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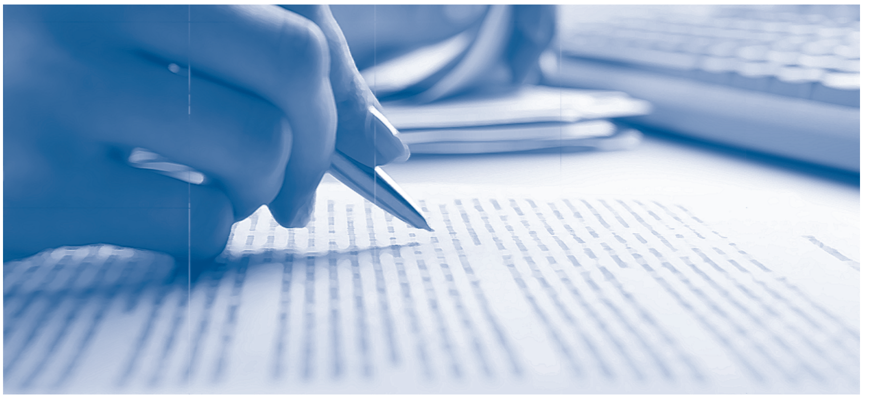

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Abstract

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.

In this paper we present systemic risk measures based on contingent claims approach, banking sector multivariate density and cluster analysis. These indicators aim to capture credit risk stress and its potential to become systemic. The proposed measures capture not only individual bank vulnerability, but also the stress dependency structure between them. Furthermore, these measures can be quite useful for identifying systematically important banks. The empirical results show that these indicators capture with considerable fidelity the moments of increasing systemic risk in the Brazilian banking sector in recent years.

Keywords: Systemic Risk; Joint Default Indicator; Clusters.

JEL Classification: C61, G01, G21.

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1 Introduction

Since the early 19th century it is well known that one bank may jeopardize the soundness and/or confidence of the whole financial sector (Thornton (1802)). The advances in information technology and computing sectors, among other factors, have paved the way for financial innovation and strong and continuous integration between global and local financial markets. As a consequence, the complexity and systemic consequences of risk materialization have largely increased over time.

Unlike other types of risk to which financial institutions are exposed, systemic risk is much more recognized for its effects rather than its causes. Systemic risk generally occurs in many distinct forms and is the result of the interconnection of a number of factors. These traits make it difficult to describe systemic risk clearly *ex ante*, but, once materialized, this risk becomes easily identifiable. The consequences of a systemic risk materialization can be quite dire, specially when affecting the real sector.

Ever since the genesis of the discipline, researchers have tried to find ways to better comprehend systemic risk and the means to mitigate it. The sub-prime crisis has renewed the interest of academics, regulatory bodies and Central Banks on this issue. The result was the production of a wide array of papers regarding the measurement of systemic risk, its regulation and the identification of threats to financial system stability.

The definition of systemic risk is the first step to measure it accurately. However, despite the ever increasing number of works regarding this issue, there is still no agreement over a unique systemic risk definition. For example, Kaufman (1995) defines it as the risk of occurrence of a chain reaction of bankruptcies. The European Central Bank (ECB (2004)), on the other hand, describes systemic risk as the probability that the default of one institution will make other institutions default. This risk interdependence would harm liquidity, credit and the stability and confidence of the markets. Acharya et al. (2009) affirm that systemic risk may be seen as generalized bankruptcies or capital market freezing, which may cause a substantial reduction in financial intermediation activities.

On the one hand, a wide spectrum of definitions may indicate the comprehension of the various nuances of systemic risk. On the other hand, it makes systemic risk measurement harder. Besides, it suggests the need for more than one type of measure in order to properly capture the complexity and the adaptability of the financial system. Using only one single measure might not be adequate or even possible as its relative simplicity may not reflect an unpredicted aspect or a new mechanism created by the market. On the contrary, a robust framework for monitoring and managing financial stability must incorporate a range of perspectives and a continuous process of revaluation of the financial system structure and adaptation of systemic risk measures to reflect eventual changes. This premise is supported by the literature, where one may find various models of systemic risk measurement.

Considering only the most recent literature, Lehar (2005) proposes a method, derived from correlated assets portfolios, to measure systemic risk. Based on the structural approach, he uses the contingent claims analysis to estimate the market value of a bank's assets and Monte Carlo simulations to encounter the probability of a these assets falling below a given proportion of the total assets of the financial system. Gray et al. (2008) also use the contingent claims analysis to provide a general form of systemic risk measurement between countries and various sectors of the economy.

Other examples of systemic risk measuring are found in the literature, among then: De Jonghe (2009) uses the extreme-value analysis; Acharya et al. (2010) use Systemic Expected Shortfall (SES) to measure the contribution of each single financial institution to systemic risk, i.e., its propensity to become undercapitalized when the system is also undercapitalized. Brownlees and Engle (2010) measure systemic risk by focusing on the Marginal Expected Shortfall (MES). They develop ways to estimate and predict MES using econometric tools (GARCH and DCC - Dynamic Conditional Correlation) together with non-parametric tail expectation estimators. Using CDS (Credit Default Swap) of financial firms and correlations between their stock returns, Huang et al. (2009) estimate a systemic risk indicator as the credit portfolio's expected loss that is above a proportion of a sector's total obligations. Huang et al. (2011) propose some methodological changes developed by Huang et al. (2009), such as the heteroskedasticity of banks interconnectivity and the possibility of estimating each bank's contribution to systemic risk. Adrian and Brunnermeier (2011) measure the Value of Risk (VaR) of the financial sector conditioned by the VaR loss in one single bank of the system, denoted by CoVaR, using quantile regressions. Segoviano and Goodhart (2009) define the financial sector as a portfolio of individual financial firms and build the multivariate density of this portfolio tail adjusted with empirical data from each institution. This density provides some measures of systemic risk.

In this paper we will define systemic risk as a consequence of an event that make financial markets stop functioning properly, increasing asymmetric information. In this outlook, prices no longer provide useful information for decision taking. Systemic risk steams from different sources. In general, a systemic event starts with a shock to a specific market, which is amplified through different channels to other markets (including real sector). Credit risk is a very important risk source as well as banks connectivity is an important amplifier. This paper focuses on systemic risk that comes from bank credit risk and the connectivity of the banks.

This paper contributes to the systemic risk indicator construction literature in several ways. First, using accounting data and following the approach in Souto et al. (2009), we adapt the method for building the banking system multivariate density proposed by Segoviano and Goodhart (2009). Accounting data becomes relevant when analyzing banking system stability when Credit Default Swaps, stocks and other public information are not available for every bank. Therefore, this paper expands the applicability of the measures proposed by Segoviano and Goodhart (2009) including the analysis of important banks which are not listed on the stock exchange.

Second, we propose feasible new measures of systemic risk. One of the main critiques on the methodology developed by Segoviano and Goodhart (2009) is the quadratic growth of the dependency matrix. In order to circumvent this methodological limitation, we propose indicators built upon the joint distribution of pairs of banks and the analysis of clusters generated by the correlation of individual default probability of each bank. We also propose indicators from the analysis of pairs of banks that enable the measurement of the first effects of the bankruptcy of one bank over the whole system. This indicator may be used to identify systematically important banks. Third, we include the idea of Loss Given Default in the construction of risk indicators. Fourth, we apply the measures proposed in this paper to the Brazilian case to analyze the effects of the recent global crises on the banking system. The empirical results show that the systemic risk proposed measures have features of early warning indicators, since they anticipate moments of stress in the market such as the global and euro crisis.

The paper is organized as follows. Section 2 presents the methodology used to build the systemic risk indicators. Section 3 present definitions of the indicators. Section 4 presents a detailed description of the data, and the empirical aspects of these indicators, and the empirical analysis for the Brazilian case. Section 5 presents final considerations.

2 Methodology

The structural approach is one of the most important methods of modeling the credit risk of a loan portfolio. The basic premise of this approach lies in the stochastic evolution of the value of the underlying asset through time and the default due to a reduction of the value of an asset below a predefined barrier. Once the parametric distribution of the underlying asset value and the corresponding value barrier are defined, the probability of default can be calculated.

Assuming that the basic premise of the structural approach is valid, Segoviano (2006) proposes a methodology, called CIMDO (for Consistent Information Multivariate Density Optimizing Methodology), to recover the multivariate distribution of a portfolio based on the minimal cross-entropy approach presented by Kullback (1959). The idea is to build a multivariate distribution that is updated with the empirically observed barriers and individual probabilities of default. Once the multivariate distribution is calculated, it allows for a wide spectrum of financial stability measures.

We follow a five steps methodology to develop the systemic risk measures proposed in this paper. First, we obtain empirical individual probability of default for each bank of the system, and estimate the implied market loss given default. Second, we conceptualize each pair of bank as a portfolio. Third, for each portfolio, we estimate a Bivariate Density making use of the Consistent Information Multivariate Density Optimizing (CIMDO) (Segoviano (2006)), taking as input the probabilities of default estimated in the first step. Fourth, we establish clusters of banks using the correlation between the probabilities of default calculated in first step. Fifth, we estimate the proposed systemic risk indicators.

In order to estimate the probabilities of default we use the contingent claims approach. In this theoretical framework the firm's asset value evolve stochastically and credit risk is related to the possibility that the bank's assets (granted loans) are worth less than its obligations (deposits received) in T. If this risk materializes, the bank will default. To evaluate the probability of credit risk materialization, we use the contingent claims model proposed by Merton (1974).

The basic methodological idea of Merton (1974) is modeling bank capital as an European call option, with strike price equal to the promised payment for the obligations and maturity T, where T is the maturity of the bank's obligations. Then, considering the promised obligation payment as being the face value of contract bonds F, in case of default, shareholders receive nothing, otherwise they receive the difference between asset and debt values.

Although Merton's theoretical model establishes that a default happens when the asset values are lower than the face value of debts, in the real world, however, default usually happens with higher asset values. This is due to contract breakage or liquidity scarcity problems when the bank needs to sell assets or due to debt renegotiation (Gray and Malone (2008)). In order to capture this characteristics, we follow the literature using, as a trigger for default, a threshold called distress barrier (DB), set to be higher than the face value of debts.

The distress barrier was based on the KMV model (KMV (1999) and KMV (2001)), where the barrier level is calculated using accounting data and is defined as:

$$DB = (\text{short-term debt}) + \alpha(\text{long-term debt}), \tag{1}$$

where short term debts are those with maturity equal to or less than one year, while long term debt has maturity greater than one year, and α is a parameter between 0 and 1, generally equal do 0.5[1].

[1]A practical rule to calculate the long-term component of the distress barrier established in De Servigny and Renault (2007) is using 0.5 from long-term debt if the ratio between long-term (LT) and short-term (ST) debts is lower than 1.5; otherwise, multiply long-term debt by $(0.7 - 0.3ST/LT)$.

Applying the option pricing formula of Black and Scholes (1973) for the Merton Model option, we have:

$$E = A\mathcal{N}(d_1) - DBe^{-rT}\mathcal{N}(d_2), \tag{2}$$

where r is the risk-free interest rate and $\mathcal{N}(.)$ is the rate of cumulative normal standard distribution,

$$d_1 = \frac{\ln\left(\frac{A}{DB}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{3}$$

and

$$d_2 = \frac{\ln\left(\frac{A}{DB}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}. \tag{4}$$

We assume that the firm's asset values are log-normally distributes, which, according to Crouhy et al. (2000) is a quite robust assumption. Then, the probability of default of a bank in time horizon T is defined as:

$$\begin{aligned} PD &= Prob(A_T \leqslant DB) \\ &= Prob(lnA_T \leqslant lnDB) \\ &= \mathcal{N}\left(-\frac{ln\frac{A_0}{DB} + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right) \\ &= \mathcal{N}(-d_2^*). \end{aligned} \tag{5}$$

The PD above is the expected probability in $t = 0$ of a bank defaulting at T, when the asset values is less than the distress barrier. Following the literature we will define the time horizon T as one year.

$\mathcal{N}(d_2)$ is the probability that the call option would be exercised, and the bank wouldn't default. So, $1 - \mathcal{N}(d_2) = \mathcal{N}(-d_2)$ characterizes the probability of default. However, while $\mathcal{N}(-d_2^*)$ gives us the probability of default in a real world, $\mathcal{N}(-d_2)$ represents the probability of default in a risk-neutral world. In the real world, investors demand a return rate μ_A higher than the risk-free return rate r used in a risk-neutral world. Then, $d_2^* > d_2$, indicating that the risk-neutral probability of default is an upper bound to the actual probability of default ($\mathcal{N}(-d_2^*) < \mathcal{N}(-d_2)$). This paper is conservative using the risk-neutral probability of default.

From the equation (5), we can observe that the PD is a function of the distance between the current value of the assets and the distress barrier DB. So, the distance to the distress ($D2D$), considering the risk-neutral probability of default, is defined as:

$$D2D = -d_2 \tag{6}$$

and gives us, in terms of standard deviations, how distant the market value of assets is from the distress barrier.

The difference between the actual and risk-neutral probabilities of default can be seen graphically in the figure 1. The actual and risk-neutral probabilities of default are, respectively, the areas of the actual distributions of asset values (continuous line) and adjusted to risk (dashed line) under the distress barrier.

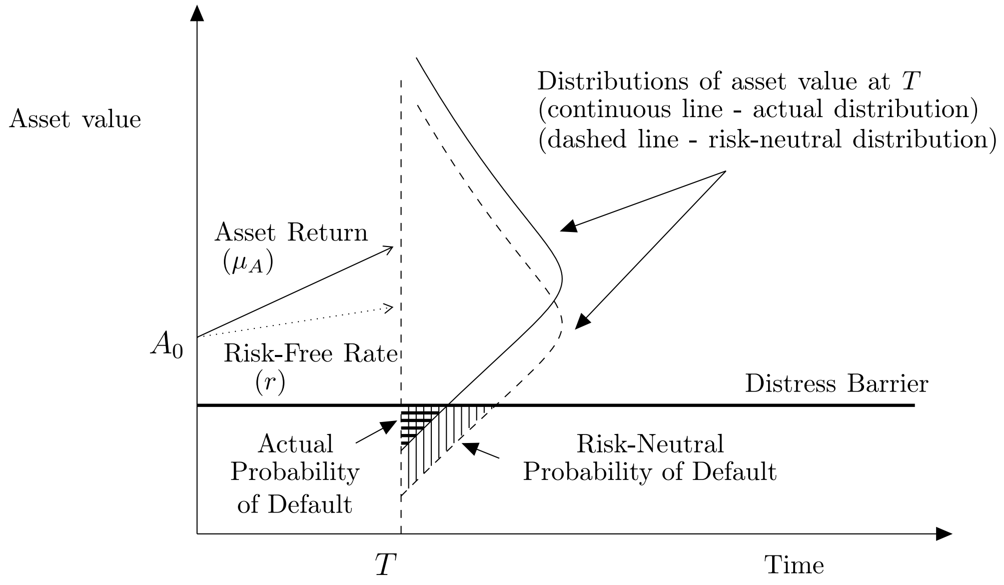


Figure 1: Contingent Claims Approach

Source:Gray and Malone (2008)

2.1 Loss Given Default

Besides individual PDs, we will use the expected loss concept to build systemic risk indicators. The expected loss given default (LGD) is usually defined as the incurred loss percentage over owed credit in case of default. When faced with the counterpart's default, the lender will recover only a fraction of the amount lent. The percentage of recovered amount, called recovery rate (RR), complements the LGD when recovery costs are null; $RR + LGD = 1$. There are three ways to measure LGD: market LGD - observed from market prices of defaulted bonds or marketable loans right after the actual default event; workout LGD - obtained from the set of estimated cash flows resulting from the workout and/or collections process, properly discounted, and the estimated exposure; and finally, the implied market LGD - derived from risky (but not defaulted) bond the prices using a theoretical asset pricing model (Schuermann (2004)). In this paper, we use the implied LGD.

Similarly to the case of PDs, there's a distinction between actual and risk-neutral recovery rates. To obtain the risk-neutral rate. The risk-neutral recovery rate is lower than the actual counterpart. Therefore, actual LGD is higher than risk-neutral LGD, given that $LGD = 1 - RR$ when recovery costs are null.

When considering bankruptcy administrative costs, denoted by φ, the implied LGD in risk-neutral terms at time T can be estimated from the asset value at time $t = 0$ as:

$$LGD_0 = 1 - (1 - \varphi)\frac{A_0}{DB} \exp\left[rT\right] \frac{\mathcal{N}(-d_1)}{\mathcal{N}(-d_2)}, \tag{7}$$

being d_1 e d_2 defined as in equations (3) and (4).

Details on how to reach this formula can be found at 6.

We can then estimate at t the expected bank loss for time T, as being:

$$EL_t = PD_t.LGD_t.EAD_t, \tag{8}$$

where EAD (Exposure at Default) is the amount of the bank's assets that are exposed to losses due to its counterpart's default.

2.2 Cluster Definition

The clusters were established considering banks that are strongly related. The definition of pairs of banks with more intense relationship is based on a concept analogous to the distance between the knots of a web. Following Bonanno et al. (2004), we define distance $d(i, j)$ between banks i and j, as:

$$d(i, j) = \sqrt{2(1 - \rho(i, j))} \tag{9}$$

where $\rho(i, j)$ is the correlation between PDs of banks i and j. Having calculated these distances, a Minimum Spanning Tree (MST) is drawn. Given a graph G, a MST is a tree that minimizes the distance between the knots of G. Given the distance definition above, the MST generated has the trait that knots connected by a corner have lower distances and higher correlations.

2.3 Banking Portfolio Bivariate Density

The Consistent Information Multivariate Density Optimizing methodology or simply CIMDO methodology, established in Segoviano (2006) is based on the concept of cross-entropy introduced by Kullback (1959).

The CIMDO methodology can be used by considering the banking system as a portfolio of N banks. However, we will consider a portfolio composed of two banks: bank X and bank Y, with logarithmic returns defined as the random variables x and y. It is assumed that the portfolio's stochastic process bivariate distribution follows a parametric distribution $q(x, y) \in \mathscr{R}^2$, called *a prior* distribution from now on. The initial hypothesis about the distribution of returns is taken according to economic hypotheses (default is deflagrated by the decline of asset value below a given barrier) and theoretical models (structural approach), but not necessarily in accordance with empirical observation.

The CIMDO methodology allows for the inference of a bivariate distribution $p(x, y) \in \mathscr{R}^2$ (*a posterior* distribution) from the *prior* distribution. This is done by means of an optimization process in which the *prior* density is updated with empirical information extracted from PDs and DBs by means of the restrictions set. At the end of this process we will have Banking Portfolio Bivariate Densities for all pairs of banks. Details about the optimization problem to recover the *posterior* density can be found at Appendix II.

The Banking Portfolio Bivariate Density (BPBD) characterizes individual and joint movement of asset values for the two banks of the portfolio. BPBD incorporates the linear and non-linear distress dependencies between banks included in the portfolio. Such dependency structure is characterized by the copula function related to BPBD, called CIMDO copula, which changes for each time period in a way consistent with the changes in the empirically estimated PDs. Therefore, the BPBD captures the linear and non-linear distress dependency between the assets of the banks in the portfolio and its changes throughout economic cycles[2].

3 Financial Stability Indicators

The BPBD characterizes the probabilities of default of the banks included in the portfolio, the stress dependency between them and changes in economic cycles. This set of information allows us to analyze the financial stability indicators that quantify (i) the common distress between banks, (ii) distress between specific banks and (iii) distress in the system associated with a specific bank. This section presents the systemic risk indicators proposed in this paper using BPBD, contingent claims approach and cluster analysis.

Before defining the indicators, let's formalize the joint, individual and conditional probabilities calculated from BPBD. These probabilities are stability indicators by themselves, as established in Segoviano and Goodhart (2009). As in the CIMDO methodology presentation, we'll consider, for parsimony, the banking system as being made of two banks, X and Y.

- **Individual Probability of Default (PD(X))**

  The probability of bank X defaulting can be calculated from the marginal distribution of BPBD:

[2]For more details regarding the copula associated with BPBD, see Segoviano and Goodhart (2009).

$$
\begin{aligned}
PD(X) &= P(X \geq DB^x) \\
&= \int_{-\infty}^{+\infty} \int_{DB^x}^{+\infty} \widehat{p(x,y)} dx dy.
\end{aligned} \tag{10}
$$

- **Joint Probability of Default (PDConj(X,Y))**

  The probability that all the banks of the portfolio (banking system) default is given by the joint probability of default (PDConj):

$$
\begin{aligned}
PDConj(X,Y) &= P(X \cap Y) \\
&= P(X \geq DB^x, Y \geq DB^y) \\
&= \int_{DB^y}^{+\infty} \int_{DB^x}^{+\infty} \widehat{p(x,y)} dx dy.
\end{aligned} \tag{11}
$$

- **Conditional Probability of Default (PDCond(X,Y))**

  The probability of default of bank X given that bank Y has defaulted is given by conditional probability:

$$
\begin{aligned}
PDCond(X,Y) &= P(X|Y) \\
&= P(X \geq DB^x | Y \geq DB^y) \\
&= \frac{P(X \geq DB^x, Y \geq DB^y)}{P(Y \geq DB^y)}.
\end{aligned} \tag{12}
$$

Having formalized the individual, conditional e joint probability equations, let's define the systemic risk indicators proposed in this article. For such, consider a banking system (portfolio) with N banks, denoted by $B_1, B_2, \ldots, B_N$.

- **IndPD Indicator**

  The *IndPD Indicator* is built considering the average of the individual probabilities of default weighted by assets:

$$
IndPD = \sum_{\substack{j=1 \\ j \neq k}}^{N} w_j PD(B_j), \tag{13}
$$

where w_j is the ratio between the assets of bank B_j and the total assets of the banking system.

This indicator is an upper bound to the probability of default of one or more banks of the system. As it does not consider the dependency structure between financial institutions, this bound is overestimated and must be seen as an indicator of the stability tendency of the banking system. As the indicator is made of the PDs of all banks, an increase in the PD of one single bank would have to be quite large to change the whole tendency. That means that changes in the indicator would only happen if the PD of more than one bank also changed. Therefore, an increase in this indicator suggests that the banking system as a whole is more exposed to systemic risk.

- **IndPDcond indicator**

  The *IndPDcond indicator* is built considering the average of the conditional probabilities of default weighted by assets:

  for each $k \in \{1, 2, \ldots, N\}$, we define:

$$IndPDCond = \sum_{k=1}^{N} \sum_{\substack{j=1 \\ j \neq k}}^{N} w_j P(B_j | B_k), \tag{14}$$

  where w_j is the asset share of bank j compared to the total assets of the system.

  The IndPDCond indicator tries to capture the first round effects of the default of one bank over the probability of default of other banks. The higher it is, the higher is the vulnerability of the financial system and the higher is the propagation possibility of shocks to the system.

  This indicator can be calculated for several periods to allow for the analysis of its evolution through time.

- **IndPDConj Indicator**

  The *IndPDConj Indicator* is built considering the weighted average of the probability that any two banks default at the same time:

$$IndPDConj = \sum_{i \neq j} w_{ij} PDConj(B_i \cap B_j), \tag{15}$$

where $i, j \in \{1, 2, \ldots, N\}$ and w_{ij} are the shares of assets of banks i and j compared to the total assets of the banking system.

The IndPDConj indicator aims to capture the macruprudential risk effects. An increase in its value means that the financial system is more exposed to this kind of risk.

- **Evolution of the Expected Loss given the default of two banks (IndLGD)**

  For each pair of banks (i, j), we calculate the joint probability of default $P(B_i \cap B_j)$. Considering LGD_i and LGD_j as expected loss rates due to banks' i and j defaults, and EAD_i and EAD_j the amount of assets of the banks i and j that are exposed at risk, we define the maximum expected loss and LGD statistics, quantiles for example, in each period of time t:

$$ELmax_t = Max_{i,j}(LGD_i.EAD_i + LGD_j.EAD_j)P(B_i \cap B_j). \tag{16}$$

  This indicator allows us to evaluate the evolution of expected losses in the worst case scenario, when both banks default and the losses are maximum. We have then an upper bound to expected losses.

  This indicator can be specified for joint default of three or more banks. The literature supports that LGD is higher in periods of financial market stress, an increase in this indicator would then suggest that the market is indicating the existence of vulnerabilities in the banking system.

4 Empirical Results

This section presents the details of PDs and LGDs estimations as well the empirical systemic risk indicators for the Brazilian Banking System.

4.1 Data and Estimations of PDs and LGDs

The risk-neutral PDs were estimated using a structural approach, as described in section 2. As there's no market data (bonds, derivatives and Credit Default Swaps) for many Brazilian banks, it's pretty much impossible to apply methodologies that depend on this type of data in order to obtain asset volatility for the majority of the banking system. As we want to estimate the proposed indicators for as many banks as possible, we try to incorporate asset volatility in PD estimations using accounting data as in Souto et al. (2009). Despite losing the "collective view" that characterizes Merton's Model, accounting data still offers relevant information. We used monthly accounting data from the Brazilian Central Bank's database from January 2002 to June 2012. The sample includes banks and conglomerates from Independent Banking Institutions I and II, with a minimum of 20 observations in the studied period.[3] Beyond filtering the data for the number of observations, banks with low deposits or with a low number of loans were also excluded from the sample[4]. The sample does not include treasury or assembler's banks. By applying these filters we focus our sample on financial institutions with commercial bank activities. Banks may also be excluded from the sample due to bankruptcy or M&A, or included due to the start of its activities. This flexibility eliminates the survivorship bias problem in the estimation of our indicators. The sample then represents 65 banks, equivalent to about 68% of the Brazilian Financial System's assets, considering data from June 2012.

Given that the PDs have unit roots, the in-difference correlations between them were used to identify clusters. To calculate these correlations we need to consider a fixed number of banks through time. Thus, clusters were established considering only banks that were active during the whole period analyzed.

By using accounting data to estimate indicators, the book value of assets and its volatility were used to estimate the indicators D2D and PD, defined by equations (6)

[3] Banking Institutions I is composed of one of the following independent financial institutions (not part of a conglomerate): Commercial Bank, Universal Bank holding a commercial bank portfolio or a Savings and Loans. Banking Institutions II is made of financial institutions that are not part of a conglomerate and are either an Universal Bank not holding a commercial bank portfolio or an Investment Bank.

[4] Banks with average loans over assets lower than 15% were excluded from the sample.

and (5), respectively, substituting μ_A for the risk-free rate r. For the asset volatility estimation, we used the standard definition in finance literature, i.e., the annualized standard deviation of the book value of assets considering a moving time frame of 12 months; that is:

$$\sigma_{A_t} = \sqrt{\frac{\sum_{i=0}^{11}(A_{t-i} - \overline{A})^2}{11}} \cdot \sqrt{12}, \tag{17}$$

where $\overline{A}$ is the average book value of assets inside the moving time frame. [5] As said in section 2, the distress barrier is usually calculated as the short-term obligations plus a proportion of long-term obligations. Given that this information was not available for the whole period, we calculated the distress barrier as 85% of the liabilities. This percentage was chosen for being the closest to the barrier that would be built from the short-term obligations plus 50% of the long-term obligations in the period with available data.

As with the PDs, the risk-neutral LGDs were estimated considering the rate of CDI (*Certificados de Depósito Interbancário*, Interbank Certificates of Deposit) as the risk-free rate. Administrative costs for asset recovery were set to 15% based on experts opinion. Given these parameters, average LGD is about 30%.

In order to build the BPBD, we follow the literature considering that ban returns follow a Student distribution with 5 degrees of freedom. Results using a normal distribution are quite similar.

4.2 Systemic Risk Indicators for the Brazilian Banking System

The proposed risk measures are used to analyze the Brazilian Banking System systemic risk and. Also, how the banking system was affected by the 2008 crisis (global

[5] The assets' volatility was calculated using the semi-variance and downside variance concepts, however, given the characteristics of some banks with positive returns over long periods of time, these definitions have shown to be inadequate for the construction of a credit risk indicators time series. RoA (Return on Assets) and RoE (Return on Equity) volatilities were also tested, but the results were not reasonable.

financial crisis). It is widely perceived that the crisis has had important effects worldwide and capturing such effects is very relevant for policy makers.

Five bank clusters were identified based on the correlation of the in-difference probabilities of default (given that these probabilities present unit roots)[6]. The cluster identification suggest that the Brazilian banking system has features of "money centers", as described by Freixas et al. (2000). Each cluster is composed of: Group 1 - Eighteen banks, Group 2 - Ten banks, Group 3 - Thirteen banks, Group 4 - Seven banks, Group 5 - Ten banks (Figure 2, where the ball size stands for the bank size: large, medium or small). The clusters have distinct features regarding its joint probability of default and contagion possibility.

The clusters were identified considering the correlation of the in-difference probabilities of default during the whole period analyzed. Thus, we estimate the proposed indicators considering that the clusters will be the same during the period studied. However, it is possible some transformation in the clusters if we considered the correlation for different periods. It will depend on how stable the relationship are among banks. If the relationship between banks suffer significant transformation over time, the clusters will change as a consequence.

Regarding the indicators built from the PDs and the multivariate density, we can observe that they anticipate moments of higher tension in the Brazilian banking system in 2002, due to the election period, and in 2007/2008 due to the global financial crisis, and the 2011/2012 euro crises (Figures 2 and 6).

Banks that form group 5 have higher IndPD than banks of other groups. Unlike other groups, group 5 does not have a large bank among its members. This result may indicate that smaller banks are more vulnerable to credit market volatilities. Furthermore, group 5 has higher IndPDCond, indicating that its banks would be more affected if another bank in the system defaulted (3 e 4).

The IndPDCond and IndPDConj consider not only the individual probability of default, but they also incorporate dependency structures between banks. Thus, these measures may present higher non-linear increases than individual PDs. This can be observed when comparing the results of group 4 and 5. Group 5 banks have

[6]Clusters defined with the PDs correlation are similar to those identified considering correlation of the in-difference PDs.

higher individual PDs (see figure 3). However, in moments of higher market stress, the IndPDCond and IndPDConj measures of group 4 banks are higher than those of group 5 (see figures 4 and 5). This reflects that in stressful moments not only individual PDs increase, but there is also an increase in stress dependency.

When stress is detected in the banking system at 2007 the IndPD for all banks is 35% above of the annual average of IndPD at normal years (before the crisis 2004-2006). Some clusters, such as clusters 1, 2 and 4, present even higher growth in the IndPD during 2007. Similar analysis applies to IndPDCond regarding all banks and clusters 2 and 4. This result suggests an increase in the possibility that one bank may be affected by the default of another bank within the same cluster.

Regarding the indicators using the *Loss Given Default* rate, figure 6 suggests that the use of value losses due to default is more informative than the use of descriptive statistics such as the quantile and maximum.

The values of the indicator $ELmax$ is an upper bound to the expected losses in the banking system due to default of a pair of banks. The rate of administrative costs used to estimate $ELmax$ was based on experts opinion. However, this is a controversial number. Therefore, the values of $ELmax$ cannot be seen in absolute terms. On the contrary, its trajectory is more important. Since LGD is higher in periods of financial stress, higher values of the indicator $ELmax$ means that the vulnerability of the banking system is increasing.

5 Final Considerations

In this paper we presented measures of systemic risk that may be used to evaluate eventual vulnerabilities of the banking system due to credit risk. The theory establishes that the uncertainty regarding the value of an asset is a source of risk to the banking system, given that it may fall below such a point that it becomes impossible for the bank to honor its obligations with shareholders. The measures obtained were built considering this theoretical framework, as well as the stress dependency structure between banks captured by the multivariate density of the banking system.

Regarding the indicators proposed using Loss Given Default, the results suggest that the use of value losses due to default is more informative than the use of descriptive

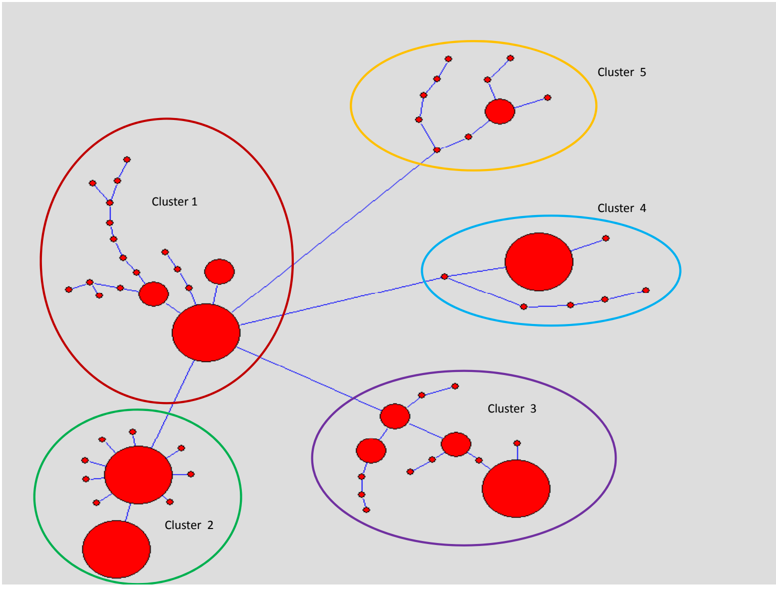


Figure 2: Cluster Definition

Bank groups are determined using a Minimum Spanning Tree (MST), considering the in difference PDs correlations as the distance. The size of the circles corresponds to bank size: large, medium and small.

Figure 3: Probability of default in the banking system (IndPD)

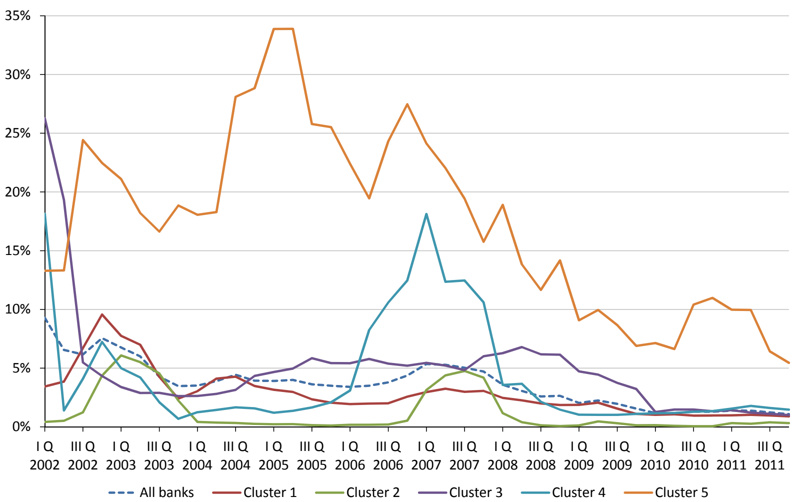


Figure 4: First round effects of a bank's bankruptcy (IndPDCond)

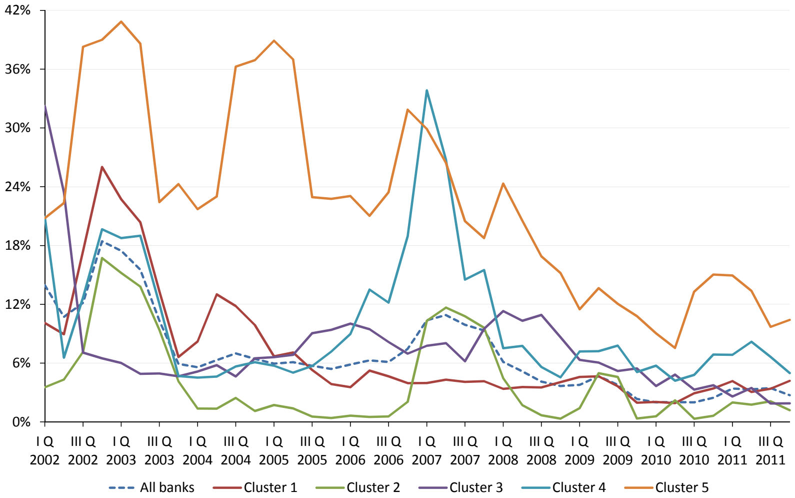


Figure 5: Probability that two banks default simultaneously (IndPDConj)

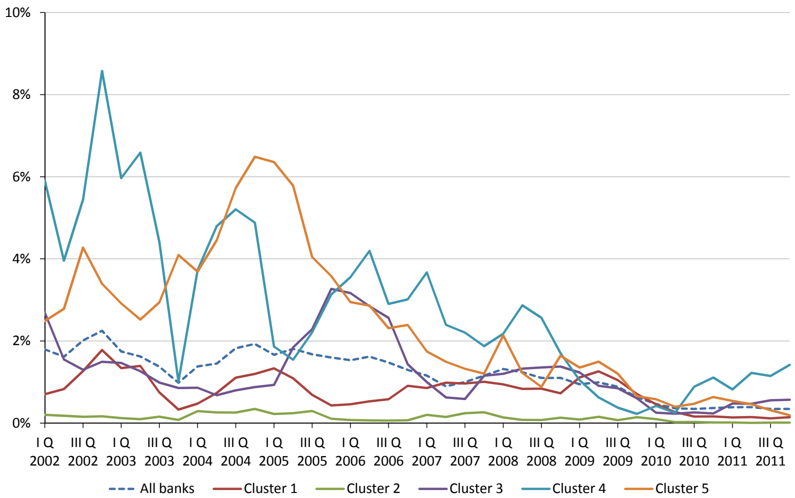
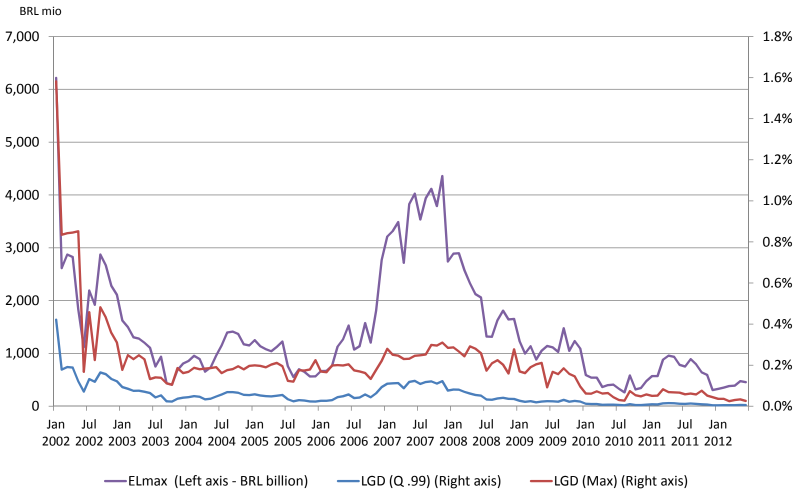


Figure 6: Expected Loss indicators and rate of *Loss Given Default*



statistics such as the quantile or the maximum.

The empirical results show that the systemic risk measures proposed present characteristics of early warning indicators since they anticipate the moments of stress in the banking system such as the global crisis of 2008.

The proposed measures are useful tool for stress tests and policy makers. The cluster analysis can be used for scenarios design or for detailed risk analysis of specific group of banks that interest to the policy makers. Furthermore, the indicators can be used to identify banks systemically important due to its connection and to its effects on PDs of other banks.

Further research will be use for other dependence measures to establish the clusters such as copula dependence measures, and forecast the clusters composition. Nonetheless, it is an important step in the construction of systemic risk measures that can help the prevention of future crisis.

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6 Appendix I - Loss Given Default

The recovery rate, assuming no liquidation cost after the default, is given by the ratio between the bank's asset value in T over the face value of debt F, given the occurrence of a default. Formally,

$$RR = E(\frac{A_T}{F} \mid A_T < F) = \frac{1}{F}E(V_T \mid V_T < F), \tag{18}$$

given that the firm's value V is equal to its asset values A.

Note that when we assume that asset value is a log-normal variable, we have that lnA is normally distributed with mean μ and variance σ^2. Therefore, $Z = \frac{(lnA-\mu)}{\sigma}$ follows the normal standard distribution and the value of the assets can be described by: $A = \exp(\sigma Z + \mu)$. So,

$$\begin{aligned} E(A \mid A < F) &= E(\exp[\sigma Z + \mu] \mid \exp[\sigma Z + \mu] < F) \\ &= E(\exp[\sigma Z + \mu] \mid Z < (lnF - \mu)/\sigma) \end{aligned} \tag{19}$$

Defining $g = (lnF - \mu)/\sigma$ e $h = \mathscr{N}(g)$, where $\mathscr{N}(\cdot)$ is the cumulative standard normal distribution function, (19) becomes:

$$\begin{aligned} E(A \mid A < F) &= \frac{\int_{-\infty}^{g} \exp[\sigma z + \mu](2\pi)^{-1/2} \exp[-z^2/2]dz}{h} \\ &= \frac{\int_{-\infty}^{g} \exp[(2\sigma z)/2 + \mu + \sigma^2/2 - \sigma^2/2](2\pi)^{-1/2} \exp[-z^2/2]dz}{h} \\ &= \exp[\mu + \sigma^2/2]\frac{\int_{-\infty}^{g} (2\pi)^{-1/2} \exp[-(z-\sigma)^2/2]dz}{h} \\ &= \exp[\mu + \sigma^2/2]\frac{\mathscr{N}((lnF - \mu)/\sigma - \sigma)}{\mathscr{N}((lnF - \mu)/\sigma)}. \end{aligned} \tag{20}$$

Considering the parameters of the normal distribution of lnA:

$$lnA_T \sim \mathscr{N}\left[lnA_0 + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T, \sigma_A^2 T\right], \tag{21}$$

we can write the expected value of A_T given that $A_T < F$ as:

$$\begin{aligned} E(A_T \mid A_T < F) &= \exp\left[lnA_0 + \left(\mu_A - \sigma_A^2/2\right)T + (\sigma_A^2 T)/2\right] \\ &\cdot \frac{\mathcal{N}\left((lnF - (\mu_A - \sigma_A^2/2)\,T)\,/\left(\sigma_A^2\sqrt{T}\right) - \sigma_A^2\sqrt{T}\right)}{\mathcal{N}\left((lnF - (lnA_0\mu_A - \sigma_A^2/2)\,T)\,\sigma_A^2\sqrt{T}\right)} \\ &= \exp\left[lnA_0 + \mu_A T\right]\frac{\mathcal{N}\left(-\frac{ln\frac{A_0}{F} + \left(\mu_A + \sigma_A^2/2\right)T}{\sigma_A\sqrt{T}}\right)}{\mathcal{N}\left(-\frac{ln\frac{A_0}{F} + \left(\mu_A - \sigma_A^2/2\right)T}{\sigma_A\sqrt{T}}\right)} \\ &= A_0\exp\left[\mu_A T\right]\frac{\mathcal{N}(-d_1^*)}{\mathcal{N}(-d_2^*)}. \end{aligned} \tag{22}$$

Substituting the term above in equation (18), we get an expression for the expected recovery rate in time T, in $t = 0$:

$$RR = \frac{A_0}{F}\exp\left[\mu_A T\right]\frac{\mathcal{N}(-d_1^*)}{\mathcal{N}(-d_2^*)}. \tag{23}$$

Similarly to the case of PDs, there's a distinction between actual and risk-neutral recovery rates. To obtain the risk-neutral rate, we substitute μ_A for the risk-free rate r and debt face value F for the distress barrier.

$$RR = \frac{A_0}{DB}\exp\left[rT\right]\frac{\mathcal{N}(-d_1)}{\mathcal{N}(-d_2)}. \tag{24}$$

The risk-neutral recovery rate is lower than the actual counterpart. Therefore, actual LGD is higher than risk-neutral LGD, given that $LGD = 1 - RR$ when recovery costs are null.

Having analyzed the theoretical aspects in the calculation of LGD, we get the final formula to estimate the expected loss rate at time T from the asset value at time $t = 0$, measured in tual terms and including bankruptcy administrative costs, denoted by φ:

$$LGD_0 = 1 - (1 - \varphi)\frac{A_0}{DB}\exp\left[rT\right]\frac{\mathcal{N}(-d_1)}{\mathcal{N}(-d_2)}, \tag{25}$$

being d_1 e d_2 defined as in equations (3) and (4).

We can then estimate in t the expected bank loss for time T, as being:

$$EL_t = PD_t.LGD_t.EAD_t, \tag{26}$$

where EAD (Exposure at Default) is the amount of the bank's assets that are exposed to losses due to its counterpart's default.

7 Appendix II - Consistent Information Multivariate Density Optimizing methodology

Segoviano and Goodhart (2009) present a set of banking stability measures, built from an adjusted multivariate density with empirical information, denominated Consistent Information Multivariate Density Optimizing methodology or simply CIMDO methodology, established in Segoviano (2006). This section aims to detail this methodology.

The CIMDO methodology can be used by considering the banking system as a portfolio of N banks. However, as to avoid notation overloading, we will consider a portfolio composed of two banks: bank X and bank Y, with logarithmic returns defined as the random variables x and y.

It is assumed, from an initial hypothesis, that the portfolio's stochastic process multivariate distribution follows a parametric distribution $q(x, y) \in \mathscr{R}^2$, called *a prior* distribution from now on. The initial hypothesis about the distribution of returns is taken according to economic hypotheses (default is deflagrated by the decline of asset value below a given barrier) and theoretical models (structural approach), but not necessarily in accordance with empirical observation.

The CIMDO methodology allows for the inference of a multivariate distribution $p(x, y) \in \mathscr{R}^2$ (*a posterior* distribution) from the *prior* distribution. This is done by means of an optimization process in which the *prior* density is updated with empirical information extracted from PDs and DBs by means of the restrictions set.

Formally, the Banking System Multivariate Density (BSMD) is obtained by the resolution of the following optimization problem:

$$\text{Min}_{p(x,y)} C[p,q] = \int\int p(x,y) \ln[\frac{p(x,y)}{q(x,y}]dxdy, \tag{27}$$

sujeito a

$$\int\int p(x,y)\mathscr{X}_{(DB^x,\infty)}dxdy = PD_t^x \tag{28}$$

$$\int\int p(x,y)\mathscr{X}_{(DB^y,\infty)}dydx = PD_t^y \tag{29}$$

$$\int\int p(x,y)dxdy = 1 \tag{30}$$

$$p(x,y) \geq 0. \tag{31}$$

where $p(x,y)$, the multivariate *posterior* distribution, is to be found. PD_t^x and PD_t^y are the empirically estimated probabilities of default of banks x and y, respectively, at time t. $\mathscr{X}_{[DB^x,\infty)}$, $\mathscr{X}_{(DB^y,\infty)}$ are indicator functions. The restrictions (28) and (29), imposed on the marginal densities of the BSMD ($p(x,y)$), assure that the information obtained through the empirical estimation of PDs and distress barriers of each bank of the portfolio are integrated in the BSMD. The restrictions (30) and (31) assure that the solution of optimization problem $\widehat{p(x,y)}$ is a valid density; that is, they guarantee that the solution satisfies de additivity and non-negativity conditions.

Therefore, the CIMDO density is generated by minimizing the functional:

$$\begin{aligned} L[p,q] &= \int\int \ln p(x,y)dxdy - \int\int p(x,y)\ln q(x,y)dxdy \\ &+ \lambda_1 \left[\int\int p(x,y)\mathscr{X}_{(DB^x,\infty)}dxdy - PD_t^x\right] \\ &+ \lambda_2 \left[\int\int p(x,y)\mathscr{X}_{(DB^y,\infty)}dydx - PD_t^y\right] \\ &= \mu\left[\int\int p(x,y)dxdy - 1\right]. \end{aligned} \tag{32}$$

Through the calculation of variations, one can obtain the optimal *a posterior* multivariate density:

$$\widehat{p(x,y)} = q(x,y)\exp\{-\left[1 + \hat{\mu} + \left(\hat{\lambda}_1\mathscr{X}_{(DB^x,\infty)}\right) + \left(\hat{\lambda}_2\mathscr{X}_{(DB^y,\infty)}\right)\right]\}. \tag{33}$$

Intuitively, the set of restrictions guarantees that the BSMD, $\widehat{p(x,y)}$, contains marginal densities that satisfy the empirically observed PDs for each bank of the portfolio.

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