Survival analysis of private Banks in Brazil

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Abstract

The objective of this research is to analyze the private banks survival. This subject is very important because banking crises around the world show that some instability in the banking system causes many financial and social costs. In this way, to identify problems in the banking system is fundamental. In fact, the financial system is very important for a country economy and a bank system supervision becomes necessary. The banking failure prediction models are able to identify a bank financial condition through the probability of failure. In this research, 66 private Brazilian banks were analyzed, of which 29 are failure banks and 37 are survival banks, between 1994 and 2007. It is used the survival analysis to find the main indicators which can explain the private banking failure in Brazil. Once the survival analysis has a big set of techniques to construct a prediction model, it was necessary to elect one. A Cox proportional hazard model was chosen by a test of Cox-Snell residuals. It was possible to find the main financial ratios to explain the bank failure in Brazil through a construction of a banking failure prediction model. Some peculiar differences were detected in this research result comparing with others studies found in literature.

Key Words: Banking Failure Prediction, Survival Analysis, Cox Proportional Hazard Model.

JEL: C4, C41, G2, G21

1. Introduction and Motivation

The banking crises occurring worldwide throughout history have shown that instability of the financial system generates enormous financial and social costs. In fact, when banks become insolvents, its impacts generate financial difficulties to the population, since individuals and corporations entrust their resources to these institutions. Thus, the banks insolvency affects not only the financial system, but also the population as a whole. The Brazilian banking scenario was marked by sharp changes between 1994 and 1999. According to Matias (1999), eleven of the seventeen major private banks in the national retail period disappeared. Sales (2005) showed that from July 1994 to December 1998, 83 banks, including commercial banks, multiple banks and building societies, have suffered some type of intervention. Following these changes, the Central Bank of Brazil implemented, in 1995, the Program of stimulating the Restructuring and Strengthening of National Financial System (PROER). In order to strengthen the national financial system, the program of preventive character ordered the merger and acquisition of banks in Brazil by rules dictated by the Central Bank. Thus, faced with a banking financial distress, the Central Bank could determine its capitalization, transfer of stock control, merger, acquisition or division. However, for this determination and the constant financial system supervision, it is necessary some mechanism to identify problems in the banking scenario. Janot (2001) mentioned that can be possible to identify, in advance, the financial institutions with greater probability of insolvency in Brazil. According to the author, a bank prediction failure model based on financial indicators could be used to adopt corrective measures in time for the Department of Supervision of the Central Bank.

The prediction failure models, also known in the literature as early warning models, whose explanatory variables are usually represented by financial ratios. Its applicability extends to various factors such as companies, banks and other institutions. In the models for prediction of failure bank, the response variable is capable of measuring the current financial situation of banks. Thus, the main contribution of these studies concerns the use of these models by banks, government, businesses and institutions in general. Banks may know your current financial status and pay attention to the critical variables to its survival. Moreover, government can supervise the banking system, companies and institutions in general. It is possible, with these models, to check the current status of banks in which some institution wish to entrust its resources.

The researches on this type of analysis use statistical techniques to construct failure prediction models, however, studies concerned with the failure banking analysis are scarce. The technique used in this study, survival analysis, differs from the other techniques used to incorporate the analysis of survival time of banks. In this sense, the objective of this work is using the survival analysis to identify the main financial ratios that can explain the bankruptcy of private banks in Brazil in the 1994 to 2007.

This article is organized by sections, including this brief introduction. In the following section, failure prediction models are presented in the banking literature and the statistical techniques used in its development. In the third section, the main concepts of the analysis used are described. In the fourth section, the data and the model used in this study are exposed. In the fifth section, the results of the analysis are presented and therefore the conclusion is described in the sixth section.

2. Failure prediction models

The increasing emergence of studies on mortality business using financial indicators occurred after the performance of the dichotomous classification of Beaver (1966) and, especially, the discriminant analysis of Altman (1968). The evolution of these studies led to its applicability not only in companies of various sectors, as well as analysis of banks. According to Altman (1968), studies concerned with insolvency signs were evident in the 30s. The author mentioned that many studies concluded that the bankrupt companies had different measures of indicators than entities that had survived. Similarly, it is plausible that banks in good financial conditions have different financial indicators than banks with weak financial situation. However, studies concerned with the bank insolvency have not been much explored in the national and international literature. Moreover, there is a large discrepancy between the financial indicators found to explain the probability of banks insolvency. For Alexandre, Canuto and Silveira (2003) the results of analysis in the literature differ because the statistical analysis, samples of banks, financial indicators and periods used are different. Picture 1 shows some studies that developed bank failure prediction models in Brazil and abroad.

The first works done on the development of a failure prediction model for banks were made by Meyer and Pifer (1970) and Sinkey (1975). The authors used the discriminant analysis in the creation of theses models. Meyer and Pifer (1970) concluded that it is possible to verify a state of bankruptcy up to two years ahead of time, however, from three years prior to bankruptcy, the values of financial indicators, presented by the discriminated analysis, were not able to foresee a situation of future failure. But, it is important to remember that the use of discriminant analysis is restricted, because this method supposed normality of data. Thus, other techniques were used to construct failure prediction models for banks such as logistic regression analysis and survival analysis. As can be seen in Table 1, the technique of logistic regression analysis was widely used. It is a probabilistic model where the response variable is between 0 and 1, where 0 represents a solvency bank and 1 represents insolvency. However, only Martin (1977), Lane, Looney and Wansley (1986), Espahbodi (1991) and Janot (2001) were concerned with the comparison of statistical techniques used to develop models to predict the insolvency of banks.

Author	Country	Year	Technique used
Meyer and Pifer	USA	1970	Discriminant Analysis
Sinkey	USA	1975	Discriminant Analysis
Martin	USA	1977	Discriminant Analysis and Logit Regression
Lane, Looney and Wansley	USA	1986	Discriminant Analysis and Cox Proportional Hazards Model
Whalen	USA	1991	Cox Proportional Hazards Model
Espahbodi	USA	1991	Discriminant Analysis and Logit Regression
Matias and Siqueira	Brazil	1996	Logit Regression
Araújo	Brazil	1998	Logit Regression
Matias	Brazil	1999	Logit Regression
Rocha	Brazil	1999	Cox Proportional Hazards Model
Janot	Brazil	2001	Logit Regression and Cox Proportional Hazards Model
Kolari, Glennon, Shin and Caputo	USA	2002	Logit Regression
Alexandre, Canuto and Silveira	Brazil	2003	Logit Regression
Sales	Brazil	2005	Survival Analysis
Canbas, Cabuk and Kilic	Turkey	2005	Discriminant Analysis, Logit and Probit Regression
Corrêa, Costa and Matias	Brazil	2006	Logit Regression
Costa	Brazil	2007	Logit Regression

Picture 1 - Studies about bank failure prediction models
Source: Own elaboration

Martin (1977) and Espahbodi (1991) compared the logistic analysis with discriminant analysis, while Janot (2001) compared this analysis with the statistical technique of survival analysis. Although the analysis made by Martin (1977) has pointed out a similarity in the models developed, whereas the ability to forecast the result, for both models, was low. Espahbodi (1991) showed that both models had high capacity to provide correct results for the insolvency, but the logistic regression model was more accurate to predict the bankruptcy a year ahead, while the model of discriminant analysis was more precise to predict it two years ahead. To Janot (2001), the model estimated by analysis of survival obtained a better result to classify a bank as a solvent or insolvent at a time frame of six months prior to bankruptcy.

Lane, Looney and Wansley (1986) were also concerned to compare techniques for development of failure prediction models. However, the authors compared the survival analysis with discriminant analysis and showed that both models had similar ability to hit, although the model developed using the technique of survival analysis has shown better results for a horizon of two years prior to the insolvency of banks[1].

Canbas, Cabuk and Kilic (2005) presented a combination of statistical techniques to construct a forecasting system of insolvency, rather than comparing them. The authors used the discriminant analysis, logit and probit analysis in an attempt to establish not only a model to predict the insolvency of banks, but also a system called "integrated early warning system". This system, according to Canbas, Cabuk and Kilic (2005), was presented to explain the failure of banks in Turkey. However, the same model could not be used to explain the financial situation of banks in other countries. To Ooghe and Balcaen (2002), not all types of failure prediction can be used in other countries without losing their efficiency.

Whalen (1991), Rocha (1999) and Sales (2005) used the survival analysis to develop models for prediction of bank insolvency. However, Whalen (1991) and Rocha (1999) presented the use of semi-parametric analysis of survival analysis model, called Cox proportional hazards model, while Sales (2005) introduced the use of a technique for parametric analysis of survival. Whalen (1991) presented explanatory variables to the insolvency of banks indicators total loans in total assets, operating expenses in total assets, net profit on total assets, total deposits of U$ 100,000 or more on total assets, total non performing loans in total assets and percentage of households to change more in 1986 compared to 1984. Meanwhile, it is important to emphasize that the author is more concerned to assess the ability of their model of success at different times than in explaining the impacts of financial indicators in the probability of insolvency. Thus, Whalen (1991) examined the capacity of adjustment of the model developed for 12, 18 and 24 months preceding the bankruptcy of American banks. The author concluded that, for all periods, the model presented a high ability to hit: 88%, 81%, 75% of accuracy, the respective horizons of 12, 18 and 24 months prior to bankruptcy. Similarly, Rocha (2001) developed models for prediction of insolvency for banks in Brazil in two different periods, 12 and 24 months prior to insolvency of banks, and concluded that the ability of both models was relatively high. However, her analysis showed that only the net margin indicator explains the failure of banks in Brazil a year prior to bankruptcy and the composition of the net margin and net leverage indicators explains the insolvency with two years prior to bankruptcy. In another way, Sales (2005) suggests a bigger set of financial indicators that explain the state of insolvency of Brazilian banks. According to the author, the best model estimated, as significant, the following variables: industrial production

[1] Lane, Looney and Wansley (1986) and Janot (2001) used the Cox proportional hazards model to create a bank failure prediction model. This model is a semi-parametric technique based on survival analysis. Its concepts are presented in third section of this work.

indicator, SELIC accumulated in the month, administrative expenses recovery for provide services income, active participation of business unusual in the active portfolio, monthly average operating margin in semester, leveraging equity resources with debt capital, default rate of credit operations, level of provisioning for credit operations, administrative cost of the average total assets, participation of other resources in liabilities and the return rate on total assets adjusted. Although Whalen (1991) and Sales (2005) have used the same analysis for the construction of a prediction model for bank bankruptcy, it is possible to notice a big difference between the models developed by both authors. This difference can be explained by the fact that the set of indicators used were not the same.

In fact, the differences on the models developed can be explained by the use of various financial ratios, as above, and furthermore, due to different techniques used in its construction. However, most models developed to predict insolvency of Brazilian banks used of the logistic regression analysis, such as Matias and Siqueira (1996), Araújo (1998), Matias (1999), Alexandre, Canuto and Silveira (2003), Correa, Costa and Matias (2006) and Costa (2007). Matias and Siqueira (1996) showed that the indicators that best explain the probability of insolvency for banks in Brazil were administrative cost, stockholder's equity commitment with credits in arrears and liquidation, and evolution of the resources funding. To Araújo (1998), the following indicators are statistically significant to the risk of bank insolvency: an indicator of capital and operational expenditure on total equity. For Matias (1999), the model elaborated for six months prior to the failure of banks presented the indicators of net margin, voluntary coverage, administrative cost and stockholder's equity commitment as significantly statistical variables to the probability of failure. This model showed 83% accuracy. Alexandre, Canuto and Silveira (2003) showed that the indicator of administrative costs in the model of Janot (2001) does not explain the probability of insolvency in the wholesale banks. For these, the cost of intermediation is relevant, which in fact occurs, the authors explained, as wholesale banks operate with a more lean that incurs lower costs with longer periods that increase the costs of intermediation. For Correa, Costa and Matias (2006) the set of variables that explains the failure of banks is composed by indicators to long-term funding adjusted, to foreign currency funding adjusted, floating funding, applications in credit operations, cash applications, cost of people, return on assets, share of cash result, spread, general liquidity, default and bankruptcy. Finally, Costa (2007) presented as explanatory variables to the model the following indicators: capitalization, funding adjusted, leverage, demand deposit funding, time deposit funding, floating funding, tax and labor liabilities, credit application, the cost of people, exchange profitability, share of services revenue, immediate liquidity, interbank dependence and adequation.

However, from the studies presented above, there are differences between the models developed by the authors, which may be based on the use of different statistical techniques and sample periods used. Moreover, there is, as can be seen, no standard set of financial indicators for the construction of models. About the techniques used in Brazilian studies, only Rocha (1999) and Janot (2001) used the statistical technique of survival analysis proposed in this study. Like other statistical tools, this phenomenon points to advance the future of insolvency, however, this method considers as response variable to model a function of survival time data shown in the next section.

3. Survival Analysis: Model and Data

The objective of the statistical technique, known as survival analysis, is to analyze the maintain time of an element in its current state, in order to estimate the variables that might explain the behavior of this time. Kiefer (1988) presents a highly informative and introductory research on this type of analysis, where he describes clearly and objectively the main concepts of the survival analysis: the survival function and probability of failure conditional function, also known by hazard function. The hazard function represents the central concept of this statistical analysis. This function is the estimation of conditional probabilities of a particular event to occur at different moments. The analysis of survival not only considers the probability of the event itself, but also the likelihood that the same event may occur with a previous condition. In studies using the survival analysis, as a statistical tool, you can find the variable response of the models developed for the survival function given in probabilistic terms, as set out below:

$$S(t) = P(T \geq t) \tag{3.1}$$

where, $S(t)$ is the survival function, which is defined as the probability of an observation does not fail until some time *t*, or in other words, the probability of the survival time be more than the time *t* ($P(T \geq t)$). However, in this study, the response variable of the model corresponds to the function of conditional probability of failure, called hazard function ($\lambda(t)$). This function, presented by equation 3.2, is a conditional probability which is not only the likelihood of a particular event occurs, but also a likelihood of its occurrence given that the event did not occur until the time t.

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t / T \geq t)}{\Delta t} \tag{3.2}$$

The hazard function can also be described as the ratio of the density function and the survival function.

$$\lambda(t) = \frac{f(t)}{S(t)} = -\frac{d}{dt}(\ln(S(t))) \tag{3.3}$$

where, $\lambda(t)$ corresponds to the hazard function, $f(t)$ is the density function and $S(t)$ is the survival function.

While the value of the hazard function in a given time *t* has been made, it is necessary to know the determination of the cumulative function, because from this it is possible to determine the function of survival. Thus, the relation between the function of cumulative hazard, $\Lambda(t)$, and the survival function is given below:

$$\Lambda(t) = \int_0^t \lambda(u)du = -\ln(S(t)) \tag{3.4}$$

And, similarly the function of survival can be estimated as follows:

$$S(t) = \exp\{-\Lambda(t)\} = \exp\{-\int_0^t \lambda(u)du\} \tag{3.5}$$

However, there is a concept to be clarified before the estimation of hazard function: the event of interest, also called failure event, which corresponds to the time when a company, individual or equipment no longer remain as they were before. Colosimo and Giolo (2006) emphasize the importance, in studies of survival, of defining clearly and precisely what is the failure event. The delimitation of the event failed to establish the variable time until the event that failure in turn is called the survival time, or also called time before the bankruptcy. Thus, in this study, the event of interest is the moment in which it ordered the extrajudicial liquidation of a bank.

3.1. Model adequacy

Aiming at proper use of survival analysis, it was needed to determine the technique to be used as this analysis includes a variety of techniques: non-parametric model, model semi-parametric and parametric models. The technique non-parametric is called Kaplan-Meier estimator. This method does not consider the inclusion of explanatory variables, however, this technique was used only for comparison purposes. The semi-parametric model of survival analysis known as Cox proportional hazards model presents a non-parametric part composed by a constant and a parametric part composed by explanatory variables. This model does not suppose any probability distribution for the survival times, but the parametric models, also consisting of explanatory variables, varies depending on the distribution of survival times. In this way, if the distributing of survival time is known like an exponential distribution, the parametric model is called exponential regression models. Thus, the model can be consider Weibull regression model, log-logistic, gamma or generalized gamma models in accordance with the behavior of the survival times. As it can be seen, in face of the diversity of techniques in survival analysis, it was used the residues test of Cox-Snell (1968), which is a method that generates curves of the relationship of waste, in order to choose the most appropriate statistical technique for the survival analysis of private banks. In this sense, the semi-parametric model of survival analysis, known as Cox proportional hazards model, was the best technique to data adjusted[2].

The general expression of the model considers the hazard function as response variable, represented by the conditional probabilities of risk in the presence of explanatory variables, designated by values of x:

$$\lambda(t/x) = \lambda_0(t)g(x'\beta) \tag{3.6}$$

where, $\lambda(t/x)$ corresponds to hazard function conditional on explanatory variables, $\lambda_0(t)$ corresponds to baseline hazard function, and $g(x'\beta)$ corresponds to a function, in this case, exponential, of the matrix $x'\beta$ given by:

$$g(x'\beta) = \exp\{x'\beta\} = \exp\{\beta_1 x_1 + ... + \beta_p x_p\} \tag{3.7}$$

In this model, the coefficients are the parameters that measure the effects of explanatory variables on the response variable. The interpretation of these parameters is not direct and not measurable, however, we conclude that the explanatory variable is positively or negatively related to the response variable.

3.2. Data

The data used in this work were provided by INEPAD (Institute of Teaching and Research in Administration). We analyzed 66 private banks, among them, 29 failed banks and 37 survival banks between the years 1994 and 2007. The specifications of the main

[2] The Cox-Snell (1968) test is an estimation of distributions of waste, commonly known as errors of the models. The curve of waste generated by this method lists two distributions of waste, estimated by the first non-parametric technique and the second by any other technique for the survival analysis that you want to analyze. The most appropriate method for elaborating the failure prediction model is a technique in which the distribution of residues most closely approximates of the distribution of waste estimated by non-parametric technique.

financial ratios used, and their average values, are presented in Table 1. These indicators are classified into three types of categories: strategy indicators, efficiency indicators, and solvency indicators. The strategy indicators relate the form in which a bank manages its resources, in other words, these indicators may represent the abstraction or use of resources of the bank. The efficiency indicators relate the bank expenses with its revenue and, finally, solvency indicators refer to the ability of a bank liquidate their funding and other obligations. Thus, funding resources indicators are classified as indicators of strategy, while indicators of cost and profitability are classified as indicators of efficiency. The solvency indicators used are represented by interbank dependence and liquidity[3].

Table 1 - Average Values and Standard Deviation

Financial Ratios		All Banks		Insolvent Banks		Solvent Banks	
		Average Value	St. Dev.	Average Value	St. Dev.	Average Value	St. Dev
STF	Short-term funding adjusted	75.7784	21.2028	66.8043	18.4824	86.2879	19.4457
DDSF	Demand deposit and savings funding	4.8585	6.7667	4.0415	6.0189	6.0153	7.5505
TDF	Time deposit funding	30.5142	23.2384	24.3796	20.8903	37.9039	23.9535
TLL	Tax and labor liabilities	4.6960	12.0919	6.9353	16.0538	2.1785	3.6060
LTRT	Long-term resources in turnover	8.6755	56.7287	27.8270	33.0960	-13.8485	68.9937
ERT	Equity resources in turnover	162.8139	252.1546	191.6522	236.6809	130.0015	268.3406
FC	Funding cost	16.8613	22.4611	5.7399	5.2094	29.9670	27.1543
CP	Cost of people	4.0603	5.5521	1.2650	1.0766	7.3694	6.6972
AC	Administrative cost	5.7905	7.1541	3.3355	5.8291	8.7597	7.4897
NROE	Net return on equity	1.8811	47.6438	21.7474	24.9981	-21.5979	56.2798
ROAE	Return on equity activity adjusted	-2.3865	63.7000	27.9511	33.2710	-38.1673	71.5622
ROA	Return on total assets	-0.1372	12.0966	3.9607	7.1885	-4.9236	14.6411
RBA	Return on bank activity	-0.1140	10.6076	4.1080	5.0793	-5.0491	12.9574
ROCA	Return on Cash	21.6748	61.0495	10.5171	10.8026	34.8427	87.0781
ROCR	Return on credit	41.1182	45.8021	22.4557	24.8036	64.0841	54.1113
PORCL	Participations of operating revenue from credit and leasing operation	56.3975	35.8753	47.1678	40.7462	67.7306	25.7117
PCR	Participation of cash result	30.2921	39.2927	37.8329	46.5000	21.2803	27.3348
GM	Gross margin	23.6056	36.2535	26.4143	45.8323	20.2027	21.2080
BAM	Bank activity margin	3.9272	26.1455	15.8095	25.5358	-10.0518	19.3866
OM	Operating margin	12.5428	34.1591	26.0097	39.0226	-3.2085	18.3725
NL	Net margin	9.0104	35.3564	22.4689	40.8186	-6.6642	18.9316
GL	General liquidity	114.3091	34.8472	120.8581	45.3869	106.9945	14.0058
CL	Current liquidity	132.7707	127.9285	158.2713	170.8742	103.8985	28.7974
IL	Immediate liquidity	109.1739	214.0108	163.8770	278.3970	46.8582	64.0348
ID	Interbank dependence	15.8749	20.5251	14.1500	20.4302	18.4003	20.7439

The short-term funding indicator measures how much of adjusted current liability there is in adjusted debt capital. The indicator demand deposits and savings funding verifies the deposits composed in debt capital. Similarly, the indicator of time deposit

[3] It was decided to not remove the outliers in the analysis because, in most cases, these items were characteristic of insolvent banks. Furthermore, failure prediction models made with the presence of these points presented to be more appropriate, according to the selection criteria of maximum likelihood, BIC and AIC, in comparison with models performed in the absence of outliers.

funding verifies total deposits on debt capital. In other words, these indicators represent indicators of debt from banks. As can be noted in Table 1, the insolvent banks have higher medium value of debt than solvent banks. Therefore, it is expected that these indicators show a positive relation with the response variable of the model, probability of insolvency, that is, as their values increase, also increases the risk of a bank became to be an insolvent bank. The tax and labor liabilities indicator corresponds to indicator that analyzes how much of debt capital is composed by tax and labor liabilities. The expectation of its impact in insolvency probability is negative, as banks solvent showed higher medium values compared to insolvent banks.

Indicators of equity resources in turnover and long-term resources in turnover represent the percentage of equity resources and long-term resources are used in working capital. It is expected that an increase in the indicator of long-term resources in turnover decrease the risk of insolvency, as banks solvents apply more long-term resources in turnover than insolvent banks, which do not apply. Based on the medium negative values of the equity resources in turnover, both solvent and insolvent banks do not apply their resources in the short-term operations. It is expected a positive relation between these indicators and the response variable in according to medium values presented. However, it is important to note that the analysis of these ratios is not elementary, neither direct, and, because of this, it shall be done in conjunction with others ratios.

The insolvent banks have higher average funding costs, costs of people and administrative cost in relation to insolvent banks. Thus, it can be expected a positive relation of these indicators with the response variable, probability of insolvency. When other average values were observed, some values of the profitability indicators we noted as higher for insolvent banks. The indicators of return on cash and credit, which quantify the cash and credit profitability, are higher for insolvent banks, indicating higher average interest rate in applications. Also the participation of credit operating revenue and leasing operation indicator, which measures how much of the total revenue the result with credit operations and leasing is composed of, presented the highest average value for insolvent banks.

Thus, we can expect positive relations between these indicators with the response variable, which means, the higher the profitability, the greater will be the bank probability of insolvency, it means, higher the average rate of the credit and cash portfolio and their participation in revenue from brokerage, greater will be its probability of insolvency. Besides, it does not seem plausible to assume that banks in financial difficulty are more profitable than banks solvent. This relation cannot be confirmed according to the average values of other indicators of profitability, which is higher for banks solvent, as occurs with all other indicators of profitability shown in Table 1. Accordingly, further analysis on the financial indicators that explain the failure of private banks will be carried out after obtaining the results. Accordingly, the return on equity, return of equity activity adjusted, return on total assets and return on bank activity, providing returns after costs and expenses, show negative results for insolvent banks, indicating as characteristic, that work with higher rates, higher costs and expenses, with negative final results.

Finally, the impact of the liquidity indicators in the response variable, probability of insolvency, should be presented as negative, because of the higher average values presented by solvent banks. On the other hand, the variable represented by the indicator of interbank dependence should be positive in probability of insolvency, once insolvent banks showed higher values for this indicator.

4. Results

In this section are presented de main results obtained by survival analysis of the private banks in Brazil. As this analysis allowed the development of various failure prediction models, it was made various combinations of financial ratios to elaborate the most adequate failure prediction model. In this way, it was necessary to use criteria for selection of models to choose the most appropriate statistical model in explaining the bank insolvency in Brazil. It were used the maximum likelihood test, the BIC (Bayesian information criteria) and the AIC (Akaike information criteria) selection models criteria. The AIC selection is very used to determine the most adequate model in survival analysis applying medical researches. However, it was possible to note that in failure banks researches it was not applied. In this study, the most adequate model for private bank failure prediction was chosen by all the selection criteria cited. Table 2 shows the parameters of the financial indicators most appropriate to explain the bankruptcy of private banks in Brazil.

Table 2 - Hazards function and estimated parameters

Financial ratios		**Hazard**	**Parameters**
TLL	Tax and labor liabilities	0.7995***	-0.2236***
		(0.0549)	(0.0686)
ERT	Equity resources in turnover	1.0112***	0.0112***
		(0.0028)	(0.0028)
FC	Funding cost	1.0886***	0.0849***
		(0.0217)	(0.0200)
CP	Cost of people	1.3914***	0.3303***
		(0.1208)	(0.0868)
RBA	Return on bank activity	1.5896***	0.4634***
		(01664)	(0.1046)
ROCA	Return on cash	1.0081*	0.0080*
		(0.0044)	(0.0044)
PORCL	Participations of operating revenue from credit and leasing operation	0.9503***	-0.0509***
		(0.0161)	(0.0169)
OM	Operating margin	0.8327***	-0.1830***
		(0.0368)	(0.0442)
IL	Immediate liquidity	0.9737***	-0.266***
		(0.0086)	(0.0088)
ID	Interbank dependence	1.0648***	0.0628***
		(0.0225)	(0.0211)
Number of Banks		66	
Failure Banks		29	

The symbols ***, **, * indicate statistical significance of 1%, 5% e 10%, respectively.

The tax and labor liabilities indicator presented a negative impact on the probability of banks insolvency. This result was similar to some indicators of return represented by the participation of operating revenue from credit and leasing operations and operating margin. This means that an increase in these indicators should reduce the probability of insolvency of private banks in Brazil. As the descriptive statistics, this relation was not expected only for the participation of operating revenue from credit and leasing operations (PORCL). It was expected that the impact of this indicator in the response variable should be positive, it means, if the value of this variable increases the probability of bank insolvency increases too, as the insolvent banks had greater value for this indicator. However, instead of there is mores variability in the values of PORCL to insolvent banks, in financial terms, a bank represents lower probabilities of failure with the increase of the credits revenue. Although, it is incurring much risk in the credit operations, the increase of credits would be understood like a result of credibility bank. Similarly, this argument can be used to explain the impact of the indicators of operating margin (OM) and immediate liquidity (IL) in the probability of bank insolvency. As the credit revenues are considered as operating revenues for banks, it is possible to assume that its increase would reduce the risk of bank insolvency. Moreover, the hypothesis that an increase in immediate liquidity reduces the probability of bank insolvency is easy to be understood, since the banks credibility and liquidity indicators are highly related to the survival of banks. Good market liquidity facilitates the raising of funds to pay their obligations, especially in the short term.

However, regarding the impact of the indicator TTL (tax and labor liabilities), seems unlikely to say that an increase in spending with tax and labor costs lead to lower probability of insolvency. This relationship should be examined with caution, but as descriptive statistics, solvent banks have more tax and labor charges than insolvents banks. At first, it would likely assume that in moment of weakness financial the managers of a bank will opt for a policy of cost reducing with the increase in layoffs, for example. But, this hypothesis is rejected when looking to the cost of people indicator. As insolvent banks have higher costs and this variable has positive relation with the response variable, like an increase in costs with people increases the probability of bank insolvency. Additionally, we can assume that higher costs lead to an increased probability of insolvency when the positive indicator of the funding cost with a response variable is observed. Thus, a plausible hypothesis to explain this relation is that the insolvent banks have lower operating assets due to the tax and labor.

The variables represented by the indicators equity resources in turnover, return on bank activity, return on cash and interbank dependence showed positive relation with the probability of insolvency of private banks in Brazil. This means that an increase in the values of these ratios, increases the probability of bank insolvency. These relations are presented in accordance with the descriptive statistics performed, since the highest values of these indicators were presented by insolvent banks. Thus, the positive relation between these variables and the insolvency of banks was expected, given the negative values of the equity resources in turnover for both groups. Included the positive impact of the indicator of return on bank activity in the probability of insolvency of banks, is presented according to the data sample, because although they had more value for solvent banks, showed greater variability for insolvent banks. However, only the interbank dependence (ID) ratio represents a direct and easy to understand relation with the response variable. This indicator verifies the interbank deposits on the debt capital, or shows how a bank depends on the transactions with other banks. Accordingly, it is likely to assume that an increase in interbank dependence increases the risk of bank insolvency. As for the indicators of return on bank activity (RBA) and return on cash (ROCA), the analysis indicates that the insolvent banks operate with higher interest rates.

Although according to descriptive statistics, insolvent banks have lower return on bank activity (RBA), these banks may have higher values of RBA for solvent banks, since its greater variability. Accordingly, the positive impact of this variable on the probability of insolvency can be understood. However, it not seems plausible to assume that an increase in the return on bank activity increase the risk of a bank being liquidated. But, it is likely that banks in situations of financial difficulty choose to incur higher risk bearing higher funding rates and thus have higher return in comparison to banks that survived.

5. Conclusion

This study aimed to analyze the survival of 66 private banks in Brazil, with 37 solvent banks and 29 insolvent banks, between the years 1994 to 2007. We used the technique of survival analysis for elaborate a failure prediction model for bank capable of measuring the current financial situation of private banks in Brazil. In general, these models are characterized by predict the phenomenon of insolvency and are composed with explanatory variables, usually represented by financial ratios. The Cox proportional hazards model, semi-parametric technical of survival analysis, was used to determine the set of financial indicators most appropriate to statistically explain the phenomenon of the bankruptcy of private banks in Brazil.

In this study, the failure prediction model estimated for private banks in Brazil had several findings. The main findings are related to the variables that reduce or increase the probability of private banks insolvency. In that sense, the banks themselves may be aware the main accounts that favor its survival. Thus, the negative impacts of tax and labor liabilities, participation of operating revenue from credit and leasing operations, operating margin and immediate liquidity indicators in the probability of bankruptcy indicate that an increase of these indicators reduces the probability of insolvency of a private bank in Brazil. The positive impacts on the probability of insolvency of the other indicators, equity resources in turnover, funding cost, cost of people, return on bank activity, return on cash, interbank dependence, had an inversion relation. According to the analysis, the increase of costs and interbank dependence increases the probability of insolvency, and increases in the values of immediate liquidity, operating margin and participations of operating revenue from credit and leasing operations reduces the risk of default for private banks in Brazil. Furthermore, it was possible to identify which private banks in financial difficulty may present higher values of profitability than solvent banks, as work with higher funding rates due to its difficulty in raising funds in the market. The situation of private banks insolvency can be detected by the ratios presented and the use of the private banks failure prediction model estimated.

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