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The Brazilian Interbank Network Structure and Systemic Risk*

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Abstract

We explore the structure and dynamics of interbank exposures in Brazil using a unique data set of all mutual exposures of financial institutions in Brazil, as well as their capital reserves, at various periods in 2007 and 2008. We show that the network of exposures can be adequately modeled as a directed scale-free (weighted) graph with heavy-tailed degree and weight distributions. We also explore the relationship between connectivity of a financial institution and its capital buffer. Finally, we use the network structure to explore the extent of systemic risk generated in the system by the individual institutions.

Keywords: contagion, systemic risk, macro-prudential regulation, liquidity, leverage.

JEL Classification: C10, E44, E58, G01, G21.

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1 Introduction

The recent financial crisis has emphasized the importance of systemic risk, defined as macro-level risk which can influence the entire stability of a financial system. Control over systemic risk has been the main motivation of the recent bailouts of large financial institutions in United States. Regulators have had great difficulties anticipating the impact of defaults partly due to a lack of both visibility and relevant indicators on the structure of the financial system. Therefore the focus on *Too big to fail*, maybe is not the right criterion, but contribution to financial stability and possibility for contagion could be better ones, i.e., *Too interconnected to fail*, see Griffin (2008). Availability of better indicators of systemic risk would have greatly helped formulating a consistent approach to *bailout*. Elsinger et al. (2006), Furfine (2003), Forbes and Rigobon (2002), Upper and Worms (2004), Wells (2004). In particular, Elsinger et al. (2004).

Section 2 provides details about the financial institutions and details about exposures and capitals comprising the data sets. Section 3 provides an empirical analysis of the topology of the interbank network for the Brazilian Financial System. As far as we know this is the first study to provide a full detailed description of the interbank topology considering only real data. Most of the studies so far have either focused on clearing financial systems, e.g., Ágnes Lublóy (2006), Iori et al. (2008), Cajueiro and Tabak (2008), Rørdam and Bech (2009) or considered incomplete sets of data, Elsinger et al. (2004), Upper and Worms (2004), Degryse and Nguyen (2007), thereupon, completing the data set with methods such as maximizing entropy or cross-entropy. An interesting approach was suggested by Elsinger et al. (2006), where the analysis of interbank network was extended to other sources of risk, such as the credit and market risks originated from non-financial institutions. However, it was required many assumptions regarding the estimation of the data set. In Section 4, we study the relationship between capital reserves and exposures. We propose a linear model for the concept of capital buffer and provide additional insights for the distribution behavior of residuals of the model proposed, therefore, complementing the previous section. Section 5 is mainly concerned with systemic risk. We identify the impact of contagion if any particular bank fails with its obligations with respect to other financial institutions. To analyze contagion in this context, we define what is *default* in terms of tier I and tier II capital. This is crucial and many authors usually don't give it the proper importance, hence, considering unrealistic assumptions, Mistrulli (2007), Cont and Moussa (2009). In this section, we extend the systemic risk analysis incorporating other sources of risk, such as market, credit and liquidity risks. Section 6 provides the conclusions for the study.

2 Data Description

2.1 Mutual Exposures

The Brazilian Financial System encompassed 2,400 financial institutions chartered by *Banco Central do Brasil.* Table 1 shows that the number of financial institutions of Type I and Type II are less than of type III. Type I banking institutions have commercial portfolios, and Type II represent all other banking institutions excluding Type III which are subject to particular regulations. Despite their reduced number, financial institutions of Type I and II accounts for the majority of total assets in the Brazilian Financial System (close to 98%), see Table 2. This is intuitive, since the majority of financial institutions that are of our interest are considered as either Type I or II, such as multiple banks, savings banks, investment banks, development banks, and other security brokerage or distribution companies. In addition, the majority of Type I and Type II financial institutions, which can be seen as a good proxy of the Brazilian Financial System, are mainly held by private capital (approximately 70%) and operate as a financial conglomerate (approximately 75%).

Since most of the financial institutions belong to a conglomerate, it is quite meaningful to analyze contagion from a consolidated perspective because funds and liquidity are managed as if all affiliated financial institutions are only one. To cope with this fact, we consider only consolidated information for financial conglomerates. The accounting standards for consolidation of financial statements were established by Resolutions 2,723 and 2,743, BCB (2000a,b), and they are very similar to IASB and FASB directives. If we regard financial institutions of Type I and II as conglomerates, the number of institutions is reduced substantially.

In summary, our database considers 6 dates, i.e., June 2007, December 2007, March 2008, June 2008, September 2008 and November 2008. The interbank exposures for all financial conglomerates contemplate all sources risk, that is, fixed-income instruments (certificate of deposits and debentures), borrowing and lending (credit risk), derivatives (including over-the-counter instruments such as swaps) and foreign exchange (currencies). It is important to note that all derivatives were accounted by their market prices when available, or fair value when a model-based valuation is required. It is also important to remark that all the exposures represent real operations.

2.2 Capital Reserves

We consider three types of capital, as defined in the guidelines provided by Basel Accord I, BIS (1988), that is, the *Required Capital* C_r, the *Capital tier I* C_1 and the *Reference Capital* C_2.[1]

Considering both the Brazilian legal system and the types of financial instruments Brazilian banks have access to build their capitals, *Banco Central do Brasil*, in accordance with the Basel I and II Accords, issued Resolution 3,444, BCB (2007a), determining that banks compute tier I Capital as the accounting concept of shareholder's equity plus net income (loss), deducted by redeemed preferred stocks, capital and revaluation of fixed assets reserves, deferred taxes, and non-realized gains (losses), such as mark-to-market adjustments from securities registered as available-for-sale and hedge accounting. Eligible tier II Capital is equal to the sum of these same deductions, excepted for the deferred taxes, in addition to complex or hybrid capital instruments and subordinated debt. Reference Capital is just the sum of tier I and tier II capitals.

The Required Capital is a function of the associated risks regarding each financial institution's operations, whether registered in their balance sheets (assets and liabilities) or not (off-balance sheet transactions), as defined in Resolution 3,490, BCB (2007b). Roughly speaking, the Required Capital C_r, can be computed as

$$C_r = \delta \times \text{Risk Base}, \tag{1}$$

where the δ is the minimum required *Basel Index* and *Risk Base* is the sum of the following components: credit exposures weighted by their respective risk; foreign currencies and gold exposures; interest rate exposures; commodity prices exposures; stocks prices exposures; and, operational risk exposures. It is important to remark not only that these exposures include all the financial conglomerate counterparties, including corporations, mutual and hedge funds, individuals and government, but also that the maximum allowable leverage for the Brazilian financial institutions is approximately 9.10, instead of 12.50. This last observation is a consequence of the minimum required *Basel Index* of $\delta = 0.11$ which is different from the American financial system which requires a minimum Basel Index of $\delta = 0.08$ for its financial institutions.

[1]Brazil is in the process of implementing the Basel II Accord guidelines, BIS (2005). Significant changes will occur mostly in required capital methodology, and not in tier I and tier II eligible capitals. Nonetheless, netting exposures, as contemplated in the Basel II Accord, is still not allowable by Brazilian legislation for most financial operations.

3 Interbank Network Topology

3.1 Network Representation

We could view the interbank system as a directed network Γ_t for $t = 1, 2, \ldots, T$. The interbank system Γ_t is defined as the triplet $\Gamma_t = (\mathcal{V}_t, \mathcal{L}_t, \mathcal{C}_t)$, where the vertices $\mathcal{V}_t = \{1, 2, \ldots, n_t\}$ are the existing financial conglomerates on time t, the matrix $\mathcal{L}_t$ of dimension $n_t \times n_t$ represents the exposures among these financial institutions and $\mathcal{C}_t = \{C_r, C_1, C_2\}$ is the capitalization structure. Each element $\ell_{ij} \in \mathcal{L}_t$ represents that bank i has an exposure to bank j, that is, if all exposures should be cleared in time t, bank i should receive from bank j the amount ℓ_{ij}.

From $\mathcal{L}_t$, we may define the adjacency matrix $\mathcal{A}_t$ of same dimension as $\mathcal{L}_t$ whose elements are defined as the indicator function of the elements of the exposure matrix $\mathcal{L}_t$, that is $a_{ij} = \mathbb{1}_{\{\ell_{ij}>0\}}$ for all $a_{ij} \in \mathcal{A}_t$. We may also represent the adjacency matrix $\mathcal{A}_t$ as a vector $\mathcal{E}_t$ of edges, listing the financial conglomerates that are connected. The elements are defined as positions of the elements of the adjacency matrix that are equal to 1, that is, all the pairs $\{(i, j)\}$ $i, j \in \mathcal{V}_t$ for which $a_{ij} = 1$. This representation will be useful for the clustering and mixing assortativity analysis in Subsection 3.5.

For a directed network the number of edges in respect to a vertice is denoted *degrees* and depends on the direction of the exposure. The *in-degree* $k_{in,i}$ and out-degree $k_{out,i}$ of bank $i \in \mathcal{V}_t$ are defined as

$$k_{in,i} = \sum_{j \in \mathscr{V}_{in,i}} a_{ij}, \qquad k_{out,i} = \sum_{j \in \mathscr{V}_{out,i}} a_{ji}, \tag{2}$$

where $\mathscr{V}_{in,i} = \{j : a_{ij} = 1\}$ and $\mathscr{V}_{out,i} = \{j : a_{ji} = 1\}$. Consequently, the degree of financial conglomerate i is equal to $k_i = k_{in,i} + k_{out,i}$. From a statistical point of view, the degree distribution of vertices plays a very important role to generate random networks as shown in Subsection 3.2.

In a similar manner, the *in-weighted degree* $w_{in,i}$, *out-weighted degree* $w_{out,i}$ and weighted degree w_i of financial conglomerate $i \in \mathcal{V}_t$ are defined as

$$w_{in,i} = \sum_{j \in \mathscr{V}_{in,i}} \ell_{ij}, \qquad w_{out,i} = \sum_{j \in \mathscr{V}_{out,i}} \ell_{ji}, \tag{3}$$

and $w_i = w_{in,i} + w_{out,i}$. The weighted degree distributions are analyzed in Subsection 3.3.

3.2 Connectivity

An important issue that has never been scrutinized in the financial literature due to the lack of available data for different dates is whether the distribution of in-degree, out-degree and degree are stationary, that is, they do not change across time. [2]

Hypothesis 1 (Distribution Stationarity of Degrees). *The in-degree* $\mathbb{P}(K_{in} \leqslant k)$*, out degree* $\mathbb{P}(K_{out} \leqslant k)$ *and degree* $\mathbb{P}(K \leqslant k)$ *distributions are stationary.*

Figure 2 shows the Q-Q Plot of the Cumulative Density Function (CDF) $\mathbb{P}(K \leqslant k)$ of the degree distributions of two networks for consecutive dates. It is easy to verify that data are plotted around a 45 degree line, indicating that the degree distribution doesn't change with time. The Komolgorov-Smirnov test between CDFs for consecutive dates, see Massey Jr. (1951), can be written as $KS = \sup_k \left|\hat{F}_{t+1}(k) - \hat{F}_t(k)\right|$, where $\hat{F}_t(k)$ is the empirical CDF of degrees in $t = 1, 2, \ldots, T-1$. The p-values are all greater than 0.6, suggesting that for relatively high levels of significance the null hypothesis H_0 cannot be rejected. Therefore, this strongly supports that the connectivity structure of the Brazilian interbank network is stable over time. This is not what would be expected, since the data spanned over turbulent times, such as the years 2007 and 2008, where financial stability was a big issue.

Figures 3, 4 and 5 show, respectively, the log-log plot of the empirical complementary cumulative distribution for in-degree $\hat{\mathbb{P}}(K_{in} \geqslant k)$, out-degrees $\hat{\mathbb{P}}(K_{out} \geqslant k)$, and degrees $\hat{\mathbb{P}}(K \geqslant k)$, for $k \geqslant 1$. It is possible to notice that above a particular threshold k_{min} the distributions demonstrate a linear decay in the tail, suggesting a power-law nature of the distribution. This property is typical of *scale-free networks* such as the World Wide Web. For a comprehensive description of scale-free graphs see Albert-Lászó et al. (2003) and Newman et al. (2006).

Hypothesis 2 (Power Distribution of the Tail of Degrees). *The tail distributions of in degrees* $\mathbb{P}(K_{in} = k|k \geqslant k_{min})$*, out degrees* $\mathbb{P}(K_{out} = k|k \geqslant k_{min})$ *and degrees* $\mathbb{P}(K = k|k \geqslant k_{min})$ *follow a discrete power law with parameters* α *and* k_{min} *defined as*

$$\mathbb{P}(K = k|k \geqslant k_{min}) = \eta \; k^{-\alpha}, \tag{4}$$

where

$$\eta = 1/\,\zeta(\alpha, k_{min}), \tag{5}$$

[2] We defined connectivity in a narrow context, which comprises only degrees. However this definition is not a consensus and other indicators that we explore latter in this paper, such as exposure size, clustering and assortativity are also considered measures of connectivity.

and η is the reciprocal of the Hurwitz (or Generalized) Riemann Zeta function $\zeta(\alpha, k_{min}) = \sum_{k=k_{min}}^{\infty} k^{-\alpha}$.

The power law distribution is characterized by the slope of the linear relation $\log(\mathbb{P}(K \geqslant k)|k \geqslant k_{min}) = -\alpha \log(k) + c$ where c is a constant and α is called the *tail exponent*. Applying the MLE approach introduced by Clauset et al. (2009), we may jointly estimate the tail exponent α and the minimum threshold k_{min} by maximizing the likelihood function, see equation (25) in the Appendix.

Table 3 shows some statistics for the MLE estimates for in-degree, out-degree and degree distributions' parameters $\hat{\alpha}$ and $\hat{k}_{min}$. It is possible to see that the MLE estimate ranges from 2 to 3. Although these results agree with those found for the Austrian interbank network, see Elsinger et al. (2004), the Austrian network estimates did not considered the joint estimate of α and k_{min}. They determined an arbitrary value for k_{min}, which greatly impact the estimated value of α.

It is important to notice that MLE estimates are not consistent in case of misspecification of the distribution for the data generating process underlying the tails of degrees. Therefore, a better way to test the goodness-of-fit of the power law distribution is investigating the null hypothesis H_0 via Komolgorov-Smirnov test for CDF (cumulative distribution function) of a power law distribution, i.e., $KS = \sup_{k \geqslant k_{min}} \left| \hat{F}(k) - F(k|\alpha, k_{min}) \right|$, where $\hat{F}$ is the empirical CDF and F the power-law with parameters α and k_{min}. The results in Figures 3, 4 and 5 provide ample evidence that that the power-law distribution null hypothesis should not be rejected. This is supported through the p-values of KS test that are all greater than a 1% level of significance for all distributions, except for both June 2007 and September 2008 out-degrees distributions. Nevertheless, the total degree for these same dates do not reject the null hypothesis.

3.3 Exposures' Sizes

Following the same pattern for degrees, the distribution of exposures indicates that exposures also behave in accordance to the power law.

Hypothesis 3 (Power Distribution of the Exposures' Sizes)**.** *The tail of the distribution for exposures $\mathrm{d}\mathbb{P}(L_{ij} \leqslant \ell|\ell \geqslant \ell_{min})$ $i, j \in \mathcal{V}_t$ follows a continuous power law with parameters α and ℓ_{min}, i.e.,*

$$\mathrm{d}\mathbb{P}(L_{ij} \leqslant \ell|\ell \geqslant \ell_{min}) = \eta\ \ell^{-\alpha}, \tag{6}$$

where $\eta = (\alpha - 1)\ell_{min}^{\alpha-1}$.

The last column of Table 3 shows some statistics of the MLE parameters $(\hat{\alpha}, \hat{\ell}_{min})$ estimates for the power law distribution of the exposures, see equation (27) in Appendix. It is important to remark that for all in-exposures exist an analogous out-exposure, so under this circumstance, the distribution of in and out exposures are equal. The only difference is how this exposures are allocated among the banks, that is, how we allocate these exposures within the rows and columns of matrix $\mathcal{L}_t$. Following the same *modus operandi* for the degrees' tail distribution, Figure 6 shows that under a 1% level of significance it is not possible to reject the null hypothesis that the exposures for all dates are generated by a power law distribution.

3.4 Relationship between exposure size and connectivity

Another important property that we shall probe is the relationship between degrees and exposures' size. It is intuitive that if financial conglomerate $i \in \mathcal{V}_t$ has a low (high) level of connectivity, i.e., a small number of degrees k_i, it should have less (more) weighted-degrees w_i. The reverse is also true, the higher the number of degrees, the higher the amount of exposures. However, a more meaningful way to determine whether there is a relationship between degree and exposures is to investigate the relationship between degrees k_i and the mean weighted-degree w_i/k_i.

Hypothesis 4 (Degrees and Weighted Degrees Dependence)**.** *The the number of degrees k and the mean weighted-degree w_i/k_i for $i \in \mathcal{V}_t$ are not independently distributed.*

There is strong evidence that we cannot reject the null hypothesis H_0 that a linear relationship between the two variables does not exist. Table 4 shows the Pearson Coefficient $\rho_{Pearson}$ for the Brazilian network and their respective p-values, where $\rho_{Pearson}$ gauges the strength and direction of the linear relationship between these variables. Nevertheless, just looking for linear relationships is not sufficient to guarantee that degree k_i and the mean weighted-degree w_i/k_i are independently distributed, this would only be true for a multivariate normal distribution, and the previous results show that this is not the case.

Table 4, also shows the Kendall tau $\tau_{Kendall}$ and the Spearman coefficient $\rho_{Spearman}$. On one's hand, the $\tau_{Kendall}$ is a non-parametric correlation coefficient that can be used to assess correlations between the distributions of the variables, and, on the other hand, $\rho_{Spearman}$ is a rank correlation coefficient and measures how well an arbitrary monotonic function could describe the relationship between two random variables without making any assumption about their distributions. The p-values for both the Spearman coefficient and the Kendall tau test the null H_0 that there is no relationship between degree k_i and the mean weighted-degree w_i/k_i. The results are complementary to the Pearson Coefficient $\rho_{Pearson}$, in the sense that the p-values indicate that we should reject the null hypothesis for both the $\rho_{Spearman}$ and $\tau_{Kendall}$, therefore, not rejecting the alternative hypothesis H_a that there is a non-linear relationship between the number of degrees k_i and the expected exposures w_i/k_i. As a consequence, forasmuch there is evidence in favor a non-linear relationship, we should consider modeling these variables as dependently distributed. The source of this dependence appears to be represented by a logarithmic shape between these variables.

3.5 Clustering and Assortativity

The *clustering* and *mixing assortativity* (or affinity) provide aditional information about the network representation. Following Watts and Strogatz (1998), the local clustering coefficient $c_i \in [0, 1]$ for $i \in \mathcal{V}_t$ assesses the connectivity density of vertices' neighbors. If $c_i = 0$ then all possible vertices are directed disconnected, and if $c_i = 1$ then all possible vertices are directed connected. Moreover, the local clustering coefficient c_i of financial conglomerate i is the ratio of the number of directed connected neighbors of i and the maximum possible number of connections among these neighbors given the degree k_i.

Figure 7 shows the relationship between the local clustering coefficient and number of degrees for the Brazilian interbank network. The negative slope of the plots shows that financial conglomerates with fewer connections (degrees) have counterparties that are more connected to each other than financial conglomerates with many connections. We may appreciate this property as existence of fierce competition among highly connected financial conglomerates. For example, highly connected financial conglomerates compete for businesses with same less connected financial institutions, but they do transact that much with each other. On the other hand, less connected financial conglomerates tend to operate more often with each other, possible because of the lack of power for choosing their counterparties.

The assortativity coefficient measures how connected financial conglomerates are to other financial conglomerates with the same properties. Therefore, we might interpret mixing assortativity as a means to verify affinity within financial conglomerates, for example, affinity of degrees ρ_k or exposures ρ_ℓ. One compelling way to calculate mixing assortativity patterns is the approach proposed by Newman (2003), which evaluates linear dependence of edges' properties. Since each directed edge $(i, j) \in \mathcal{E}_t$ and

$i, j \in \mathcal{V}_t$ can be associated with both degrees $(k_{in,i} - 1, k_{out,j} - 1)$ and weighted degrees $(w_{in,i}, w_{out,j})$, Newman (2003) approach for directed networks is to calculate the Pearson correlation of this pairs, see equations (31) and (32). As a result, the assortativity coefficient assumes values in the range $\rho \in [-1, 1]$, so that in case $\rho = -1$, it means that the network is *perfectly mixing dissortative*, and in case $\rho = 1$, it means that the network is *perfectly mixing assortative*, and, lastly, $\rho = 0$ means that there is no clear mixing assortative pattern.

Corroborating the clustering analysis, in the Brazilian network, the assortativity coefficient ρ_k shows that highly connected financial conglomerates tend to be linked to low connected financial conglomerates, see Table 4. This property can be verified by the significant negative sign of the coefficient for all dates $\rho_k < 0$, and their respective small standard deviations. Following the same reasoning, the analysis of ρ_ℓ shows that there is no clear mixing assortativity pattern. That means that financial conglomerates with large exposures tend to be either connected to financial conglomerates with small or large exposures. However, the sign $\rho_\ell < 0$ changed over time from positive to negative, which could also means a tendency for more concentration of exposures in the prospective future. Merges of financial conglomerates with large weighted degrees in Brazil during 2008 could be the explanation for that characteristic, suggesting that if this trend persists in the future, then financial conglomerates with large exposures' will be more likely to be connected to financial conglomerates with small exposures.

4 Capital Structure

To avoid any abuse of notation, we will denote $\bar{B}_2$ as total capital buffer adjusted for non-banking activities, $\bar{B}_1$, Tier I capital buffer adjusted for non-banking activities, B_2, total capital buffer. Therefore, the bar means the necessary adjustments that will be made for non-banking activities, see equation (9). We will still continue with the previous notation C_2 total capital, C_1 tier I capital, and C_r required capital.

4.1 Cross-Sectional patterns of Capital Buffer

As we point out in Section 2, Reference Capital (tier I plus tier II capitals) depends on the *Risk Base*, which is a measure of risk for all operations, and not just risk generated by interbank transactions. In this sense, Reference Capital is not a good measure for liquidity reserves to cover interbank losses. Moreover, in Brazil, some interbank operations do not require capital allocation, such as REPO's (repurchase agreements) and reverse REPO's, since the majority of these transactions are collateralized with Brazilian government securities which are exempted from capital requirements.

Therefore, models that consider only minimum Basel ratio requirements such as $\delta = 0.11$ in the case of Brazil are not very meaningful when we deal with contagion under a short term perspective. Another issue are the costs involved when banks want to increase or reduce their capital. This is more clear for banks that have shares traded in stock exchanges. Raising money to finance capital usually required preparing financial statements and auditing expenses. So it is natural that banks allocate their capital in respect to what risk they expect to bear from their current and future operations. A more interesting way to analyze systemic risk is to consider the capital buffer B as a proxy for liquidity reserves, i.e.,

$$B_2 = C_2 - C_r. \tag{7}$$

Table 6 shows different plausible linear models for the capital buffer B_2 as defined in equation (7). Although, the results contemplate pooled data from all dates, the robustness was also verified within individuals dates. The regressors that were considered in our analysis were in-degree k_{in}, out-degree k_{out}, weighted in-degree w_{in}, weighted out-degree w_{out}, and the interaction among these variables, more especially, $w_{in} \times k_{in}$, $w_{out} \times k_{out}$, $w_{in} \times w_{out}$, and $k_{in} \times k_{out}$. Initially, we consider OLS estimates for *betas* coefficients, given that there is no evidence that the residuals will follow a normal distribution.

Hypothesis 5 (Capital Buffer Linear Model)**.** *The weighted in-degree w_{in} is the variable that most explains the Capital Buffer B_2 in a linear model.*

The plausibility of these models were verified by the F-statistic p-value. Under very small levels of significance level all models in Figure 6 did not reject the null hypothesis that the β coefficients were jointly different than zero.

Nevertheless, not all the t-statics from individuals β's of each model seem to be significantly different than zero. For example, models 3 and 4, which do not include exposures as regressors, suggest that the constant is not different than zero. In addition, interaction between degrees and exposures usually have p-values for the t-statistics greater than 1%, except for model 14, giving evidence that interaction doesn't improve the regression substantially.

Moreover, the R^2 shows that there are models that explain more than others. Except for models 2, 3 and 4, all models have a very similar R^2 ranging around 0.44.

Nonetheless, model 1 which is very parsimonious, considers only one regressor, i.e., the weighted in-degree w_{in} and it has approximately the same explanatory power of all other competing models. This means that including other variables is actually not very helpful. From the R^2 of models 1 and 2, it is clear that weighted out-degree w_{out} have little relevance in explaining capital buffer B_2, while the weighted in-degree seems to dominate the set of relevant information.

From the Akaike (AIC) and the Bayesian (BIC) Information Criteria, see respectively Akaike (1974) and Schwarz (1978), we can corroborate that models 1 and 10 represent the best model alternatives. However, as pointed earlier, not all β's from from model 10 could be considered significantly different than zero. Since the BIC penalizes the inclusion of more regressors, and both the R^2 and the adjusted R^2 are very close to those of model 1, we have that model 1 is the most parsimonious model.

In view of these facts, we select model 1 as the most appropriate for modeling the behavior of capital buffer B_2, i.e.,

$$B_{2,i} = \beta_0 + \beta_1 \times w_{in,i} + \varepsilon_i. \tag{8}$$

Model 1 also has a meaningful economic interpretation. It would be natural to expect that capital buffer B_2 depends on the weighted in-degree, since this is the main counterparty source of risk. A financial conglomerate with have higher level of weighted in-degree w_{in} will be more susceptible to their conterparties because the effect in term of losses in case some of them default is likely to be greater. On the other hand, it is natural that out-exposures and out-degree will play no role in the allocation of resources to capital buffer, since there is no counterparty risk in this exposures for the financial conglomerate.

On this ground, the greater the number of counterparties (in-degrees) k_i and the higher the average weighted in-degree w_i/k_i, the higher the weighted in-degree w_i will be for financial conglomerate i and, consequently, the greater the amount of resources will be allocated for capital buffer. Surprisingly, model 1 shows that, if banks i and j have the same level of connectivity in terms of in-degree $k_i = k_j$, and the same amount of weighted in-degree $w_i = w_j$, but bank i is mainly concentrated to only one counterparty, while bank j has even exposures to all its counterparties, they will allocate the same amount of capital buffer regardless that bank i seems to be riskier, these structures will have different impact on systemic risk.

The OLS estimates for the parameters were $\beta_0 = 50.8826$ and $\beta_1 = 0.1887$. β_0 means that independent of the size of the financial conglomerate, it will have minimum capital buffer to operate a banking business of BRL 50.9 million of BRL, and β_1 indicates that for each BRL of weighted in-degree the bank will allocate BRL 0.1887 to its capital buffer. Figure 9 (upper left plot) shows the regression plot of the model 1 described in equation (8).

4.2 Distribution of Residuals and Leverage

The residuals of the model presented in equation (8) can be viewed as shocks in the capital buffer B_2. Since financial conglomerates are dynamic entities, the remaining capital buffer that is not explained by the linear model in equation (8) can be understood as resources allocated to capital buffer to cover risks associated with their non-banking operations. The shocks ε_i seem to be generated by a distribution with fat tails.

Hypothesis 6. *The residuals ε of the capital model proposed in equation (8) follow a scaled t-student distribution*

$$\frac{\mathrm{d}}{\mathrm{d}\varepsilon}\mathbb{P}(\varepsilon) = \frac{\Gamma\left(\frac{\alpha+1}{2}\right)}{\sigma\sqrt{\alpha\pi}\;\Gamma\left(\frac{\alpha}{2}\right)}\left[1+\frac{\left(\frac{\varepsilon-\mu}{\sigma}\right)^2}{\alpha}\right]^{-\left(\frac{\alpha+1}{2}\right)}, \tag{9}$$

where μ is the location parameter, $\sigma > 0$ is the scale parameter, $0 < \alpha < 1$ is the shape parameter, and Γ is the Gamma function $\Gamma(z) = \int_0^\infty \xi^{z-1}e^{-\xi}\mathrm{d}\xi$.

Figure 9 (upper right plot) shows the Normal Probability plot for the fitted residuals $\hat{\varepsilon}_i$ for $i \in \mathcal{V}_t$. The $45°$ line represents the cumulative distribution of a standard normal distribution. It is clear that the fat tails are relevant in the analysis. On the other hand, the fitted residuals show a behavior similar to the Scaled t-student distribution. The parameters of the distribution were obtained numerically maximizing the log-likelihood function. In addition, under high levels of significance the Komolgorov-Smirnov test p-value (0.42) gives strong evidences that we cannot reject the null hypothesis that the liquidity shocks follows a Scaled t-student distribution.

Moreover, Figure 9 (upper left plot and lower plots) provides enough evidence that $\alpha < 1$. Both the MLE estimate for the parameter $\alpha = 0.5962$ and the hill estimator of the tail exponent $\alpha = 0.7260$ corroborate that the tail behavior has an exponent index less than one. Remark that we calculated the Hill estimator following the approach presented by Resnick (2006), Section 4.4. The heavy tail of the scaled t-student distribution has to be analyzed carefully, especially in the context of OLS regression, where the residuals mean and variance must be finite, i.e., $\mathbb{E}(\varepsilon) < \infty$ and $\sigma^2(\varepsilon) < \infty$. This is clearly not the case when $\alpha < 1$, since the scaled t-distribution will not have a well defined mean $\mathbb{E}(\varepsilon)$ and its variance will be infinite $\sigma^2(\varepsilon) = \infty$. As a consequence we could not guarantee that the β's for the regression models presented in Table 6 would be stable in terms of consistency. However, this seem to be case, since after regressing the same models in Table 6 via MLE considering the scaled t-distribution we find very similar values for the β's providing evidence of the robustness of the results for the OLS estimators.

Furthermore, if we rewrite equation (8) as

$$\frac{B_{2,i} - \beta_0}{w_{in,i}} = \beta_1 + \bar{\varepsilon}_i, \tag{10}$$

where $\bar{\varepsilon}_i = \varepsilon_i / w_{in,i}$ then we could interpret β_1 as the leverage coefficient. Adopting the same *modus operandi* we find that leverage also follows a student t-scaled distribution and its tail coefficient $\alpha = 0.6966$ is less then one. Since the coefficient does't change this provides additional evidence for the scaled t-student distribution not just for the leverage but also for the model presented in equation (8).

5 Systemic Risk

As we noted before, supervisory agencies, such as central banks, demand that financial conglomerates maintain minimum capital requirements. Therefore, if a financial conglomerate shows a *Basel Index* smaller than what was established, then it is susceptible to legal sanctions. The Basel Index is defined as

$$I_{Basel} = \frac{C_2}{\text{Risk Base}} \geqslant \delta, \tag{11}$$

where the *Risk Base* was defined in equation (1). For the Brazilian case $\delta = 0.11$ and for the United States financial system $\delta = 0.08$. There is a strong connection between the Basel Index I_{Basel} and the capital buffer B_2. Since they both depend on the same variables, you may also state an equivalent condition in terms of capital buffer B_2, i.e.,

$$B_2 \geqslant 0. \tag{12}$$

It is important to remark that capital and exposures should represent the same basis of assets. Since we have considered only interbank exposures in our matrix $\mathcal{L}_t$, then the capital buffer should be calculated accordingly. Since capital are only required for in-exposures, an interesting approach should be adjust the required capital for these sources of risk. Therefore, our capital buffer will only represent all capital available to absorb losses not related to non-banking exposures.

Definition 1 (Capital Buffer). *The capital buffer of financial institution $i \in \mathcal{V}_t$ is defined as*

$$\bar{B}_{2,i} = C_{2,i} - C_{r,i} - \delta \times \sum_{j \in \mathscr{V}_{in,i}} \ell_{ij}. \tag{13}$$

In this sense, capital buffer will represent all required capital for banking exposures (interbank exposures) and any discretionary additional capital that the financial conglomerate management considers necessary.

Therefore, in our model we will establish that a financial conglomerate is not in condition to absorb losses spilled over from its exposures if the financial conglomerate is not well capitalized. Although the terminology may be used in different contexts, we will define this situation as a *default*.

Definition 2 (Default). *A financial conglomerate $i \in \mathcal{V}_t$ is in default if the banking capital buffer is negative, i.e.,*

$$\bar{B}_{2,i} < 0. \tag{14}$$

In the Brazilian case, this situation could mean, in extreme cases, the intervention in the financial conglomerate's management or liquidation of its assets by *Banco Central do Brasil*.

5.1 Contagion via Default

A contagion model is concerned with risk propagation. This means that when a financial conglomerate defaults, a natural question arises: What would be the impact of this *default* to other financial conglomerates?

To answer this question, it is important to notice that exposures don't represent cash flows until they are due. Therefore, a realistic approach is to consider losses as write-offs to the capital buffer, which is in accordance to banking practices. If in time t, financial conglomerate j has good reason to believe that its counterparty i will not honor exposure ℓ_{ij} when it is due, then, in time t, financial conglomerate i has to write-off exposure ℓ_{ij} from its asset portfolio, and this procedure will negatively affect its capital buffer in the same amount. As a consequence from the initial defaulting state, some financial conglomerates in $i \in \mathcal{V}_t$ could also default in the subsequent state, and this process of defaulting financial conglomerates causing other financial conglomerates to default could go on for several rounds (defaulting states) until the system achieves an equilibrium (final state). Clearly, write-offs will drive the default mechanism of our contagion model.

Definition 3 (write-off procedure)**.** *Let the set*

$$\mathscr{D}^{(s)} = \left\{ j \in \mathcal{V}_t : \bar{B}_{2,j}^{(s)} < 0 \right\} \tag{15}$$

represent the financial conglomerates in default in state s, where $\bar{B}_{2,i}^{(s)}$ for all $i \in \mathcal{V}_t$ are the capital buffers in this state s. Then the write-off procedure will be given by the capital buffer dynamics

$$\bar{B}_{2,i}^{(s+1)} = \bar{B}_{2,i}^{(s)} - \sum_{j \in \mathscr{D}^{(s)}} \ell_{ij}, \tag{16}$$

where $s + 1$ is the subsequent state.

Note that the our analysis comprises a short-term perspective, where the financial institution is required to write-off the losses in its financial reports, but has no sufficient time to recover some of all of its losses. This doesn't mean that the financial institution will not take advantage of any legal procedure it has to execute liens and guarantees. On the other hand, it is easy to generalize the above equation rewriting the right-hand sided term as $\sum_{j \in \mathscr{D}^{(s)}} (1 - r_j)\ell_{ij}$, where r_j is the recovery rate for financial conglomerate j. From Definition 3, it is possible to calculate the contagion impact of each financial conglomerate. The contagion impact is the sum of the losses suffered by all financial conglomerates within a financial system given that a set of financial conglomerates default. Initially, we arbitrarily established a set of defaulting financial conglomerates $\mathscr{D}_0$. The set of defaulted financial conglomerates in state $s = 0$ will be given by

$$\mathscr{D}_0^{(0)} = \mathscr{D}^{(0)} \bigcup \mathscr{D}_0, \tag{17}$$

where the superscript indicates that $\mathscr{D}_0^{(s)}$ will depend on the choice of the initial set $\mathscr{D}_0$. If we choose a nonempty set $\mathscr{D}_0 \neq \emptyset$, then, according to the *write-off procedure*, financial conglomerates $\Omega \setminus \mathscr{D}_0$ will suffer losses, and their capital buffers in the next state will be given by

$$\bar{B}_{2,i}^{(1)} = \bar{B}_{2,i}^{(0)} - \sum_{j \in \mathscr{D}_0^{(0)}} \ell_{ij}. \tag{18}$$

Then on the next state $s = 1$, some financial conglomerates in $\Omega \setminus \mathscr{D}_0$ will eventually join the set

$$\mathscr{D}_0^{(1)} = \left\{ j \in \mathcal{V}_t : \bar{B}_{2,j}^{(1)} < 0 \right\} \tag{19}$$

and, as a consequence, new losses will be incurred by financial system. This processes can take many states until the financial system finds an equilibrium state s^* characterized as

$$s^* = \inf \left\{ s : \mathscr{D}_0^{(s)} \setminus \mathscr{D}_0^{(s+1)} = \emptyset \right\}. \tag{20}$$

Consequently, the dynamics presented through equations (17), (18), (19) and (20) will represent our *contagion mechanism*, which is similar to the one presented in Mistrulli (2007), Cont and Moussa (2009), however adapted to our context.

Suppose we choose that our initial defaulting set comprises only one financial conglomerate, i.e., $\mathscr{D}_0 = \{j\}$ for one $j \in \mathcal{V}_t$, then it is possible to verify how much losses other financial conglomerates will suffer and eventually come up with the most contagious financial conglomerate in the system.

Definition 4 (Default Impact)**.** *The default impact DI_j of financial conglomerate $j \in \mathcal{V}_t$ for $t = 1, \ldots, T$ is defined as*

$$DI_j = \frac{\sum_{i \in \mathcal{V}_t} \left\{ \max\left(\bar{B}_{2,i}^{(0)}, 0 \right) - \max\left(\bar{B}_{2,i}^{(s^*)}, 0 \right) \right\}}{\sum_{i \in \mathcal{V}_t} \bar{B}_{2,i}}, \tag{21}$$

given that the initial defaulting set is $\mathscr{D}_0 = \{j\}$.

From this definition it is clear that a financial conglomerate cannot lose more than its capital, and that the DI_j is the sum of the losses suffered by the system, in case financial conglomerate j defaults, expressed as a percentage of the total capitalization of the system. Therefore, $DI_j \in [0, 1]$ for $j \in \mathcal{V}_t$ represents the percentage of capitalization that is destroyed if bank j defaults. From a regulatory agency perspective the DI is an important measure because it shows both which financial conglomerates poses more risk to the system stability and how the losses propagates throughout financial conglomerates, helping these agencies to allocate their resources in the supervision of the most riskier financial conglomerates.

Figure 8 (lower left plot) shows the histogram of the DI distribution. It is possible to notice that there is an exponential shape, which means that most of the financial institutions will destroy not more than 4% of the system capitalization. However, there are few financial institutions which are very risky, that could destroy as much as 15% of the system capitalization. We argue that central banks should focus its efforts in supervising those more risky financial conglomerates in terms of DI.

5.2 Market and Credit Risks

Following the terminology presented by Bandt and Hartmann (2000), it would be interesting to introduce an index for the systemic risk that considers not only contagion such as the DI but also systemic events, such as exogenous shocks that incorporates market and credit information that could affect the capital buffer of all financial conglomerates at the same time. We will follow the idea proposed by Cont and Moussa (2009), however adapted to the results presented in Subsection 4.2.

Definition 5 (Systemic Risk Index)**.** *The Systemic Risk Index of financial conglomerate $i \in \mathcal{V}_t$ is given by*

$$SI_i = \mathbb{E}\left[DI_i^{\varepsilon} \middle| \bar{B}_{2,i} + \sigma_i \varepsilon_i < 0\right] \tag{22}$$

where the Default Impact DI_i^{ε} is computed considering capital buffer after the effects of exogenous shock ε_i and σ_i is a scale factor to adjust the exogenous shocks for the credit risk.

Following this definition the SI_i is the expected contagion loss considering scenarios where capital buffer of financial conglomerate i is wiped out by systemic events. Remark that the exogenous shocks will comprise the market and credit risk information. Let $u_1, u_2, \ldots, u_i, \ldots, u_{n_t}$ be a sequence of correlated uniform random variables.[3] Lehar (2005) gives estimates for volatilities and correlations of assets of international banks. Following his estimates, we considered a correlation coefficient of 0.4 for the uniform sequence. From the uniform sequence we generate a sequence of heavy tail random variables $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_i, \ldots, \varepsilon_{n_t}$ obtained from the inverse of the cumulative density function of the scaled student distribution with parameters given by the MLE estimates found in Subsection 4.2.

Although the moments are not well defined when the tail exponent is less than 1, the cumulative density function F is well established, and therefore we can find σ_i, such

[3]One easy way to obtain a sequence of correlated uniforms is generating a sequence of $n_t + 1$ IID standard normal $\mathcal{N}(0, 1)$ random variables, such as $z_0, z_1, \ldots, z_{n_t}$. Let ρ be the desired correlation coefficient then, applying the gaussian copula, we have that

$$u_i = \Phi\left(\sqrt{\rho}\, z_i + \sqrt{1-\rho}\, z_0\right),$$

for $i = 1, \ldots n_t$, where Φ is the cumulative density function of a standard normal distribution. In this case z_0 could be interpreted as the systemic event and z_i the effects of systemic events on individuals financial conglomerates.

that the cumulative density function matches the *probability of default* π_i of financial conglomerate i. Since the condition $\bar{B}_{2,i} + \sigma_i \varepsilon_i < 0$ is equivalent to $\varepsilon_i < -\bar{B}_{2,i}/\sigma_i$, follows that the constant σ_i is

$$\mathbb{P}\left(\varepsilon_i < -\frac{\bar{B}_{2,i}}{\sigma_i}\right) = F\left(-\frac{\bar{B}_{2,i}}{\sigma_i}\right) = \pi_i \Leftrightarrow \sigma_i = -\frac{\bar{B}_{2,i}}{F^{-1}(\pi_i)}. \tag{23}$$

To compute the Systemic Risk Index given by equation (22), we consider Monte Carlo simulation with 10,000 number of iterations and applied the Importance Sampling to improve the performance of the algorithm, see for example Asmussen and Glynn (2007), Chapter V. Moreover, the probabilities of default π were basically obtained from credit rating agencies, such as Standard & Poor's, Moody's, and Fitch Ratings. Figure 8 (upper left plot) shows the histogram of the SI distribution. It is possible to notice the log normal shape of the distribution with a positive skewness. The skewness suggests heterogeneity among the SI of Brazilian financial conglomerates, and could be explained mainly by the fat tails of the scaled student distribution and idiosyncratic probabilities of default, respectively, representing market and credit risk factors. In addition, we have that a mode within the range of 15% to 20% which is relatively higher then the DI. Following the same analysis, there are few financial institutions which are very risky, that could destroy as much as 40% of the system capitalization.

5.3 Liquidity Effect

Besides market and credit risks, during financial crisis, systemic events are reinforced by lack of liquidity. Therefore, liquidity risk plays a crucial role in the analysis of systemic risk under stress conditions. Encompassing liquidity risk in our analysis can be easily accomplished by considering capital buffer of financial conglomerates in terms of tier I capital C_1. This is equivalent to substituting the Reference Capital C_2 to only tier I capital C_1, yielding capital buffer equal to

$$\bar{B}_{1,i} = C_{1,i} - C_{r,i} - \delta \times \sum_{j \in \mathscr{V}_{in,i}} \ell_{ij}. \tag{24}$$

The idea behind this analysis is to consider only capital that can be redeemed at the option of the the financial institution shareholders. Therefore, tier I capital is the only capital that is really under the financial management's control, and, consequently the only instrument available to manage liquidity and leverage, especially during crisis. Accordingly, we share the view that tier I capital is a conservative way to measure the bank's financial strength from a regulator's point of view. This view is also shared by representatives of other governmental and non-governmental regulatory organizations, such as the U.S. Securities and Exchange Commission and Financial Services Authority (FSA) representatives, see Cox (2008). In this framework, tier I capital C_1 is seen as a metric of permanent capital which yields a better measurement of the banks' available capital to absorb losses in the short term, that is, in a *going-concern* perspective.

Figure 8 (upper and lower right plots) shows respectively the histogram of the SI and DI distributions considering the stressed scenario where financial conglomerates can rely only on tier I capital. The shape of the distribution are clearly the same as if there was no liquidity risk, notwithstanding, we can notice that the distributions shift in time. It would be natural to expect that the most right histogram would indicate periods where liquidity matters, such as crises. This is exactly what we observe for both the SI and DI. The left most histogram represents the data from June/2007 and the right most histogram is the June/2008, where the former could be associated with the development phase of the financial in the United States where negative news from bond and credit markets were affecting investors confidence and the latter date is associated with the apogeu of the same crises where banks such as Lemon Brothers and Merrill Lynch filed for bankruptcy and Citibank were suffering losses and liquidity difficulties.In addition, we have that in June/2008, the Systemic Risk Index SI comprised financial conglomerates that could destroy the financial system capitalization as much as double what would be destroyed without liquidity effects, that is 80%, and for the Default Impact DI this were even more dramatic, indicating destruction as much as six times if liquidity risk were not taken in consideration.

6 Conclusions

In the preceding sections, we explore the structure and dynamics of interbank exposures using a unique data set of all exposures of financial institutions in Brazil, as well as their capital reserves, at various periods in 2007 and 2008. We also explore the relationship between connectivity of a node and its capital buffer. We have tried to present, in some detail, a set of statistical facts which emerge from the empirical study of an interbank network topology. The properties mentioned here are model free in the sense that they do not result from a parametric hypothesis on the network topology but from rather general hypothesis of qualitative nature. As such, they should be viewed as constraints that a random graph describing the behavior of an interbank network has to verify in order to reproduce the statistical properties of the network accurately. Unfortunately, most currently existing models fail to reproduce all these statistical features at once, showing that they are indeed very constraining. Nevertheless, it seems that an interesting model that could actually and adequately capture most of these properties adequately would be a directed scale-free (weighted) graph with heavy-tailed degree and weighted distributions.

Finally, we should point out several issues we have not discussed here. One important question is whether these properties are relevant from an economic point of view. In other words, can these empirical facts be used to confirm or rule out certain modeling approaches used in economic theory? Another question is whether these empirical facts are useful from a supervisory agency perspective, such as central banks. For example, does the presence of heavy tail distributions in connectivity and exposures imply more systemic risk and eventually more capital requirements. Maybe the answer to this question is yes, but we have not explored this subject closely to withdraw any scientific conclusions. In addition, we have not explored the effects of using estimation technics for the data base, such as minimum entropy, and how these methods can be used to complete a data set without losing the statistical properties verified in this paper. We leave these questions for future research.

7 Appendix

7.1 Maximum likelihood estimates

According to Clauset et al. (2009), the likelihood function for the joint estimates of the parameters of the discrete power law random variables is given by

$$(\hat{\alpha}, \hat{k}_{min}) = \arg\max \left\{ n_t \log(\zeta(\alpha, k_{min})) - \alpha \sum_{i=1}^{n_t} \log(k_i) \right\}, \tag{25}$$

and the error of the estimate $\hat{\alpha}$ is given by

$$\sigma(\hat{\alpha}) = \frac{1}{\sqrt{n_t \left[\frac{\zeta''(\hat{\alpha}, \hat{k}_{min})}{\zeta(\hat{\alpha}, \hat{k}_{min})} - \left(\frac{\zeta'(\hat{\alpha}, \hat{k}_{min})}{\zeta(\hat{\alpha}, \hat{k}_{min})} \right)^2 \right]}}, \tag{26}$$

where $\zeta'(\hat{\alpha}, \hat{k}_{min})$ and $\zeta''(\hat{\alpha}, \hat{k}_{min})$ are respectively the first and second derivatives of zeta function ζ in respect to $\hat{\alpha}$.

Similarly, the likelihood function of the joint estimate of the parameters of the continuous power law random variable is given by

$$(\hat{\alpha}, \hat{\ell}_{min}) = \arg\max \left\{ 1 + n_t \left[\sum_{i=1}^{n_t} \log \left(\frac{\ell_i}{\ell_{min} - \frac{1}{2}} \right) \right]^{-1} \right\}, \tag{27}$$

and the error of $\hat{\alpha}$ is equal to

$$\sigma(\hat{\alpha}) = \frac{\hat{\alpha} - 1}{\sqrt{n_t}}. \tag{28}$$

7.2 Mixing Coefficient

Following Newman (2003), we have that the assortativity coefficient for the pairs

$$e_{y,k}^{(i,j)} = (k_{in,i} - 1, k_{out,j} - 1) \tag{29}$$

and

$$e_{y,\ell}^{(i,j)} = (w_{in,i}, w_{out,j}), \tag{30}$$

can be expressed as

$$\rho = \frac{\sum_{y=1}^{E_t} e_y^{(i,\cdot)} e_y^{(\cdot,j)} - \frac{1}{E_t} \sum_{y=1}^{E_t} e_y^{(i,\cdot)} \sum_{y'=1}^{E_t} e_{y'}^{(\cdot,j)}}{\sigma\left(e_y^{(i,\cdot)}\right) \sigma\left(e_y^{(\cdot,j)}\right)}, \tag{31}$$

where

$$\sigma^2\left(e_y^{(i,\cdot)}\right) = \sum_{y=1}^{E_t} \left(e_y^{(i,\cdot)}\right)^2 - \frac{1}{E_t} \left(\sum_{y=1}^{E_t} e_y^{(i,\cdot)} \right)^2, \tag{32}$$

$$\sigma^2\left(e_y^{(\cdot,j)}\right) = \sum_{y=1}^{E_t} \left(e_y^{(\cdot,j)}\right)^2 - \frac{1}{E_t} \left(\sum_{y=1}^{E_t} e_y^{(\cdot,j)} \right)^2, \tag{33}$$

where $y = 1, \ldots, E_t$ is the enumeration of edges and $E_t = \#\{(i,j) \in \mathcal{E}_t\}$, and the variance of ρ is given by

$$\sigma^2(\rho) = \sum_{y=1}^{E_t} (\rho - \rho_y)^2 \tag{34}$$

where ρ_y is the value of ρ in case we exclude edge e_y from the network.

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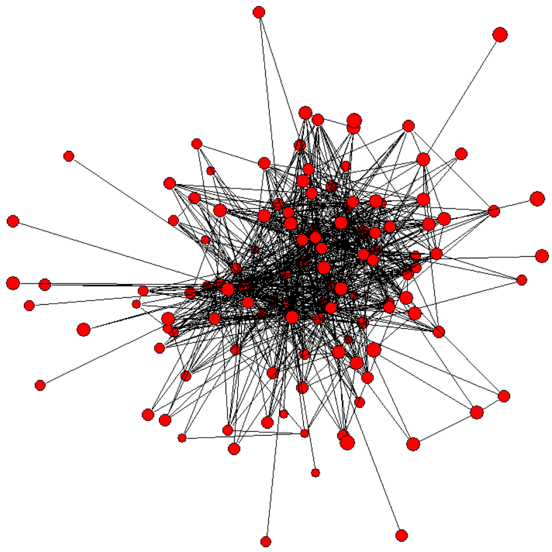

Figure 1: Brazilian interbank network as in date December 2007.

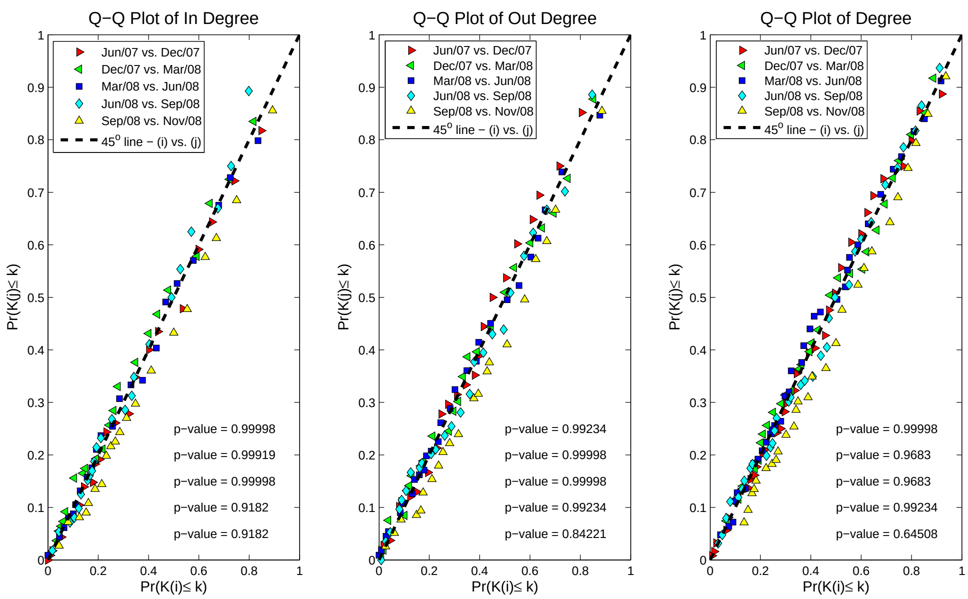

Figure 2: Q-Q plot for the Brazilian interbank network degree distribution for consecutive dates.

Type	Jun-07	Dec-07	Mar-08	Jun-08	Sep-08	Nov-08	Dec-08
Multiple Bank	135	135	135	136	139	139	140
Commercial Bank	20	20	21	20	20	18	18
Development Bank	4	4	4	4	4	4	4
Savings Bank	1	1	1	1	1	1	1
Investment Bank	17	17	17	18	18	18	17
Consumer Finance Company	51	52	51	56	55	55	55
Security Brokerage Company	113	107	114	107	107	107	107
Exchange Brokerage Company	48	46	48	46	46	45	45
Security Distribution Company	132	135	133	133	136	136	135
Leasing Company	40	38	41	37	36	36	36
Real Estate Credit Company and Savings and Loan Association	18	18	18	18	18	17	16
Mortgage Company	6	6	6	6	6	6	6
Development Agency	12	12	12	12	12	12	12
Total Banking Institutions of Type I and II	**597**	**591**	**601**	**594**	**598**	**594**	**592**
Credit Union	1.461	1.465	1.460	1.466	1.460	1.457	1.453
Micro-financing Institution	54	52	54	48	46	45	47
Total Banking Institutions Type III	**2.112**	**2.108**	**2.115**	**2.108**	**2.104**	**2.096**	**2.092**
Non-Banking Institutions	**332**	**329**	**333**	**324**	**317**	**318**	**317**
Total Banking and Non-Banking Institutions	**2444**	**2.437**	**2.448**	**2.432**	**2.421**	**2.414**	**2.409**

Table 1: Number of financial institutions by type of operation of the Brazilian Financial System. Source: Sisbacen.

Assets in Billions of USD	Jun-07	%	Dec-07	%	Mar-08	%	Jun-08	%	Sep-08	%	Dec-08	%
Banking - Type I	1,064.8	87.1	1,267.7	87.8	1,366.9	87.9	1,576.0	87.7	1,433.2	88.0	1,233.6	87.5
Banking - Type II	129.6	10.6	142.7	9.9	152.7	9.8	179.4	10.0	160.1	9.8	148.3	10.5
Banking - Type I and II	**1,194.5**	**97.7**	**1,410.4**	**97.7**	**1,519.6**	**97.7**	**1,755.4**	**97.7**	**1,593.2**	**97.8**	**1,382.0**	**98.0**
Banking - Type III	17.7	1.5	21.5	1.5	23.7	1.5	28.3	1.6	24.1	1.5	19.1	1.4
Non-Banking	10.4	0.9	12.8	0.9	12.5	0.8	14.4	0.8	11.4	0.7	9.3	0.7
Total Financial System	**1,222.6**	**100.0**	**1,444.8**	**100.0**	**1,555.8**	**100.0**	**1,798.1**	**100.0**	**1,628.8**	**100.0**	**1,410.4**	**100.0**

Number of Conglomerates	Jun-07	%	Dec-07	%	Mar-08	%	Jun-08	%	Sep-08	%	Dec-08	%
Banking - Type I	102	5.4	101	5.4	101	5.4	101	5.4	103	5.5	101	5.4
Banking - Type II	32	1.7	32	1.7	32	1.7	33	1.8	34	1.8	35	1.9
Banking - Type I and II	**134**	**7.1**	**133**	**7.1**	**133**	**7.1**	**134**	**7.2**	**137**	**7.3**	**136**	**7.3**
Banking - Type III	1,440	76.8	1,440	77.0	1,436	77.0	1,441	77.0	1,442	76.9	1,438	77.0
Non-Banking	302	16.1	298	15.9	297	15.9	296	15.8	296	15.8	294	15.7
Total Financial System	**1,876**	**100.0**	**1,871**	**100.0**	**1,866**	**100.0**	**1,871**	**100.0**	**1,875**	**100.0**	**1,868**	**100.0**

Table 2: Representativeness of Brazilian financial institutions in terms of total Assets and number. The total assets were converted from BRL (Brazilian Reais) to USD (American Dollars) with the following foreign exchange rates (BRL/USD): 1.9262 (Jun-07), 1.7713 (Dec-07), 1.7491 (Mar-08), 1.5919 (Jun-08), 1.9143 (Sep-08), and 2.3370 (Dec-08). Source: Sisbacen.

In-Degree	Jun-07	Dec-07	Mar-08	Jun-08	Sep-08	Nov-08	Mean
$\hat{\mathbb{E}}(K_{in})$	8.6	8.6	8.8	9.0	9.0	7.9	8.6
$\hat{\sigma}(K_{in})$	10.8	10.9	10.6	11.2	11.3	11.0	11.0
$\min(k_{in})$	0	0	0	0	0	0	0.0
$\max(k_{in})$	54	54	51	57	60	62	56.3
$\hat{\alpha}^{MLE}$	2.1997	2.7068	2.2059	3.3611	2.1610	2.1320	2.4611
$\hat{\sigma}\left(\hat{\alpha}^{MLE}\right)$	0.4887	0.4692	0.4756	0.5336	0.4722	0.4417	0.4802
$\hat{k}_{in,min}^{MLE}$	6	13	7	21	6	5	9.7
Out-Degree	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**	**Mean**
$\hat{\mathbb{E}}(K_{out})$	8.6	8.6	8.8	9.0	9.0	7.9	8.6
$\hat{\sigma}(K_{out})$	8.7	8.8	9.0	9.4	9.4	8.8	9.0
$\min(k_{out})$	0	0	0	0	0	0	0.0
$\max(k_{out})$	36	37	39	41	39	44	39.3
$\hat{\alpha}^{MLE}$	1.9855	3.4167	3.4000	2.9110	2.4302	2.8861	2.8383
$\hat{\sigma}\left(\hat{\alpha}^{MLE}\right)$	0.6359	0.5914	0.4884	0.4384	0.4174	0.4955	0.5112
$\hat{k}_{out,min}^{MLE}$	5	15	16	12	9	11	11.3
Degree	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**	**Mean**
$\hat{\mathbb{E}}(K)$	17.1	17.2	17.5	18.0	18.0	15.8	17.3
$\hat{\sigma}(K)$	17.5	17.5	17.5	18.2	18.6	18.3	17.9
$\min(k)$	1	1	1	1	1	1	1.0
$\max(k)$	86	87	80	87	90	106	89.3
$\hat{\alpha}^{MLE}$	2.6163	3.3750	2.2997	2.4840	2.2705	2.2311	2.5461
$\hat{\sigma}\left(\hat{\alpha}^{MLE}\right)$	0.5222	0.4767	0.4834	0.4124	0.4394	0.3580	0.4487
$\hat{k}_{min}^{MLE}$	17	34	12	15	12	10	16.7
Exposures*	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**	**Mean**
$\hat{\mathbb{E}}(L)$	1,214.8	872.5	914.3	954.0	977.1	1,364.8	1,049.6
$\hat{\sigma}(L)$	3,785.5	1,952.6	2,029.6	2,018.3	2,309.9	3,565.7	2,610.2
$\min(\ell)$	0.0	0.3	0.5	0.0	0.1	0.0	0.2
$\max(\ell)$	30,106.6	12,874.9	12,979.5	12,863.2	15,814.1	23,664.9	18,050.5
$\hat{\alpha}^{MLE}$	1.9792	2.2297	2.2383	2.3778	2.2766	2.5277	2.2716
$\hat{\sigma}\left(\hat{\alpha}^{MLE}\right)$	0.0260	0.6000	0.2140	0.6920	0.3840	0.9820	0.4830
$\hat{\ell}_{min}^{MLE}$	39.5	74.0	80.0	101.7	93.4	336.7	120.9

*values in millions of BRL (Brazilian Reals)

Table 3: General statistics and MLE estimates for the power law distribution parameters: tail exponent α, minimum tail value for in-degree $k_{in,min}$, out-degree $k_{out,min}$, degree k_{min}, and exposures ℓ_{min}.

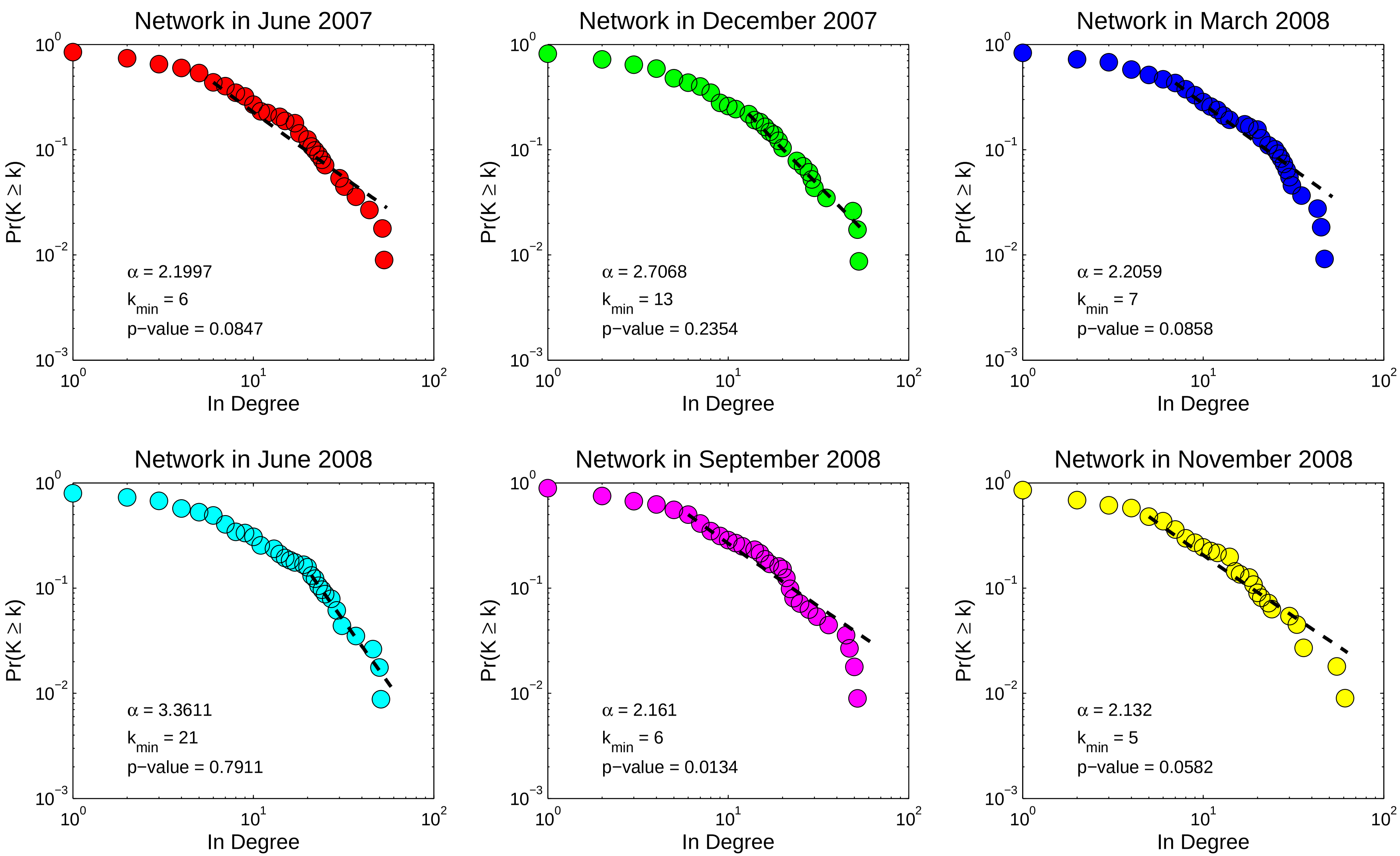

Figure 3: Brazilian interbank network: distribution of in-degree with different counterparties)

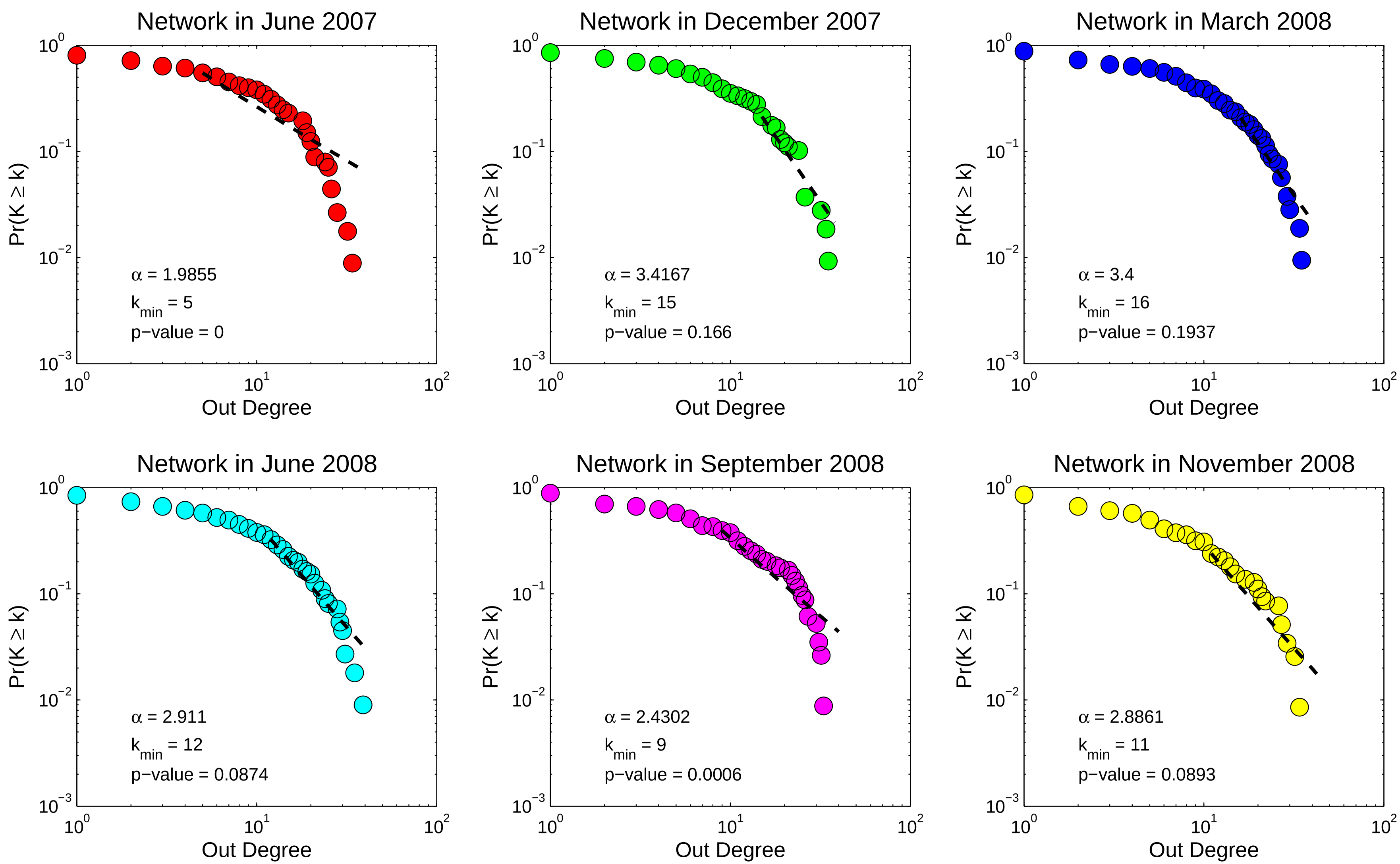

Figure 4: Brazilian interbank network: distribution of out-degree with different counterparties)

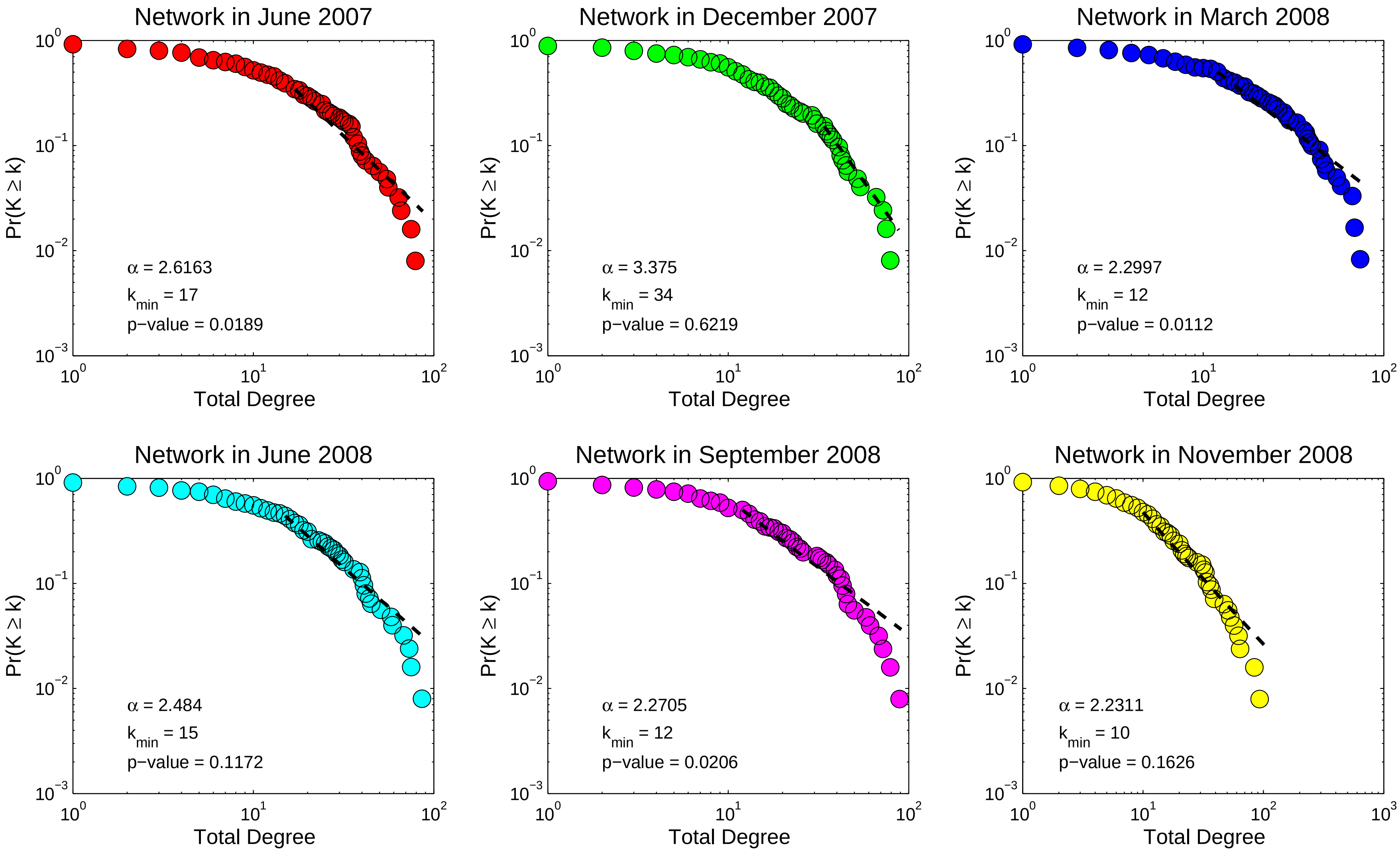

Figure 5: Brazilian interbank network: distribution of degree (sum of in-degree and out-degree).

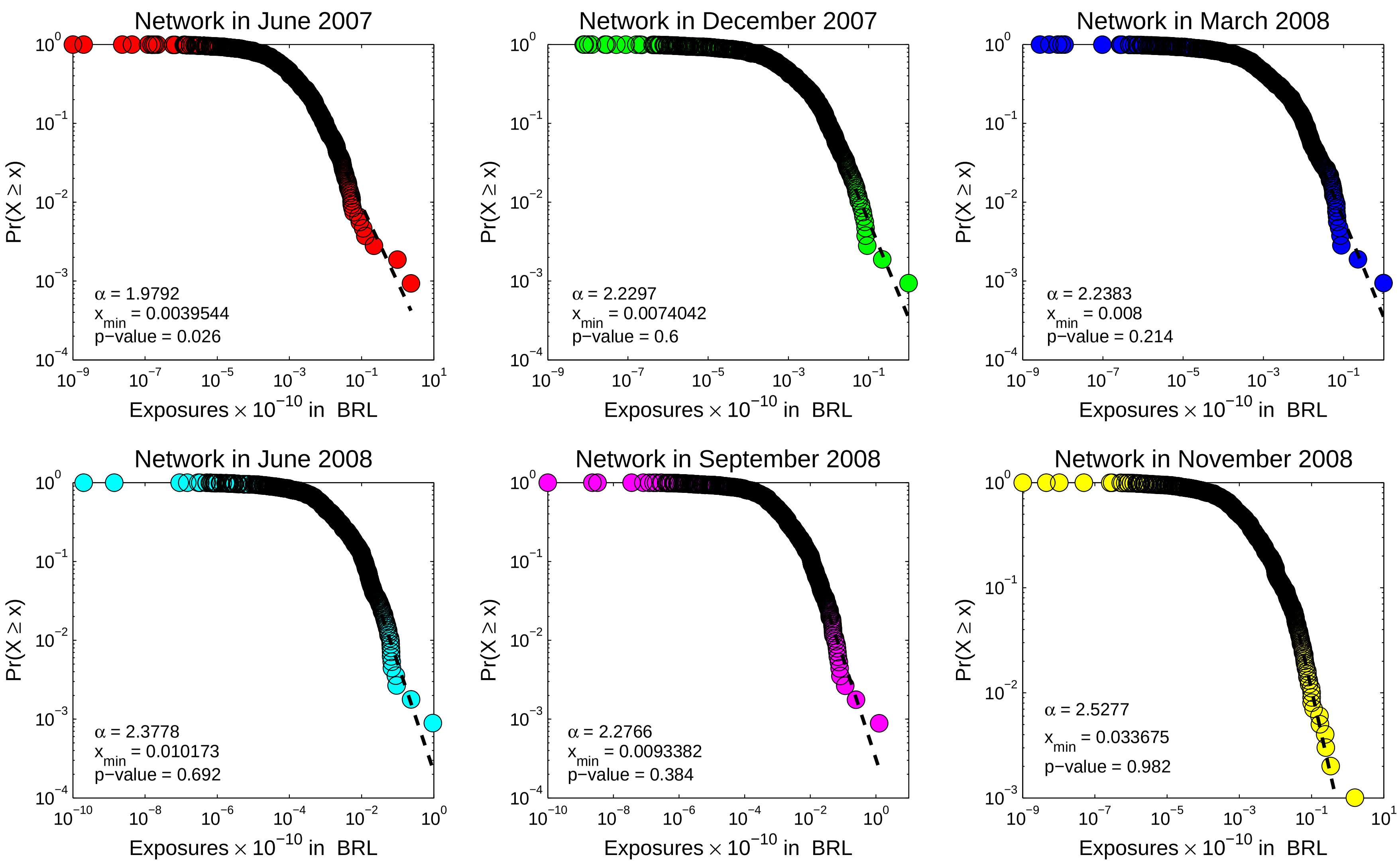

Figure 6: Brazilian interbank network: distribution of exposures in BRL.

k_{in} **vs.** w_{in}/k_{in}	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**
$\rho_{Pearson}$	0.0381	-0.0353	-0.0410	-0.0359	-0.0379	-0.0303
(p-value)	(0.6900)	(0.7082)	(0.6724)	(0.7047)	(0.6915)	(0.7523)
$\tau_{Kendall}$	0.2839	0.2554	0.2294	0.2648	0.2409	0.2144
(p-value)	(0.0000)	(0.0001)	(0.0006)	(0.0001)	(0.0002)	(0.0013)
$\rho_{Spearman}$	0.3907	0.3508	0.3109	0.3642	0.3328	0.2876
(p-value)	(0.0000)	(0.0001)	(0.0010)	(0.0001)	(0.0003)	(0.0022)
k_{out} **vs.** w_{out}/k_{out}	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**
$\rho_{Pearson}$	0.0315	0.2456	0.2415	0.2543	0.2302	0.0200
(p-value)	(0.7402)	(0.0104)	(0.0126)	(0.0071)	(0.0137)	(0.8301)
$\tau_{Kendall}$	0.2728	0.2807	0.3143	0.3274	0.3440	0.3025
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\rho_{Spearman}$	0.3787	0.3969	0.4329	0.4562	0.4704	0.4241
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
k **vs.** w	**Jun-07**	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**
$\rho_{Pearson}$	-0.0130	-0.0573	-0.0607	-0.0531	-0.0539	-0.0280
(p-value)	(0.8854)	(0.5270)	(0.5085)	(0.55610	(0.5489)	(0.7552)
$\tau_{Kendall}$	0.2460	0.2487	0.2179	0.2378	0.2386	0.2309
(p-value)	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0002)
$\rho_{Spearman}$	0.3370	0.3550	0.3086	0.3337	0.3336	0.3329
(p-value)	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.0001)	(0.0001)

Table 4: Brazilian interbank network: Pearson $\rho_{Pearson}$, Kendall $\tau_{Kendall}$ and Spearman $\rho_{Spearman}$ coefficients for in-degree k_{in} vs. in-exposures w_{in}, out-degree k_{out} vs. out-exposures w_{out}, and degree k vs. exposures w.

	Jun-07	**Dec-07**	**Mar-08**	**Jun-08**	**Sep-08**	**Nov-08**
ρ_k	-0.2546	-0.2870	-0.2783	-0.2972	-0.3207	-0.3548
$\sigma^2(\rho_k)$	0.0008	0.0008	0.0009	0.0008	0.0008	0.0008
ρ_ℓ	0.0262	0.0070	0.0115	-0.0196	-0.0102	-0.0578
$\sigma^2(\rho_\ell)$	0.0019	0.0013	0.0013	0.0011	0.0012	0.0009
$\mathbb{E}(c)$	0.1759	0.1718	0.1745	0.1774	0.1960	0.1951
d	2.7043	2.7103	2.7313	2.6651	2.6460	2.6618

Table 5: Brazilian interbank network: assortativity coefficient for adjacency matrix ρ_k and for exposure matrix ρ_ℓ, their respectives variances $\sigma^2(\rho_k)$ and $\sigma^2(\rho_\ell)$, global clustering coefficient $\mathbb{E}(c)$ and network diameter d.

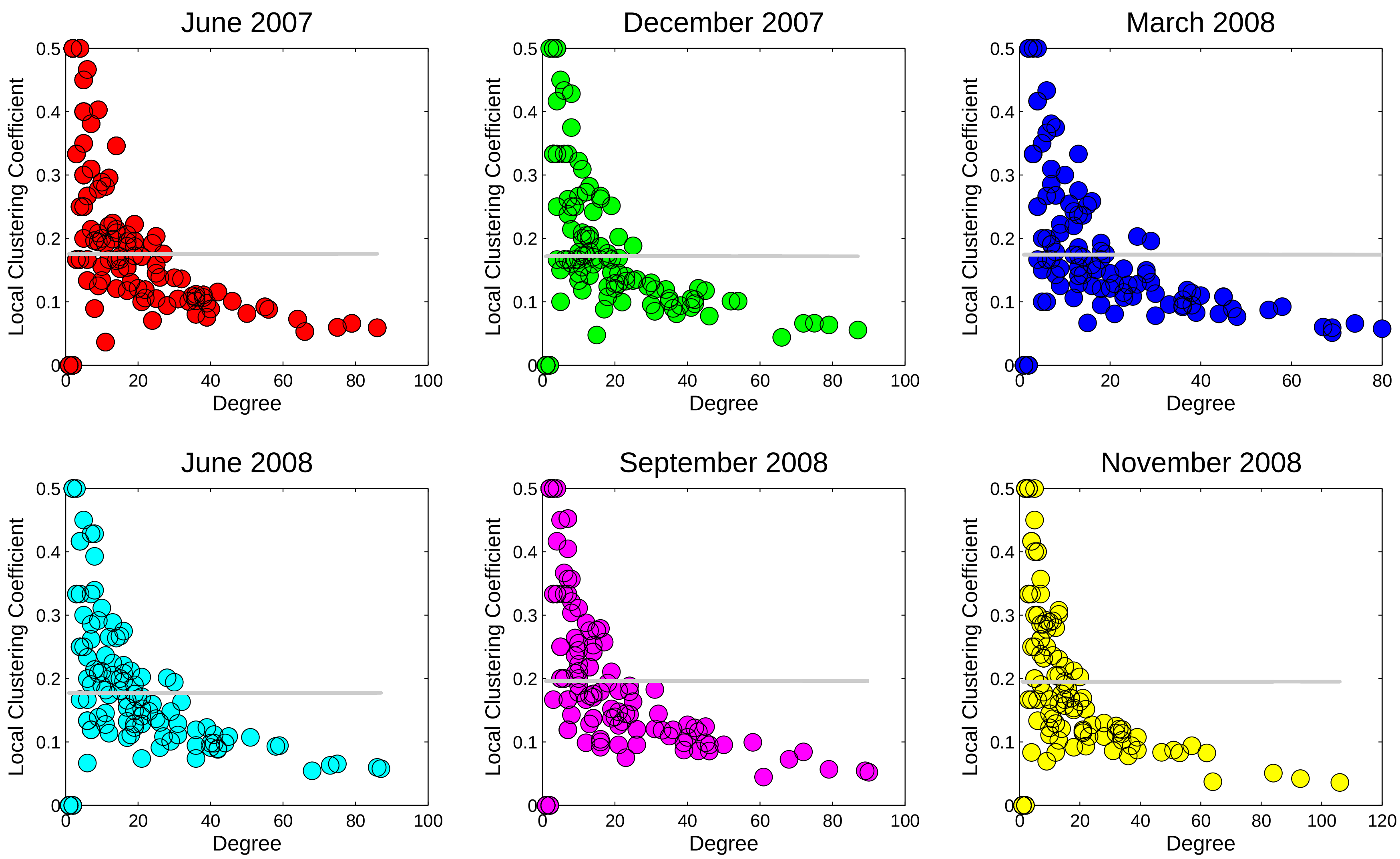

Figure 7: Degree vs. local clustering coefficient for the Brazilian Interbank Network. The grey line is the average coefficient (or global clustering coefficient).

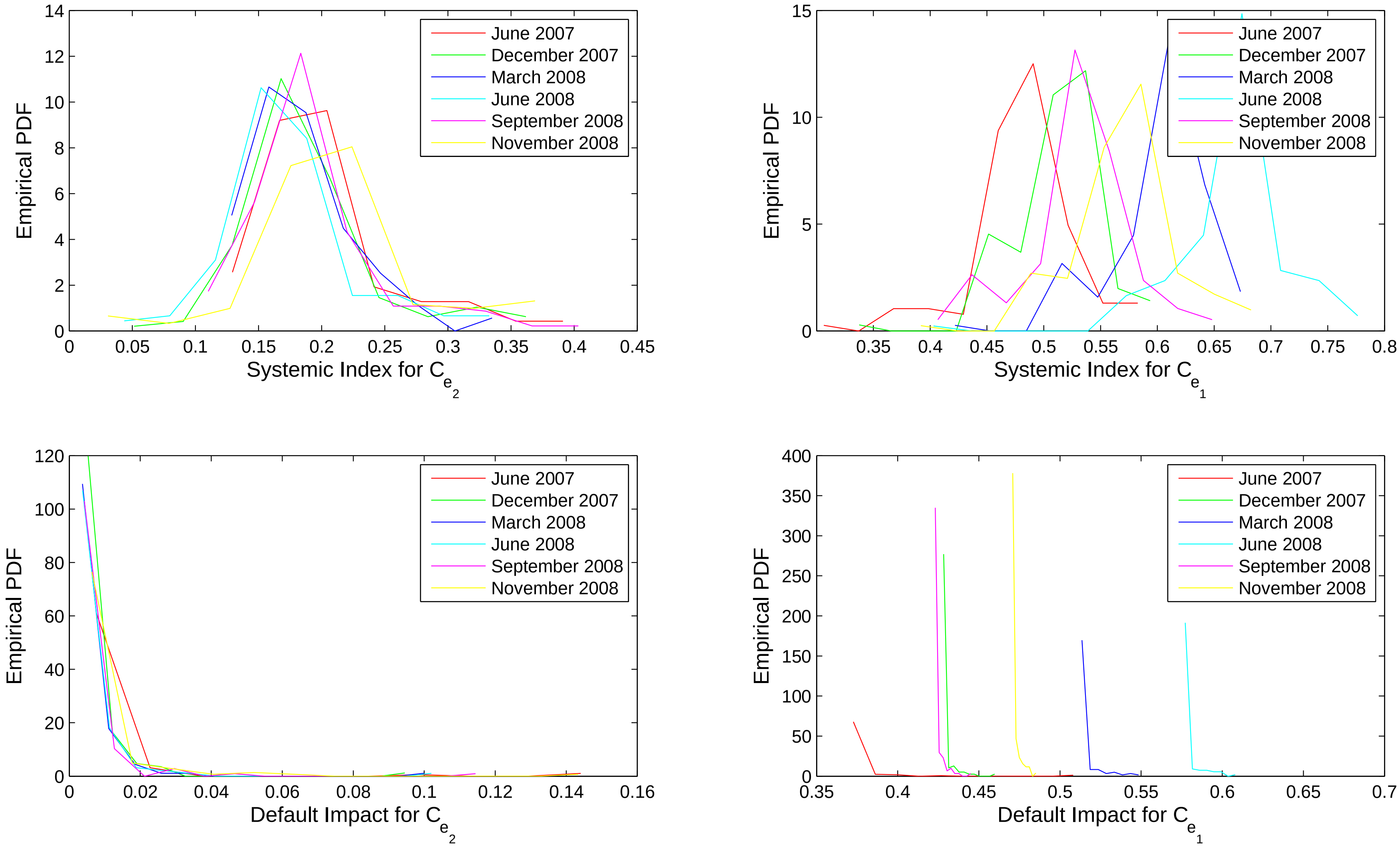

Figure 8: Brazilian interbank network: Default Impact and Systemic Risk

Model	$\hat{\beta}$ / t-statistic (p-value) *const.*	w_{in}	w_{out}	k_{in}	k_{out}	$w_{in} \times k_{in}$	$w_{out} \times k_{out}$	$w_{in} \times w_{out}$	$k_{in} \times k_{out}$	F-stat (p-value)	R^2	adj. R^2	Rank AIC	Rank BIC
1	50.8826 0.0011	0.1887 0.0000								0.0000	0.4370	0.4362	2	1
2	124.5975 0.0000		0.0484 0.0001							0.0001	0.0204	0.0191	16	16
3	(20.2225) 0.3852			19.7413 0.0000						0.0000	0.1578	0.1567	13	12
4	65.7781 0.0159				9.7704 0.0000					0.0000	0.0261	0.0248	15	14
5	49.0315 0.0023	0.1880 0.0000	0.0042 0.6573							0.0000	0.4371	0.4356	7	5
6	34.0570 0.0768	0.1811 0.0000		2.4155 0.1397						0.0000	0.4386	0.4371	4	3
7	(25.5890) 0.2752		0.0208 0.0747	19.0959 0.0000						0.0000	0.1614	0.1592	12	13
8	67.6556 0.0129		0.0322 0.0150		7.5889 0.0013					0.0000	0.0339	0.0313	14	15
9	54.1457 0.0105	0.1784 0.0000	0.0108 0.2862	5.0243 0.0108	(5.4325) 0.0138					0.0000	0.4433	0.4403	3	8
10	49.1316 0.0016	0.2137 0.0000				(0.0007) 0.0401				0.0000	0.4402	0.4387	1	2
11	51.0875 0.0010	0.1948 0.0000						(0.0001) 0.2801		0.0000	0.4379	0.4364	6	4
12	47.2623 0.0033	0.2130 0.0000	0.0043 0.6536			(0.0007) 0.0402				0.0000	0.4403	0.4381	5	6
13	43.9205 0.0073	0.1981 0.0000	0.0168 0.1621					(0.0001) 0.0873		0.0000	0.4393	0.4371	8	7
14	48.0497 0.0040	0.1868 0.6961	0.0038 0.8233						0.0137 0.0000	0.0000	0.4372	0.4349	11	9
15	48.8387 0.0026	0.2132 0.0000	(0.0130) 0.5348			(0.0007) 0.0329	0.0008 0.3556			0.0000	0.4410	0.4379	9	10
16	42.0272 0.0136	0.1962 0.0000	0.0164 0.1764					(0.0001) 0.0818	0.0247 0.6884	0.0000	0.4395	0.4364	10	11

Table 6: Plausible regression linear models for the capital buffer B_2 as defined in equation (7) for all dates pooled data, i.e., June 2007, December 2007, March 2008, June 2008, September 2008, and, November 2008.

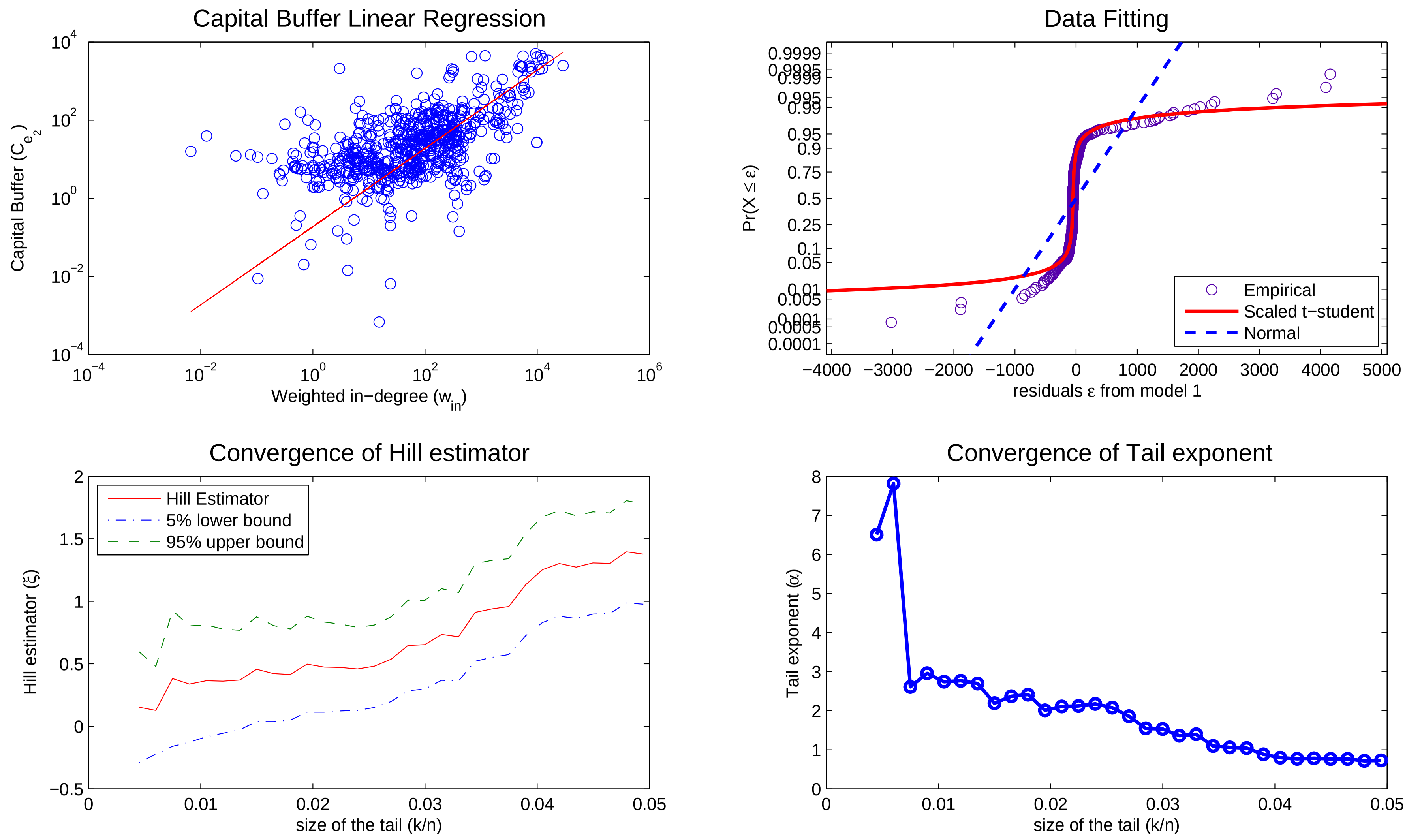

Figure 9: Hill Estimator for the tail exponent α of a Scaled t-Student distribution considering the fitted residuals (liquidity shocks) for all dates. Note that $\alpha < 1$ which determines that the distribution is heavy-tailed and the moments are not well defined.

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