] and Meeusen and Van den Broeck [1977]. Moreover, we follow the Sealey and Lindley [1977] intermediation approach, which treats banks as intermediaries that collect funds from savers and transforms those funds into earning assets, such as loans.

Two different economic efficiency concepts are usually employed to measure the efficiency of financial institutions: the cost and profit efficiency. On the one hand, cost efficiency is the most used efficiency criterion in the literature. In particular, considering that both banks produce the same output under the same conditions, cost efficiency measures how close to the minimum cost a bank is, where this minimum is determined by banks with the "best practices" in the sample (Berger et al. [2009]). On the other hand, profit efficiency is considered more informative than cost efficiency. Some researchers argue that cost efficiency offer a partial vision of the bank, since it does not considered the revenues (Maudos et al. [2002]). The profit maximization requires that goods and services be produced at minimum cost and, at the same time, the revenues be maximized. Besides cost and profit frontiers, Fang et al. [2011] and Tabak et al. [2012] estimate risk-taking efficiency frontier to evaluate bank competition. We follow this literature and analyze the impact of interconnections on bank efficiency by means of cost, profit and risk-taking efficiency frontiers.

We employ the $Z-score$ measure as proxy for risk-taking. This measure is used in many studies evaluating bank risk-taking behavior, which corroborates its acceptance in the literature (Mercieca et al. [2007], Laeven and Levine [2009], and Houston et al. [2010], Demirgu-Kunt and Huizinga [2013]). The $Z-score$ is define as $Z-score = (\overline{ROA} + \overline{CapitalRatio})/\sigma_{RoA}$, where RoA is return on assets, $CapitalRatio$ is the equity to assets ratio, and the over line stands for average. The Z-score measures the number of ROA standard deviations that a bank's RoA plus its leverage have to decrease in order for the bank to became insolvent. In other words, the $Z-score$ is inversely proportional to the bank's probability of default.

In order to investigate the impact of the bank inter-connectivity on the inefficiency, we employed the model proposed by Battese and Coelli [1995], which incorporates the possibility that the mean of the inefficiency levels can be estimated and explained by a set of environmental variables simultaneously. The Battese and Coelli [1995] specification avoids the bias of a two-step approach that considers the efficiency half-normally distributed in the first step, while in the second step efficiency is considered normally distributed and dependent of explanatory variables.

We estimate efficiency levels by means of the commonly-used translog functional form for the cost, profit and risk-taking functions. For convenience, we show only the cost function:

$$\begin{aligned}
\ln(C/w_2z)_{it} &= \beta_0 + \sum_{j=1}^{3} \beta_j \ln(y_j/z)_{it} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk} \ln(y_j/z)_{it} \ln(y_k/z)_{it} \\
&+ \alpha_1 \ln(w_1/w_2)_{it} + \frac{1}{2}\alpha_{11} \ln(w_1/w_2)_{it} \ln(w_1/w_2)_{it} \\
&+ \sum_{k=1}^{3} \theta_j \ln(y_j/z)_{it} \ln(w_1/w_2)_{it} \\
&+ \text{year dummies}_t - u_{it} + v_{it}. \qquad (1)
\end{aligned}$$

where i, t index the bank and year, respectively, $j = k = 1, 2, 3$ index the three output variables, and $\beta_{jk} \equiv \beta_{kj}$. C represents the bank's total costs. The are three outputs (y): total loans net of non-performing loans, liquid assets and total deposits; two input prices (w): interest expenses to total deposits and non-interest expense to fixed assets; and one fixed input (z): total earning assets. The normalization of the cost function by bank's total earning assets (z) reduces the heteroscedasticity and allows banks of any size to have comparable residual terms from which the inefficiency levels are estimated. The normalization by the last input price (w_2) ensures price homogeneity. The 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:

$$u_{it} = \delta_0 + \delta_{it}x_{it} + \delta_t b_t + m_{it} \qquad (2)$$

where 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

$-\delta_0 - \delta_{it}x_{it} - \delta_t b_t$. The vector x_{it} represents the explanatory variables for the bank's inefficiency and the vector b_t represents the network topology measures.

The equations (1) and (2) are estimated simultaneously by the maximum likelihood method using the implementation presented by Belotti et al. [2013].

Cost, profit and risk-taking efficiency frontiers are estimated similarly. There is, however, a problem in applying the natural logarithm of profit in equation 1, since this variable can take negative values. In order to solve this problem we follow Bos and Koetter [2011] who employ an additional independent variable - the Negative Performance Indicator (NPI) - that takes the value of 1 when profit is positive and it is equal to the absolute value of profit, when this variable take values below zero. At the same time, the dependent variable for profit frontier is defined equal to the value of the variable profit if it is positive and 1 otherwise.

2.2 Network measures for bank's inter-connectivity

In this subsection, we present the measures to characterize the individual bank inter-connectivity and the market network topology. We adapt complex network measures to characterize bank interconnections in the loan interbank market.

We represent the debt relationships between banks as a network or a graph. A network N is composed of a set of nodes V and a set of edges E between these nodes. $|V|$ is the number of nodes, and $|E|$ is the number of edges. E_i are the edges leaving from or arriving at node i. A network is *directed* if the direction of each edge is significant (that is, the edge $i \to j$ is different from $i \leftarrow j$); otherwise, it is an undirected network. For the directed case, I_i is the set of edges that end at node i, and O_i is the set of edges that begin at node i.

A network can have values or other attributes associated with its nodes or edges. For simplicity, we will assume that a *weighted network* has values called *weights* associated with each edge. Formally, let $W_{i,j}$ be the weight of the edge from node i to node j, such that $W_{i,j} > 0$ if there is an edge from i to j, and 0 otherwise. If the network is undirected, $W_{i,j} = W_{j,i}$.

In this paper, we employ a *directed* network. An edge leaving from node i and arriving at node j with weight $W_{i,j}$ means that bank i lend to bank j an amount of $W_{i,j}$.

The *degree* of a node i is the number of edges that end or originate at i. For a directed network, the *in-degree* is number of edges arriving at i, and the *out-degree* is the number of edges that begin at i. In an undirected network, the degree of a node is the same as its in-degree and its out-degree. In a directed network, a node's degree is the sum of its in-degree and its out-degree.

A *path* is a set of nodes linked by edges. The length of a path is the number of edges between its first and last nodes. If the network is weighted, the weight of the path is the sum of the weights of all edges along the path. A *loop* is a path where the same node appears more than once.

2.2.1 Basic centrality measures

Centrality is a measure of the importance of a node within the network. For our purposes, we consider *normalized* measures where each value is divided over the maximum possible value for such a measure. This facilitates the comparison of networks of different sizes. For instance *Degree centrality* simply uses the degrees of a node as a measure of importance, that is, how connected a node is. In our formulation, the value is normalized over all possible connections such that the degree centrality $C_D(i)$ of i is $C_D(i) = \frac{|E_i|}{|V|-1}$.

Betweenness centrality measures how many paths are shortest if they pass through a certain node. Given $\sigma(s,t)$ as the number of shortest (s,t)-paths (paths from s to t) and $\sigma(s,t|v)$ as the number of shortest paths from s to t that pass through v ($v \neq s,t$), the betweenness centrality $C_B(v)$ of v is given by $\sum_{s,t \in v} \frac{\sigma(s,t|v)}{\sigma(s,t)}$.

Closeness centrality measures the average distance of a node from every other node in the network. It is the inverse of the sum of distance from a node v to every other node u in the network, normalized by the number of nodes in the network. That is, the closeness centrality $C_c(v)$ of v is given by $C_c(v) = \frac{|V|-1}{\sum_{u \neq v} d(u,v)}$, where $d(u,v)$ is the length of the shortest path from u to v.

2.2.2 Dominance

Dominance is a network centrality measure introduced by VanDenBrink and Gilles [2000] that takes into account the weights of each edge. For the interbank loan network, we define dominance ($\beta(i)$) as a function of i as follows:

$$\beta(i) = \sum_j \frac{W(i,j)}{\lambda(j)} \tag{3}$$

where $\lambda(j) = \sum_i W(i,j)$ and $W(i,j)$ is the value of loans from i to j.

In an interbank loan network, we can think of dominance in both directions: the dominance of a lender (i.e., a bank that lends more) or the dominance of a borrower (i.e., a bank that borrows more).

All the network measures mentioned above proxy the inter-connectivity of a bank in the interbank market. However, each one captures different features of the interrelation among the banks. Measures from *weighted network* like lender dominance, borrower dominance and weighted betweenness centrality take into account the volume of the loans. The measures outdegree and indegree are similar to lender dominance and borrower dominance in the sense that they considered the direction of the loans. The difference among these two set of measures is that the former do not take into account the volume of the loans. Thus, in our analysis we will also refer lender and borrow dominance as weighted outdegree and weighted indegree, respectively. The measures considering only the edges closeness and betweenness are proxies for direct interconnection and indirect interconnection.

Indegree is the number of creditors that a bank has in a given time, while outdegree is the number of debtors. Banks that have higher indegree or borrower measures are those that presents many interbank liabilities. On the other hand, banks more exposed in the interbank market present higher outdegree or lender measures. Furthermore, banks that present higher in-measures, such as indegree and borrower (weighted indegree) are most systemic relevant. If they fail they may trigger failure cascades within the interbank market, generating a sequence of failures (Castro Miranda et al. [2014]).

On the other hand, banks that present higher out-measures, such as outdegree and lender (weighted outdegree) are considered to be money centers (Freixas et al.

[2000] and Cajueiro and Tabak [2008]). If these banks suffer losses and cease to operate within the interbank market they may also disrupt the funding flows, which may worsen funding conditions to other banks.

During the recent financial crisis international financial markets were frozen. In this case, many banks incur in funding problems and may not be able to replace these funds curtailing loans and investments which end up worsening financial conditions. These amplifying channel can endanger the economy and has detrimental effects on financial system efficiency.

Bank efficiency can be seen as the production of outputs or services by banks at the lower possible costs, or generating high profits or low risk-taking. When the interbank market fails to function properly bank efficiency is reduced with negative impacts on both outputs and inputs.

While the measures unweighted or weighted indegree and outdegree take into account bank interconnection from the liabilities or assets side, degree measures the bank inter-connectivity considering both aspects. Banks with higher degree are those more interconnected in the interbank market, and therefore, play a especial role for financial stability. Borio et al (2010) argue that interconnectivity is an essential feature that we have to considerate to infer which banks are systemically important.

Banks with higher betweenness measures are banks that can be considered as financial intermediaries. These banks have many inflows and outflows. Therefore, they are important in the network. If these banks suffer distress they may propagate it to other banks.

Banks with high closeness centrality measure are banks that are in a short distance to other banks. These banks can be affected with a higher likelihood in a contagion run or shocks. These banks have to be monitored in the event of disruption in interbank markets.

2.2.3 Clustering coefficient of a network

The clustering coefficient is a measure of the density of the network around a node, that is, the given $i \leftrightarrow j$ and $k \leftrightarrow j$, how likely it is that there is an edge $i \leftrightarrow k$[1]. Formally, the clustering coefficient of node i is a count of all triangles formed between nodes of the network that include i over the maximum possible number of such triangles given i's degree. The standard clustering coefficient is calculated for undirected networks , however since direction matters in the networks that are studied in this paper we use the clustering coefficient for directed networks derived by Fagiolo [2007] and used in Tabak et al. [2014].

Let A be the incidence matrix for the directed network N, d_i^{in} the in-degree of node i, d_i^{out} the out-degree of i and $d_i^{tot} = d_i^{in} + d_i^{out}$ the total degree of i. Furhermore let $d_i^{\leftrightarrow} = \sum_{j \neq i} a_{ij} a_{ji} = A_{ii}^2$ the number of bilateral edges between i and each j[2]. The clustering coefficient of i is:

$$C_i^D(A) = \frac{(A + A^T)_{ii}^3}{2\left[d_i^{tot}(d_i^{tot} - 1) - 2d_i^{\leftrightarrow}\right]} \tag{4}$$

[1]See Newman [2010].

[2]The number of nodes such that both $i \to j$ and $j \to i$ are in the network.

The clustering coefficient of a network is the average of the clustering coefficient of all its nodes. A high clustering coefficient indicates a more dense network, with many highly connected nodes. The clustering coefficient is the probability that two banks, which lend to each other, have a common counterparty.

2.2.4 Scale-free degree distribution of the interbank network

A network is scale-free if its degree distribution follows a power-law such that the probability of a node having degree k is given by a equation of the form $P(k) = \beta k^{-\alpha}$. A network with a power-law degree distribution is much more likely to have very highly connected nodes, and the upper tail of the degree distribution is "fatter" with more highly connected nodes than would be expected from a Erdös-Rény random graph or a small-world network model[3]. A higher value of α will indicates that the very highly connected nodes are fewer, or alternatively, that extreme connectivity is more concentrated.

It is possible that only the tail of the network degree's distribution follows a power law, that is, $P(k) = \beta k^{-\alpha}$ is valid only for $k > k_{min}$ for some k_{min} that is either exogenously defined or estimated together with the α parameter. The maximum-likelihood method by Clauset et al. [2009] finds both parameters endogenously, and provides a Komolgorov-Smirnov goodness-of-fit test.

Santos and Cont [2010] argue for a scale-free characterization of the Brazilian interbank network in the 2007-2008 period. They apply the maximum likelihood estimation method due to Clauset et al. [2009] and find that the degree distribution of the Brazilian interbank network follows a power law such that the Probability of a node having $P(k) = \beta k^{-\alpha}$, with α averaging around 2.5461 from June, 2007 through November, 2008.

The coefficient of the power law can be interpreted as the inverse probability that network has banks more interconnected. If the alpha increases then the banks that are more connected have a higher number of interconnections and there are less banks that have more connections. This implies that connections at the tail of the connectivity have become more concentrated. Therefore, banks that are highly connected have become more systemically relevant.

Banking systems with a very high alpha may have a few banks that are too interconnect to fail. As the alpha increases we have a high concentration of connectivity in the interbank market.

2.3 Data

We use an unique data set from Central Bank of Brazil data base, which includes all interconnections among banks and their economic conglomerate[4]. Our sample is an unbalanced panel which includes 102 Brazilian banks that operates in the interbank market over the period from 2007 to 2013, totaling 669 observations.

As proxy for bank cost, we use total expenses and for profit, we use profits before tax. The $Z - score$, as defined earlier, is proxy for risk-taking. We include

[3]See Barabasi and Albert [1999].

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

inter-connectivity measures calculated from network measures and control variables as explanatory variables to fit inefficiency, as described in the equation 2. Next we define these explanatory variables. First we include the equity to assets ratio (ETA) to assess for the influence on shareholders capital on the ability of banks to optimize their resources and maximize their profits. We use the non-performing loans to total loans as proxy for bank asset quality (variable NPL). We expect that banks that have assets of bad quality have lower efficiency, due to higher expected losses. It is well established in the literature that bank size matters to measure efficiency (For instance, see Maudos et al. [2002], Berger et al. [2009], Maudos et al. [2005]). Thus, we include the logarithm of total assets as proxy for bank size ($Size$) in the equation 2. 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. Finally, we include the individual bank inter-connectivity and network topology measures as explanatory variables of inefficiency.

In order to study the effects of individual bank interconnections, we cluster three sets of inter-connectivity measures depending on their features. First, we estimate the proposed approach adding the weighted measures: borrower or weighted indegree, lender or weighted outdegree and weighted betweenness. In the second estimation we include the inter-connectivity measures that take into account only the number of loans, but not their volumes: closenness, betweenness and degree. In order to analyze the different effects of bank lending and borrowing, we estimate a model including the two components of the degree measure: the indegree and outdegree measures.

We also study the effects of the interconnection level of the system on bank efficiency adding the power law exponent as measure for network features.

The equation 2 is estimated using the logarithm of the variables plus one, except for the dummies. Table 1 presents the descriptive statistics of the variables for both equations 1 and 2.

Place Table 1 about here

3 Empirical Results

In this section, we present the results of the regressions of cost, profit and risk-taking inefficiency level on several independent variables. Our main goal is to determine if inter-connectivity among banks and network topology have any effect on their efficiency.

In order to study the impact of bank interconnections and interbank market network topology on bank inefficiency, we fit five models using cost, profit and risk-tanking translog functions. The first one does not include network measures. It is only for comparison purposes and robustness check. The second one assesses only the effect of network topology on bank inefficiency. Models 3 to 5 include individual interconnectivity and network topology measures. Model 3 presents the weighted measures: borrower or weighted indegree, lender or weighted outdegree and weighted betwenness. Model 4 includes the inter-connectivity measures that take into account only the number of loans, but not their volume: closenness, betweenness and degree. In order to analyze the different effects of bank lending and borrowing, we estimate model 5 including the two components of the degree measure: the indegree and outdegree measures. Model 3 to 5 also study the effects of network features on bank inefficiency adding the power law exponent as measure for network topology.

Tables 2, 3 and 4 present the results for cost, profit and risk-taking inefficiency, respectively. Non-performing loans, equity to assets ratio and size are statistically significant in explaining inefficiency levels. We find that the coefficient of the NPL variable is statistically significant and positive in cost models. This suggests that an increase in risk NPL is positively associated to bank cost inefficiency. Furthermore, in line with Tabak et al. [2012] and Tabak et al. [2013] we find that large banks have lower inefficiency. This can explain, at least partially, the recent wave of mergers and acquisitions that have happened in the Brazilian banking system. There seems to be economies of scale.

Place Tables 2, 3 and 4 about here

The equity to asset ratio (ETA) is significant and positively associated to cost inefficiency. On the other hand, it is significant and negatively related to profit and risk-tanking inefficiency. These results indicates 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 and risk-taking efficiency. Bank type seems to matter to explain bank inefficiency. We find that state-owned banks are on average more cost inefficient than their counterparts for the period under analysis. On the other hand, foreign banks are on average more risk-taking inefficient.

Our main interest is on the coefficients for connectivity and for network topology and how they affect bank inefficiency. The coefficient on Borrower (Weighted indegree) is statistically significant and positive related to cost and risk-taking inefficiency. This suggests that banks that have a larger number of borrowing interconnections are relatively inefficient. The coefficient on Lender (Weighted outdegree) is statistically significant and negative associated to risk-taking inefficiency. On the other hand, indegree and outdegree coefficients are statistically significant and, respectively, negative and positively related to both cost and risk-taking inefficiency. These results suggest that not only the interconnection type matters (as a lender or as a borrower), but also that the volume of the loans has an opposite effect. For instance, a bank could reduce its cost and risk-taking inefficiency having a higher number of creditors (indegree). However, depending on the volume of the loans ($Windegree$), the bank could increase its cost and risk-taking inefficiency. The results also suggest the higher the direct interconnections (degree) the higher the cost and risk-taking inefficiency. The financial intermediation role of the bank (betweenness) has different impact on cost and risk-taking inefficiency. The former increase as the number of intermediation chains of the bank are larger; the latter decrease with the number of intermediation.

These results suggest that individual interconnectivity can increase cost and risk-taking bank inefficiency. On the other hand, the results suggest that these bank features do have not impact on profit inefficiency. It seems that banks participate of the interbank market to manage liquidity instead of searching for profitable investments opportunities.

The coefficient of the power law exponent is statistically significant in the profit and Z-Score frontiers, and has negative sign (Tables 3 and 4). Therefore, increases in concentration of connectivity decrease profit and risk-taking inefficiencies. This suggest that there may be economies of scale that originate in the interbank market and affect bank inefficiency.

A 1% increase in the alpha coefficient reduces profit inefficiency in about 4%, on average. It also reduces risk-taking inefficiency in about 9%, on average.

We also test the effects of a non-weighted directed clustering coefficient ($Clustering$) network measure. In this case, the coefficient is statistically significant for the Z-Score specification at the 1% significance level and has positive sign. This suggests that more dense networks will be more inefficient with higher risk taking (Tables 5, 6 and 7).

Place Tables 5, 6 and 7 about here

As robustness check, we account for possible remaining heteroscedasticity problems modeling a heteroscedastic stochastic frontiers as proposed by Hadri et al. [2003]. We also fit models correcting for double heteroscedasticity, using the interconnections measures to explain the one side error term and the control variables of bank features to explain random error. It is important to highlight that all models produce the same qualitative results. However, we choose the models without heteroscedasticity due to the fact that they are more general and more robust, since few heteroscedastic models produce non trivial numerical maximization problems.

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 interbank market. We address this endogeneity concerns fitting the models 2 to 5 considering the one lag interconnectivity measures as explanatory variables for bank cost, profit and risk-taking inefficiency. The results of this robustness check are presented from table 8 to table 13. We can see that the results are even more strong. We consistently find that more concentrated network reduces profit and risk-taking inefficiencies, while more dense network increase both profit and risk-taking inefficiencies. The results considering individual bank interconnectivity measures are virtually the same obtained before (Tables 2 to 7).

Place Tables 8, 9 and 10 about here

Place Tables 11, 12 and 13 about here

Overall, our results suggest that interconnections matter for bank efficiency levels. This is the first paper that relates network measures from interbank activities to banking efficiency.

We estimate the bank-level efficiency from the regressions presented in Tables 2, 3 and 4 using the definition proposed in Battese and Coelli [1988]. The bank-level efficiency is estimated as $E[exp(-u)|\varepsilon_{it}]$, onde $\varepsilon_{it} = v_{it} - u_{it}$. Table 14 presents the cost, profit, risk-taking average efficiency levels. Efficiency obtained from model 1, that does not include interconnectivity nor network measures, are higher than efficiency levels obtained from the other models. These results are consistent with the analysis above in which we claim that interconnections in the interbank market seems to increase bank inefficiency. However, a higher maximum level of efficiency obtained from some models that include interconnectivity and network measures, suggest that some banks could have efficiency gains due to interconnections. This is an issue for further research.

Place Table 14 about here

Figures 1, 2 and 3 present the evolution of cost, profit, risk-taking efficiency levels over the years. These efficiency levels are obtained from the models presented in tables 2, 3 and 4. Overall, as we can see in the figures 1, 2, and 3, bank efficiency levels decrease in 2009 and in 2010, probably due to effects of the international financial crisis. All the models produce very similar patterns of efficiency evolution over the time.

Place Figures 1, 2 and 3 about here

4 Conclusion

To the best of our knowledge this is the first paper that studies how interbank network measures explain banking efficiency. We use a translog cost, profit and risk-taking equation to model bank efficient. Our results imply those interconnections are relevant predictors of bank efficiency. Furthermore, we unveil the role of network topology on bank efficiency and present important empirical results.

The main result that we have obtained is that network topology matters for explaining bank efficiency. There are several differences if we are modeling cost or profit efficiency and with regards to risk-taking efficiency. It seems that profit and risk-taking efficiency are more affected by the network topology than cost efficiency.

Our results are important for the development of policies that aim at increasing bank efficiency. These results are also relevant for the design of proper macroprudential policies that target reducing excessive risk-taking.

References

D. Aigner, K. C. A. Lovell, and P. Schmidt. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6:21–37, 1977.

F. Allen and D. Gale. Financial contagion. *Journal of Political Economy*, 108:1–23, 2000.

Albert-Laszlo Barabasi and Reka Albert. Emergence of scaling in random networks. *Science*, 286(5439):509–512, 1999.

G.E. Battese and T.J. Coelli. Prediction of firm-level thecnical efficiency: With a generalized frontier production function and panel data. *Journal of Econometrics*, 38:387–399, 1988.

G.E. Battese and T.J. Coelli. A model for thecnical inefficiency effects in a stochastic frontier prduction function for panel data. *Empirical Economics*, 20:325–332, 1995.

F. Belotti, S. Daidone, G. Ilardi, and V. Atella. Stochastic frontier analysis using stata. *Stata Journal*, 3(4):718–758, 2013.

A. N. Berger, I. Hasan, and M. Zhou. Bank ownership and efficiency in china: what will happen in the world's largest nation? *Journal of Banking and Finance*, 33: 113–130, 2009.

J. W. B. Bos and M. Koetter. Handling losses in translog profit models. *Applied Economics*, 43(3):307–312, 2011.

J.H. Boyd and D.E. Runkle. Size and performance of banking firms: testing predictions of theory. *Journal of Monetary Economics*, 31:47–67, 1993.

D. O. Cajueiro and B. M. Tabak. The role of banks in the brazilian interbank market: Does bank type matter. *Physica A: Statistical Mechanics and its Applications*, 387(27):6825–6836, 2008.

Rodrigo C. Castro Miranda, Sergio R. Stancato de Souza, Thiago Christiano Silva, and Benjamin Miranda Tabak. Connectivity and systemic risk in the brazilian national payments system. *Journal of Complex Networks*, 2014.

A. Clauset, C. Shalizi, and M. Newman. Power-law distributions in empirical data. *SIAM Review*, 51(4):661–703, 2009.

G. De Masi and M. Gallegati. Bank-firms topology in italy. *Empirical Economics*, 43:851–866, 2012.

G. De Masi, Y. Fujiwara, M. Gallegati, B. Greenwald, and J.E. Stiglitz. An analysis of the japanese credit networks. *Evolutionary and Institutional Economics Review*, 7(2):209–232, 2010.

A. Demirgu-Kunt and H. Huizinga. Are banks too big to fail or too big to save? international evidence from equity prices and cds spreads. *Journal of Banking and Finance*, 37(3):875–894, 2013.

M. Duygun, V. Sena, and M. Shaban. Schumpeterian competition and efficiency among commercial banks. *Journal of Banking and Finance*, 37:5176–5185, 2013.

Giorgio Fagiolo. Clustering in complex directed networks. *Physical Review E*, 76 (2):026107, 2007.

Y. Fang, I. Hassan, and K. Maton. How institutions affect bank risk: Evidence from a natural experiment in transition economies. *Paper sessions, FMA Annual Meeting Program*, 2011.

Xavier Freixas, Bruno M Parigi, and Jean-Charles Rochet. Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. *Journal of Money, Credit and Banking*, 32(3):611–38, 2000.

Y. Fujiwara, H. Aoyama, Y. Ikeda, H. Iyetomi, and W. Souma. Structure and temporal change of the credit network between banks and large rms in japan. *Open-Assessment EJournal*, 3(7), 2009.

X. Gabaix. Power laws in economics and finance. *Annual Review of Economics*, 1: 255–294, 2009.

K. Hadri, C. Guermat, and J. Whittaker. Estimatinf farm efficiency in the presence of double heteroscedasticity using panel data. *Journal of Applied Economics*, VI (2):255–268, 2003.

J.F. Houston, C. Lin, P. Lin, and Y. Ma. Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics*, 96:485–512, 2010.

L. Laeven and R. Levine. Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93:259–275, 2009.

S. Lenzu and G. Tedeschi. Systemic risk on different interbank network topologies. *Physica A: Statistical Mechanics and its Applications*, 391(18):4331–4341, 2012.

J. Li, S. anmd He and Y. Zhuang. A network model of the interbank market. *Physica A: Statistical Mechanics and its Applications*, 389(24):5587–5593, 2010.

J. Maudos, J.M. Pastor, F. Perez, and J. Quesada. Cost and profit efficiency in european banks. *Journal of International Financial Markets, Institutions and Money*, 12(1):33–58, 2002.

J. Maudos, J.M. Pastor, F. Perez, and J. Quesada. Cost efficiency in latin american and caribbean banking systems. *Journal of International Financial Markets, Institutions and Money*, 15:55–72, 2005.

W. Meeusen and J. Van den Broeck. Efficiency estimation from cobb-douglas production functions with composed error. *International Economic Review*, 18:435–444, 1977.

S. Mercieca, K. Schaeck, and S. Wolfe. Small european banks: Benefits from deversification? *Journal of Banking and Finance*, 31(7):1975–1998, 2007.

Mark Newman. *Networks: An Introduction*. Oxford University Press, Inc., New York, NY, USA, 2010.

Edson Santos and Rama Cont. The brazilian interbank network structure and systemic risk. Working Papers Series 219, Central Bank of Brazil, Research Department, 2010.

C.W.J. Sealey and J. T. Lindley. Inputs, outputs, and a theory of production and cost at depository financial institutions. *Journal of Finance*, 32:1251–1266, 1977.

J. Sun, K. Harimaya, and N. Yamori. Regional economic development, strategic investors, and efficiency of chinese city commercial banks. *Journal of Banking and Finance*, 37:1602–1611, 2013.

B. M. Tabak, D.M. Fazio, and D.O. Cajueiro. The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking and Finance*, 36(12):3366–3381, 2012.

B. M. Tabak, D.M. Fazio, and D.O. Cajueiro. Systemically important banks and financial stability: The case of latin america. *Journal of Banking and Finance*, 37(10):3855–3866, 2013.

Benjamin Miranda Tabak, Marcelo Takami, Jadson M.C. Rocha, Daniel Oliveira Cajueiro, and Sergio R.S. Souza. Directed clustering coefficient as a measure of systemic risk in complex banking networks. *Physica A: Statistical Mechanics and its Applications*, 394(C):211–216, 2014.

R. VanDenBrink and R. P. Gilles. Measuring domination in directed networks. *Social Networks*, 22:141–157, 2000.

Table 1: Summary Statistics

Variables	**Mean**	**Std.Dev.**	**Min.**	**Max.**
Cost and Profit (in R$ million) and $Z-score$				
Total profits	564	2,295	-3,603	21,261
Total costs	4,062	13,431	3	90,252
$\log(Z-score)$	3.18	1.04	-1.74	6.04
Output quantities (in R$ million)				
Total loans (y_1)	16,348	60,741	0.217	588,423
Total deposits (y_2)	14,383	54,753	0.001	487,447
Liquid assets (y_3)	6,634	20,744	1.046	166,994
Fixed input (in R$ million)				
Earning assets (z)	22,983	80,117	0.003	709,751
Input prices				
Unit interest cost of deposits ($w1$)	28.2	350.5	0	7,093.5
Unit price of physical inputs ($w2$)	4.5	8.0	0.1	86.4
Control variables				
Leverage (ETA)	0.207	0.159	0.017	0.983
Asset Quality (NPL)	0.034	0.054	0	0.686
Log(Assets) ($Size$)	21.644	2.168	17.211	27.638
Individual Interconnectivity measures				
Lender dominance ($Woutdegree$)	1.300	3.509	0	29.032
Borrower dominance ($Windegree$)	1.128	2.336	0	23.076
Weighted betweenness centrality ($Wbetween$)	0.033	0.070	0	0.538
Closeness centrality ($Closeness$)	0.405	0.164	0	0.832
Degree centrality ($Degree$)	0.089	0.092	0	0.519
Indegree centrality ($Indegree$)	0.092	0.129	0	0.805
Outdegree centrality ($Outdegree$)	0.182	0.211	0	1.259
Betweenness centrality ($Between$)	0.010	0.030	0	0.234
Network Interconnectivity measures				
Non-weighted direct clustering ($Clustering$)	0.496	0.077	0.934	.0609
Power Law exponent ($Alpha$)	2.197	0.223	0.1932	2.576
Power law goodness of fit statistics				
K_{min}	0.054	0.020	0.033	0.089
N	0.612	0.093	0.472	0.727
P-value of Komolgorov-Smirnov test	0.001	0.001	0.000	0.002
Log-likelihood	87.342	15.845	60.048	102.593

K_{min} is the lower bound, in percentage, from which the Power Law holds. N is the percentage of observations for which the Power Law holds.

Table 2: Panel regressions on the relative importance of inter-connectivity in the interbank market determining cost inefficiency using Power Law exponent as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Cost inefficiency (u)		
ETA	10.61***	10.61***	6.914***	8.602***	9.716***
	(2.339)	(2.338)	(0.991)	(1.821)	(2.063)
NPL	0.246***	0.242***	0.114***	0.199***	0.210***
	(0.071)	(0.071)	(0.025)	(0.055)	(0.060)
Size	-0.784**	-0.775**	-0.412***	-0.905***	-0.874***
	(0.311)	(0.308)	(0.094)	(0.301)	(0.308)
Foreign	-0.816*	-0.812*	-0.132	-0.215	-0.216
	(0.467)	(0.465)	(0.181)	(0.373)	(0.400)
State-owned	2.010**	1.992**	1.680***	2.770***	2.984***
	(0.922)	(0.914)	(0.354)	(0.919)	(1.020)
Alpha		2.129	0.331	0.948	1.218
		-2.92	(1.212)	(2.363)	(2.594)
Windegree			0.655***		
			(0.206)		
Woutdegree			0.0806		
			(0.228)		
Wbetweenness			2.493		
			(1.728)		
Degree				8.511**	
				(4.172)	
Closeness				-0.12	
				(1.226)	
Betweenness				18.72*	
				(11.200)	
Indegree					-15.99*
					(8.942)
Outdegree					14.01**
					(5.607)
Constant	12.15**	9.478	6.508***	13.78**	12.14**
	(5.396)	(6.047)	(2.267)	(5.675)	(5.834)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-262.9	-262.6	-257.6	-255.4	-257.4

This table shows the panel regressions for cost inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes cost inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on cost inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on cost inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 3: Panel regressions on the relative importance of inter-connectivity in the interbank market determining profit inefficiency using Power Law exponent as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Profit inefficiency (u)		
ETA	-4.572***	-4.521***	-4.162***	-4.327***	-4.121***
	(1.154)	(1.010)	(0.970)	(1.019)	(1.020)
NPL	-0.0188	-0.0212	-0.0195	-0.0233*	-0.0208
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)
Size	-0.055	-0.0532	-0.0241	-0.0363	-0.000857
	(0.042)	(0.040)	(0.057)	(0.054)	(0.059)
Foreign	0.437***	0.430***	0.428***	0.443***	0.445***
	(0.160)	(0.152)	(0.150)	(0.163)	(0.164)
State-owned	-0.494	-0.480*	-0.47	-0.479	-0.505
	(0.313)	(0.290)	(0.288)	(0.304)	(0.312)
Alpha		-4.354*	-4.445*	-4.376*	-4.537*
		-2.492	(2.500)	(2.499)	(2.497)
Windegree			0.187		
			(0.150)		
Woutdegree			-0.136		
			(0.168)		
Wbetweenness			-1.716		
			(1.300)		
Degree				1.55	
				(1.534)	
Closeness				-0.589	
				(0.589)	
Betweenness				-4.783	
				(3.743)	
Indegree					-3.576
					(2.388)
Outdegree					1.612
					(1.623)
Constant	3.184***	8.215***	7.705**	7.903**	7.208**
	(0.989)	(3.058)	(3.203)	(3.171)	(3.199)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-974.7	-973.2	-971.2	-971.8	-971.4

This table shows the panel regressions for profit inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes profit inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on profit inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on profit inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 4: Panel regressions on the relative importance of inter-connectivity in the interbank market determining risk-taking inefficiency using Power Law exponent as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Risk-taking inefficiency (u)		
ETA	-12.62***	-17.05***	-10.15***	-12.16***	-10.64***
	(4.049)	(4.837)	(3.218)	(4.310)	(4.036)
NPL	0.113*	0.724***	0.102	0.122	0.103
	(0.064)	(0.216)	(0.068)	(0.095)	(0.097)
Size	-0.866***	-0.768***	-0.724***	-1.037***	-0.903***
	(0.238)	(0.219)	(0.210)	(0.254)	(0.279)
Foreign	0.883***	1.208***	0.818***	1.311***	1.169***
	(0.339)	(0.398)	(0.310)	(0.426)	(0.428)
State-owned	-12.84	-23.26	-9.951	-23.16	-12.24
	(14.310)	(21.720)	(12.590)	(32.740)	(22.850)
Alpha		-9.336**	-5.416	-6.521	-6.726
		(3.890)	(3.316)	(4.104)	(4.327)
Windegree			0.746**		
			(0.324)		
Woutdegree			-1.197**		
			(0.465)		
Wbetweenness			3.522		
			(2.613)		
Degree				13.05***	
				(4.637)	
Closeness				4.215*	
				(2.241)	
Betweenness				-57.32**	
				(26.360)	
Indegree					-12.86**
					(5.043)
Outdegree					10.76***
					(3.712)
Constant	20.59***	31.52***	23.67***	29.25***	28.17***
	(5.032)	(7.688)	(6.835)	(8.126)	(9.444)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-951.5	-946.6	-943.5	-934.9	-943.2

This table shows the panel regressions for risk-taking inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes risk-taking inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on risk-taking inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on risk-taking inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 5: Panel regressions on the relative importance of inter-connectivity in the interbank market determining cost inefficiency using unweighted direct clustering as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Cost inefficiency (u)		
ETA	10.61***	10.58***	6.914***	8.588***	9.668***
	(2.339)	(2.338)	(0.979)	(1.816)	(2.050)
NPL	0.246***	0.243***	0.116***	0.200***	0.210***
	(0.071)	(0.071)	(0.025)	(0.055)	(0.060)
Size	-0.784**	-0.780**	-0.414***	-0.909***	-0.877***
	(0.311)	(0.308)	(0.093)	(0.301)	(0.306)
Foreign	-0.816*	-0.819*	-0.134	-0.207	-0.211
	(0.467)	(0.467)	(0.180)	(0.373)	(0.399)
State-owned	2.010**	2.002**	1.675***	2.788***	2.993***
	(0.922)	(0.916)	(0.350)	(0.922)	(1.017)
Clustering		-1.674	1.083	-0.684	-1.224
		(4.254)	(1.734)	(3.559)	(3.754)
Windegree			0.663***		
			(0.204)		
Woutdegree			0.0754		
			(0.228)		
Wbetweenness			2.559		
			(1.723)		
Degree				8.588**	
				(4.168)	
Closeness				-0.0584	
				(1.268)	
Betweenness				18.68*	
				(11.180)	
Indegree					-15.92*
					(8.866)
Outdegree					14.06**
					(5.579)
Constant	12.15**	12.73**	6.506***	15.21***	14.10**
	(5.396)	(5.671)	(1.808)	(5.357)	(5.510)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-262.9	-262.8	-257.5	-255.4	-257.5

This table shows the panel regressions for cost inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes cost inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by weighted direct clustering, on cost inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on cost inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 6: Panel regressions on the relative importance of inter-connectivity in the interbank market determining profit inefficiency using using unweighted direct clustering as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Profit inefficiency (u)		
ETA	-4.572***	-4.655***	-4.216***	-4.413***	-4.176***
	(1.154)	(1.170)	(1.063)	(1.138)	(1.121)
NPL	-0.0188	-0.0213	-0.0193	-0.0236*	-0.0207
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
Size	-0.055	-0.0563	-0.0259	-0.038	-0.000113
	(0.042)	(0.043)	(0.059)	(0.057)	(0.061)
Foreign	0.437***	0.444***	0.438***	0.454***	0.452***
	(0.160)	(0.162)	(0.156)	(0.170)	(0.171)
State-owned	-0.494	-0.519	-0.493	-0.514	-0.533
	(0.313)	(0.323)	(0.307)	(0.325)	(0.330)
Clustering		3.22	3.577	3.57	3.603
		(3.617)	(3.777)	(3.650)	(3.616)
Windegree			0.189		
			(0.153)		
Woutdegree			-0.133		
			(0.172)		
Wbetweenness			-1.809		
			(1.348)		
Degree				1.587	
				(1.591)	
Closeness				-0.692	
				(0.623)	
Betweenness				-4.746	
				(3.871)	
Indegree					-3.543
					(2.447)
Outdegree					1.544
					(1.659)
Constant	3.184***	1.838	1.089	1.381	0.426
	(0.989)	(1.792)	(2.019)	(1.933)	(2.061)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-974.7	-974.3	-972.3	-972.8	-972.6

This table shows the panel regressions for profit inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes profit inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by the unweighted direct clustering ($Clustering$), on profit inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on profit inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 7: Panel regressions on the relative importance of inter-connectivity in the interbank market determining risk-taking inefficiency using unweighted direct clustering as measure of network topology

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Risk-taking inefficiency (u)		
ETA	-12.62***	-14.94**	-11.16***	-12.05***	-17.00***
	(4.049)	(7.516)	(3.620)	(4.144)	(4.498)
NPL	0.113*	0.199	0.128	0.11	0.490***
	(0.064)	(0.240)	(0.081)	(0.070)	(0.161)
Size	-0.866***	-0.979***	-0.831***	-1.047***	-0.952***
	(0.238)	(0.264)	(0.219)	(0.240)	(0.265)
Foreign	0.883***	1.016**	0.948***	1.307***	1.605***
	(0.339)	(0.451)	(0.346)	(0.406)	(0.439)
State-owned	-12.84	-28.74	-14.38	-21.78	-26.43
	(14.310)	(36.720)	(16.690)	(31.620)	(32.940)
Clustering		13.97**	13.62***	10.65**	18.03***
		(6.569)	(5.240)	(4.844)	(5.083)
Windegree			0.996**		
			(0.399)		
Woutdegree			-1.244**		
			(0.511)		
Wbetweenness			3.267		
			(2.785)		
Degree				13.07***	
				(4.517)	
Closeness				3.16	
				(2.003)	
Betweenness				-46.67**	
				(23.780)	
Indegree					-17.06***
					(5.978)
Outdegree					14.87***
					(4.383)
Constant	20.59***	17.48***	14.01***	17.89***	15.37***
	(5.032)	(4.873)	(3.943)	(4.017)	(4.911)
Observations	669	669	669	669	669
Number of Banks	102	102	102	102	102
Log Likelihood	-951.5	-946.1	-939.4	-933.7	-936.7

This table shows the panel regressions for risk-taking inefficiency using the model proposed by Battese and Coelli [1995]. Model 1 analyzes risk-taking inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by unweighted direct clustering ($Clustering$), on risk-taking inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on risk-taking inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 8: Panel regressions on the relative importance of inter-connectivity in the interbank market determining cost inefficiency using Power Law exponent as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Cost inefficiency (u)			
ETA	10.86***	9.462***	8.941***	9.746***
	(2.472)	(2.184)	(1.989)	(2.094)
NPL	0.232***	0.195***	0.190***	0.194***
	(0.066)	(0.053)	(0.051)	(0.051)
Size	-0.649**	-0.651***	-0.733***	-0.713***
	(0.276)	(0.242)	(0.269)	(0.257)
Foreign	-0.345	-0.075	0.192	0.201
	(0.419)	(0.337)	(0.334)	(0.349)
State-owned	2.190**	2.490***	2.923***	3.062***
	(0.913)	(0.819)	(0.937)	(0.959)
Lag(Alpha)	1.185	0.364	0.378	0.368
	(2.765)	(2.208)	(2.077)	(2.217)
Lag(Windegree)		0.718*		
		(0.429)		
Lag(Woutdegree)		-0.117		
		(0.536)		
Lag(Wbetweenness)		6.972*		
		(3.885)		
Lag(Degree)			9.165**	
			(4.080)	
Lag(Closeness)			0.364	
			(1.178)	
Lag(Betweenness)			11.24	
			(9.847)	
Lag(Indegree)				-13.16*
				(7.643)
Lag(Outdegree)				13.27**
				(5.261)
Constant	8.171	9.679**	11.12**	10.30**
	(5.565)	(4.756)	(4.817)	(4.854)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-203.9	-199.3	-196.6	-197.9

This table shows the panel regressions for cost inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on cost inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on cost inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 9: Panel regressions on the relative importance of inter-connectivity in the interbank market determining profit inefficiency using Power Law exponent as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Profit inefficiency (u)			
ETA	-4.146***	-3.805***	-3.849***	-3.588***
	(0.736)	(0.749)	(0.750)	(0.778)
NPL	-0.0241*	-0.0241*	-0.0246*	-0.0217*
	(0.013)	(0.013)	(0.013)	(0.013)
Size	-0.014	0.0206	0.0232	0.0649
	(0.035)	(0.053)	(0.048)	(0.056)
Foreign	0.383***	0.381***	0.359**	0.359**
	(0.133)	(0.139)	(0.143)	(0.144)
State-owned	-0.604***	-0.570**	-0.641**	-0.669***
	(0.228)	(0.237)	(0.249)	(0.253)
Lag(Alpha)	-4.314***	-4.391***	-4.244***	-4.336***
	(0.919)	(0.914)	(0.913)	(0.928)
Lag(Windegree)		0.281*		
		(0.152)		
Lag(Woutdegree)		-0.329**		
		(0.166)		
Lag(Wbetweenness)		-0.044		
		(1.192)		
Lag(Degree)			1.397	
			(1.392)	
Lag(Closeness)			-0.646	
			(0.541)	
Lag(Betweenness)			-5.831*	
			(3.348)	
Lag(Indegree)				-4.132**
				(2.083)
Lag(Outdegree)				1.64
				(1.476)
Constant	7.822***	7.110***	7.050***	6.148***
	(1.345)	(1.562)	(1.516)	(1.595)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-818.1	-815.4	-815.9	-814.9

This table shows the panel regressions for profit inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on profit inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on profit inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 10: Panel regressions on the relative importance of inter-connectivity in the interbank market determining risk-taking inefficiency using Power Law exponent as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Risk-taking inefficiency (u)			
ETA	-12.51***	-9.673***	-11.54***	-9.028***
	(3.760)	(2.237)	(3.803)	(2.197)
NPL	0.162*	0.109**	0.163*	0.102**
	(0.089)	(0.045)	(0.091)	(0.045)
Size	-0.952***	-0.857***	-1.206***	-0.942***
	(0.233)	(0.181)	(0.234)	(0.210)
Foreign	0.900**	0.940***	1.637***	1.264***
	(0.356)	(0.291)	(0.474)	(0.338)
State-owned	-12.7	-3.809	-19.33	-2.972
	(22.100)	(2.516)	(29.800)	(2.630)
Lag(Alpha)	-6.893*	-6.875**	-9.384**	-8.523***
	(3.714)	(2.915)	(4.032)	(3.233)
Lag(Windegree)		1.218***		
		(0.338)		
Lag(Woutdegree)		-0.678*		
		(0.388)		
Lag(Wbetweenness)		0.175		
		(2.644)		
Lag(Degree)			18.23***	
			(5.366)	
Lag(Closeness)			4.296**	
			(2.050)	
Lag(Betweenness)			-49.39**	
			(24.140)	
Lag(Indegree)				-17.12***
				(4.896)
Lag(Outdegree)				14.95***
				(3.629)
Constant	30.63***	28.11***	35.72***	30.89***
	(7.732)	(5.552)	(7.585)	(6.442)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-792.4	-784.3	-771.5	-778.3

This table shows the panel regressions for risk-taking inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on risk-taking inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on risk-taking inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 11: Panel regressions on the relative importance of inter-connectivity in the interbank market determining cost inefficiency using unweighted direct clustering as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Cost inefficiency (u)			
ETA	10.86***	9.467***	8.929***	9.735***
	(2.466)	(2.183)	(1.991)	(2.086)
NPL	0.233***	0.196***	0.190***	0.195***
	(0.066)	(0.053)	(0.051)	(0.051)
Size	-0.652**	-0.650***	-0.732***	-0.712***
	(0.277)	(0.242)	(0.271)	(0.257)
Foreign	-0.343	-0.0731	0.194	0.204
	(0.419)	(0.336)	(0.333)	(0.348)
State-owned	2.194**	2.488***	2.921***	3.059***
	(0.916)	(0.818)	(0.944)	(0.957)
Lag(Clustering)	-0.433	0.398	-0.137	0.0245
	(5.011)	(3.962)	(3.776)	(3.953)
Lag(Windegree)		0.724*		
		(0.428)		
Lag(Woutdegree)		-0.125		
		(0.536)		
Lag(Wbetweenness)		7.038*		
		(3.898)		
Lag(Degree)			9.196**	
			(4.081)	
Lag(Closeness)			0.359	
			(1.203)	
Lag(Betweenness)			11.2	
			(9.820)	
Lag(Indegree)				-13.19*
				(7.636)
Lag(Outdegree)				13.30**
				(5.255)
Constant	9.764*	9.936**	11.61**	10.71**
	(5.194)	(4.353)	(4.731)	(4.578)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-204	-199.3	-196.6	-197.9

This table shows the panel regressions for cost inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by weighted direct clustering, on cost inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on cost inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 12: Panel regressions on the relative importance of inter-connectivity in the interbank market determining profit inefficiency using using unweighted direct clustering as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Profit inefficiency (u)			
ETA	-4.075***	-3.908***	-3.907***	-3.753***
	(0.806)	(0.748)	(0.788)	(0.746)
NPL	-0.0217*	-0.0214*	-0.0220*	-0.0192
	(0.013)	(0.012)	(0.012)	(0.012)
Size	-0.0225	0.000186	0.00273	0.0374
	(0.040)	(0.051)	(0.049)	(0.051)
Foreign	0.350***	0.362***	0.347**	0.347***
	(0.131)	(0.129)	(0.138)	(0.133)
State-owned	-0.533**	-0.477**	-0.537**	-0.550**
	(0.226)	(0.227)	(0.242)	(0.236)
Lag(Clustering)	11.15***	10.53***	10.26***	10.14***
	(4.275)	(3.135)	(3.929)	(3.091)
Lag(Windegree)		0.279**		
		(0.140)		
Lag(Woutdegree)		-0.309**		
		(0.154)		
Lag(Wbetweenness)		-0.0271		
		(1.112)		
Lag(Degree)			1.574	
			(1.309)	
Lag(Closeness)			-0.581	
			(0.507)	
Lag(Betweenness)			-5.709*	
			(3.124)	
Lag(Indegree)				-4.094**
				(1.932)
Lag(Outdegree)				1.779
				(1.372)
Constant	-1.074	-1.321	-1.157	-1.913
	(2.299)	(1.774)	(2.116)	(1.730)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-821.6	-818.8	-819.3	-818.5

This table shows the panel regressions for profit inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by the unweighted direct clustering ($Clustering$), on profit inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on profit inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 13: Panel regressions on the relative importance of inter-connectivity in the interbank market determining risk-taking inefficiency using unweighted direct clustering as measure of network topology (Robustness test)

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Risk-taking inefficiency (u)			
ETA	-12.84***	-10.13***	-11.72***	-9.273***
	(3.815)	(2.406)	(3.332)	(2.240)
NPL	0.167*	0.117**	0.149**	0.101**
	(0.092)	(0.050)	(0.075)	(0.045)
Size	-0.973***	-0.893***	-1.202***	-0.942***
	(0.239)	(0.192)	(0.238)	(0.207)
Foreign	0.927**	1.006***	1.589***	1.280***
	(0.368)	(0.314)	(0.449)	(0.348)
State-owned	-12.82	-3.84	-25.68	-2.778
	(21.080)	(2.565)	(63.240)	(2.260)
Lag(Clustering)	11.16*	12.27**	10.53**	12.94***
	(5.825)	(4.991)	(5.075)	(4.983)
Lag(Windegree)		1.301***		
		(0.364)		
Lag(Woutdegree)		-0.632		
		(0.400)		
Lag(Wbetweenness)		-0.124		
		(2.736)		
Lag(Degree)			17.40***	
			(5.160)	
Lag(Closeness)			4.020**	
			(1.987)	
Lag(Betweenness)			-51.38**	
			(25.410)	
Lag(Indegree)				-17.09***
				(4.999)
Lag(Outdegree)				14.81***
				(3.653)
Constant	18.77***	16.09***	20.91***	16.04***
	(4.536)	(3.800)	(4.117)	(3.933)
Observations	567	567	567	567
Number of Banks	102	102	102	102
Log Likelihood	-792.4	-783.9	-773.8	-778.9

This table shows the panel regressions for risk-taking inefficiency using the model proposed by Battese and Coelli [1995]. Model 2 analyzes the impact of network topology, measured by unweighted direct clustering ($Clustering$), on risk-taking inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on risk-taking inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Standard errors in parentheses; *** , ** , * stand for 1, 5 and 10 percent significance levels respectively.

Table 14: Bank efficiency level

Models	**Mean**	**Std.Dev.**	**Min.**	**Max.**
Cost efficiency level				
Model 1	0.6960	0.2276	0.0049	0.9539
Model 2	0.6956	0.2279	0.0049	0.9538
Model 3	0.6252	0.2438	0.0052	0.9740
Model 4	0.6844	0.2308	0.0047	0.9576
Model 5	0.6928	0.2289	0.0050	0.9548
Profit efficiency level				
Model 1	0.2859	0.1904	0.0064	0.8212
Model 2	0.2793	0.1943	0.0048	0.8545
Model 3	0.2720	0.1930	0.0045	0.8571
Model 4	0.2846	0.1953	0.0048	0.8542
Model 5	0.2882	0.1967	0.0051	0.8578
Risk-taking efficiency level				
Model 1	0.5125	0.2404	0.0047	0.9222
Model 2	0.6726	0.2323	0.0106	0.9666
Model 3	0.5046	0.2441	0.0042	0.9207
Model 4	0.5523	0.2478	0.0051	0.9559
Model 5	0.5213	0.2425	0.0048	0.9326

This table shows the mean bank-level cost, profit and risk-taking efficiency estimated as defined in Battese and Coelli [1988], i.e. efficiency $E[exp(-u)|e]$, via the models presented in Tables 2, 3, and 4. Model 1 analyzes bank inefficiency without any measure for inter-connectivity. Model 2 analyzes the impact of network topology, measured by the Power Law exponent, on bank inefficiency. Models 3 - 5 analyze the impact of network topology and individual bank inter-connectivity on bank inefficiency: model 3 uses weighted network measures(borrower ($Windegree$), lender ($Woutdegree$) and weighted betweenness ($Wbetweenness$)) as proxies for individual bank inter-connectivity; model 4 uses unweighted network measures ($Degree$, $Closeness$ and $Betweenness$) as proxies for individual bank inter-connectivity; Model 5 uses two components of degree separately ($Indegree$ and $Outdegree$) as proxies for individual bank inter-connectivity.

Figure 1: Cost efficiency levels over the years

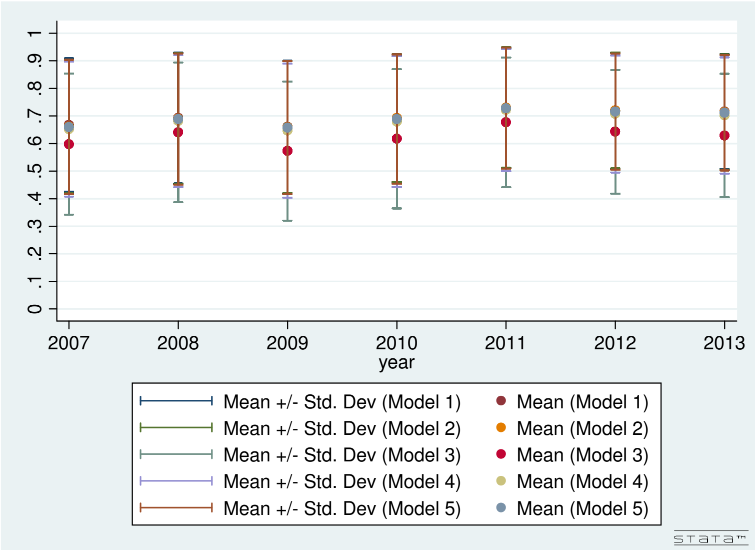


Figure 2: Profit efficiency levels over the years

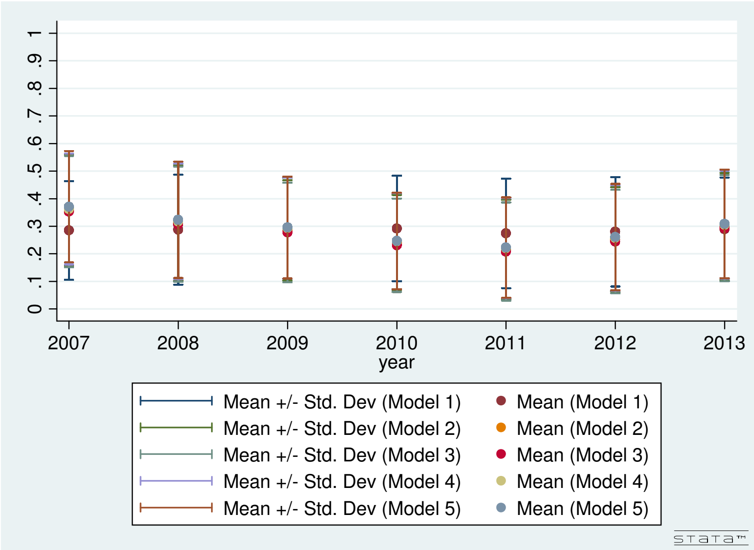


Figure 3: Risk-taking efficiency levels over the years