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Explaining Bank Failures in Brazil: Micro, Macro and Contagion Effects (1994-1998)*

Adriana Soares Sales† Maria Eduarda Tannuri-Pianto‡

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Abstract

We apply duration (survival) models with exponential and exponential piecewise-constant hazard functions to a panel of 273 banks to study the determinants of bank failure over the 1994-1998 period in Brazil. The models deal empirically with left censoring in the data. We control for macroeconomic conditions and contagion effects, as well as bank-specific factors. Our results indicate that foreign banks have distinct empirical survival functions relative to other banks. For Brazil, macroeconomic and bank-level covariates explain the likelihood and timing of bank failure. Our indicator of system-wide financial fragility (IFF) suggests that the banking industry faced increased fragility after November 1995. We find (some) evidence that the Program of Incentives for the Restructuring and Strengthening of the National Financial System (Proer) was able to distinguish solvent from insolvent banks.

Keywords: Duration Analysis; Exponential Hazard; Bank Failures; Brazil.

JEL Classification Codes: C41 and G21.

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1 Introduction

From the beginning of the Real Plan in July 1994 until December 1998, 83 banks – commercial banks, universal banks and savings and loans associations – suffered some type of intervention, including from the adoption of special regimes by the Central Bank of Brazil (BC) to any type of stockholder restructuring (mergers, incorporations, cancellations, changes of social object and split-ups) or privatizations. It is worth mentioning that 59 banks "failed" during the period, which represents around 22% of the sample of all banks alive.

That "mortality" pattern can be studied using duration analysis, which models a Markov process with two states - "alive and dead." These models are able to explain and predict how the conditional probability of failure evolves over time, which covariates affect it and when the potential failure occurs.

In this paper, we investigate the determinants of bank failure and bank unsoundness in Brazil over the 1994-1998 period. We apply duration (survival) analysis to a panel of "time-to-event" data, which allows disentangling bank - specific factors from others that lead to bank weakness. Since banking crises can be costly[1] it seems crucial that the financial system regulator collects information about the sources of banking fragility to institute remedial action at troubled banks.

We also develop an indicator of system-wide financial fragility (IFF)[2], which is useful for financial surveillance. The estimated models enable us to estimate the mean survival time of each bank in each month of the 1994-1998 period. It also provides evidence that the Program of Incentives for the Restructuring and Strengthening of the National Financial System (Proer) was able to distinguish solvent from insolvent banks and avoid contagion.

The main methodological contributions of the paper are: i) dealing with left cen-

[1] A report by the World Bank (1999) mentions an IMF study that calculates the average cost of a banking crisis in terms of a GDP loss as 14.6% (over a trend) per crisis. See also Bernanke and Gertler (1990).

[2] An economy exhibits financial fragility if it possesses a propagation mechanism that allows even small exogenous shocks to generate crises with relevant effects on the financial structure and on the real activity of the economy.

soring in the data; ii) incorporating time-varying covariates; and iii) controlling for bank-specific covariates, macroeconomic conditions, and potential contagion effects.

Our results indicate that: i) macroeconomic conditions contribute to explain bank failures and improve in and out-of-sample accuracy of the models; ii) foreign banks have a different survival function and should be analyzed disjointly; iii) there is no relevant bank-level liquidity indicator; iv) panel data information should be used in these studies; and v) there is evidence that Proer avoided deposit runs.

The paper is organized as follows. Section 2 provides some background on and discussion of the main issues in this literature. Section 3 briefly describes the Brazilian Banking system over the 1994-1998 period. Section 4 presents the data and the expected effects of the covariates on bank fragility. Section 5 develops the methodology. Section 6 discusses the results. Some illustrations of models use are presented in Section 7. Section 8 concludes.

2 Background

The literature that uses duration models to explain and predict bank failures for the US Banking system includes Lane, Looney and Wansley (1986) who use a non-parametric proportional hazard model introduced by Cox (1972) and non-time varying bank-specific covariates for banks that failed between January 1978 and June 1984. DeYoung (2000) employs a split-population duration model with log-logistic hazard function and time-varying bank-level covariates as well as regulatory and economic environment variables to examine the financial performance of commercial banks chartered between 1980 and 1985. Wheellock and Wilson (2000) model failures and acquisitions using a competing-risk hazard model framework. They utilize the Cox model with time-varying bank level covariates over the 1984-1993 period.

For the Argentinean Banking system, Dabós and Escudero (2000) use the Cox model with non-time varying bank-specific covariates (from November 1994). Bercoff *et al.* (2002) employ a lognormal hazard function and time-varying macroeconomic covariates and (non-time-varying) bank-specific covariates over the 1993-1996 period. For the Mexican Banking system González-Hemossillo *et al.* (1997) estimate a split-population survival model with a log-logistic hazard function and bank-specific, macroeconomic and contagion variables from 1991 to 1995. Only the macroeconomic variables are time-varying.[3] For the Brazilian Banking system Rocha (1999) and Janot (2001) employ the Cox model and non-time-varying covariates. The former considers banks that failed between July 1994 and December 1995 and the latter, between 1995 and 1996 (covariates from December 1994).

Usually, when duration models are used to study bank failure (for example Lane *et al.*, 1986; González-Hermosillo, 1999) the initial time period of the analysis does not coincide with the true period in which banks are born. This practice results in left censoring of the data, which is not taken into account during the statistical estimation procedure. In this article we propose a hazard function that overcomes this left censoring problem, which is the exponential function, a "memoryless" hazard.

González-Hermosillo (1999) discusses the "life cycle of bank failures" and the importance of capturing the "whole cycle". In order to accomplish this task the author suggests employing time-varying covariates. We adopt this approach in our analysis.

The simultaneous use of bank-level indicators and macroeconomic variables proves to be very important. The macroeconomic approach of bank failure cannot independently explain why some banks survive macroeconomic shocks and others fail. On the other hand, the bank-level approach ceases to be efficient if one does not account for varying economic conditions. In this sense, we include both types of variables in our models. Furthermore, we follow Bercoff *et al.* (2000), González-Hermosillo (1999), González-Hermossilo *et al.* (1997) and D'Amato *et al.* (1997) when choosing contagion proxies.

[3] It is not clear if the bank-specific covariates are time-varying as well.

3 The Brazilian Banking System and Proer

Before the implementation of the Real Plan in July 1994 the Brazilian banking system was based on high-inflation rate funds transfers from the depositors to the banks. Despite accounting for a small portion of the banks' liabilities, the demand deposits bore a strong negative *ex-post* real interest rate. If the "Ponzi-game condition" applies, which means here that the bank's deposits growth rate is higher than the interest rate paid for the bank's liabilities, then the system functions well and is likely over-dimensioned.

After the Real Plan, inflationary transfers to the banking system decreased by almost R$ 9 billion until 1996[4] (around USD 4.1 billion). It is possible that in some moment after the Plan the bank's deposits growth rate was lower than the interest rate paid by the banks to the depositors. Under this situation the banks have basically two choices: make a fund transfer from the borrowers or sell their stock of net assets. If the economy suffers a shock, as during the Mexican crisis in December 1994, and the transfers reach very high levels, the system can face a banking crisis.

During this period, the loss of floating revenue was compensated by a rise in loan revenues[5], which generated a "lending boom". There is evidence that both in industrialized and Latin American countries such booms are sometimes followed by banking crises: it becomes more difficult to disentangle good from bad borrowers. This is reinforced by the evolution of the credit default rate after the Real Plan: to consumers it increased to 16.67% of the total credit operations from July to November 1995 from 4.38% in the second semester of 1994.

Therefore, after the Plano Real, the Central Bank of Brazil had to regulate an over-dimensioned banking system. As part of the main reforms were the Basle Capital Agreement in 1994, and the inclusion of many state-owned banks such as

[4] See Cysne (1997).

[5] In such a situation, it seems that the banks are not willing to reduce costs because any bank that delays the adjustment can increase its market share.

Banespa and Banerj in the Special Regime of Temporary Administration (Raet). In spite of several preventive measures, a banking crisis seemed to have settled in after the intervention of Banco Econômico in August 1995.

To avoid the high costs of a system-wide banking crisis, the Central Bank implemented the Program of Incentives for the Restructuring and Strengthening of the National Financial System (Proer) in November 1995. The credit lines and the subsidized tax treatment granted under Proer were aimed at promoting bank mergers and incorporations by other institutions. Seven banks were either merged, incorporated or had their shareholder control transferred while making use of Proer resources. Under the Proer, the Central Bank restructured 4 private banks (Econômico, Bamerindus, Nacional and Banorte) using the "good bank/ bad bank" failure resolution method and it granted credit lines to the acquirer banks, as Table I indicates.

Table I: Sale of Banks with Resources from Proer

Regime	Operation	Amount in R$ millions[1/]
Banks under Intervention	**Sale of part of assets and liabilities to:**	19,108
Econômico	Banco Excel e Caixa Econômica Federal	
Nacional	Banco Unibanco	
Mercantil de PE	Banco Rural	
Banorte	Banco Bandeirantes e CEF	
Bamerindus	HSBC e CEF	
Banks not under Intervention	**Transfer of Stockholder Control to:**	1,251
United	Banco Antônio Queiroz	
Martinelli	Banco Pontual	

Source: Central Bank of Brazil.
[1/] Historical values.

4 Data

Our initial sample consists of all 273 banks that were operating in July 1994 or opened from July 1994 through December 1998 (24 banks). The covariates are time-varying from 1994 to 1998. The sample does not include Banco Morgan Stanley Dean Witter, Banco Holandês Unido, Banco Paraiban, Banco Banerj and Banco

Pottencial, for which complete data was not available. The bank-level series were discontinued in 1999. The sample period is homogeneous in terms of regulation, the technical production possibilities of the banking industry, and economic environment.

In this paper, we define a bank survival spell as the length of time that a bank stays solvent. As the events of bank unsoundness and legal bankruptcy do not necessarily occur at the same time, we consider as insolvent banks that have undergone Special Regimes - which include Raet, intervention and out-of-court liquidation - have been canceled, or have received financial support from the Central Bank of Brazil during the sample period.

We also consider banks that are cancelled due to change of business goals, incorporations, transfers of stockholder controls, and privatizations to have a censored lifetime, with censor date equal to the date of the event. Incorporated banks are treated like merged banks since it is not possible to split them into separated banks. Therefore, both the incorporated banks and the incorporating banks have a censored duration. Banks that suffer transfers of stockholder control operate separately and only the acquired bank has a censored lifetime.

Description of Events

Event	Indicator in the date of the event
Raet, Intervention and Liquidation	1
Proer, Proes	1
Cancellation	1
Cancellation due to change of business goals	0
Incorporation and Transfer of Stockholder Control	0
Privatization	0

Obs: 0 = censoring e 1 = failure.

Table II summarizes the breakdown of failure events in our sample.

Table II: Summary of Failure Events

Event	Number
Raet	5
Intervention	7
Liquidation	32
Proer, Proes	5
Cancellation	10
Total	59

Source: PCIF 400 from Sisbacen.
Note: The first event that occurred since July 1994.

We assume that bank stratification follows the equity capital ownership criteria: federal and state-owned banks, private national banks, foreign banks and private national banks with foreign capital, named types 1, 2, 3 and 4 respectively. Table III describes the number of failures and observed duration by type of bank.

Table III: Number of Failures and Duration by Type

Type	Nº of banks	Nº of failures	Observed duration (in months) [2/]		
			Minimum	Mean	Maximum
1- State-owned	30	9	5	43.8	53
2- Private National [1/]	163	44	2	41.2	53
3- Foreign-owned	47	1	7	46.7	53
4- Priv. Nat. w/Foreign	31	5	21	49.0	53
Total	271	59			

[1/] The Bancos Hércules and Garavelo were excluded.
[2/] The duration is calculated over the 1994-1998 period.

Our hypothesis here is that bank fragility is determined by bank-specific factors, macroeconomic conditions, and contagion effects. The covariates in Appendix A.1 control for those aspects. The Appendix A.1 also shows the expected effect of the variables (signs in the statistical models) on the estimated survival times. Our data source is the Central Bank of Brazil.

We select and test 29 out of 68 bank-level indicators from the "System of Institutions under Attendance and Control of the Central Bank of Brazil", hereafter called INDCON system, collected every semester. The INDCON system classifies the indicators into five groups representing: capital adequacy (C), asset quality (A), profitability (R), efficiency (E), and liquidity adequacy (L).[6]

We include several forward and backward-looking macroeconomic variables, available either per month or semester. Besides those variables described in the Appendix A.1 we tested the Selic nominal rate, the General Price Index-Market (IGP-M) and the spread over Treasury for the C-BOND. All macroeconomic covariates were tested under several lags and frequencies. The typical included variable varies monthly and is lagged for three-months. The variables leaded by 0, 2 and 6 remain constant over each six-month interval. For example, the ones followed by 0 are the variables in June and in December of each year from 1994 to 1998; the ones followed by 2 have a two-month lag and by 6 a six-months lag. To have some sense of the initial lags, we use an event study methodology, which consists in examining the variable in level and its mean until twelve months prior to the failure event and comparing it to the variable mean outside the twelve-month window.

We choose contagion variables that affect the banking system as a whole and have been related to herding behavior and deposits run. Economies of scale, portfolio diversification, and bank runs *a la* Diamong-Dybvig (1983) are addressed by specific covariates (see Appendix A.1). Economies of scale and portfolio diversification effects are represented by the variable *ativoreal*, which represents the asset value in the current month. For the variables *ativorealinício*, *ativorealmeio* and *ativorealfim* we make the asset value constant over the six-month interval, but employ the values at the beginning, middle and end of the half-year period, respectively.

Bank runs are addressed by the demand deposits growth rate. To avoid endogeneity problems, we instrument the variable by using the demand deposits growth rate lagged three months (*vardvlag3*). The variable *vardvmean* is the average of the demand deposits growth rate over the six-month interval.[7]

[6] The INDCON system follows the US "Uniform Financial Institutions Rating System (UFIRS)" also called the "CAMEL rating system". Under the CAMEL rating system each financial institution is assigned a composite rating based on an evaluation of components that address the capital adequacy, the assets quality, the capability of management, the quality and level of earnings, liquidity, and the sensitivity to market risk.

[7] The results including demand deposits growth rate are not reported.

Concerned about moral hazard problems, we assess whether the establishment of a formal scheme of insurance deposit in Brazil has changed the probability of bank failure. The dummy variable *fgc* (1 after December 1995 and 0 otherwise) was not statistically significant in any statistical estimation and was excluded.

5 Methodology

Duration models are usually applied to censored data, and therefore one should derive a likelihood function for such data. For a random draw i from the population, let t_i denote the time for which individual i is observed and let t_{i^*} denote the duration. If i dies with $t_i < t_{i^*}$, there is no right censoring and estimation employs traditional conditional maximum likelihood (CLE). In order to account for right censoring, we assume that the observed duration t_i is obtained as $t_i = \min(t_{i^*}, b_i)$, where b_i is the censoring time for individual i. The probability that t_i is censored is:

$$P(t_i^* > bi \mid x_i) = 1 - F(b_i \mid x_i; \theta)$$

where $F(.)$ is the conditional cdf of t_{i^*} given x_i - the vector of observed covariates - and θ - the vector of unknown parameters.

Let d_i denote a binary failure indicator that equals one if a bank fails and zero otherwise and f(.) the probability density function. The conditional likelihood function for the N-size sample is:

$$\begin{aligned} L &= \prod_{i=1}^{n} L_i = \prod_{i=1}^{n} f(t_i \mid x_i; \theta)^{d_i} [1 - F(t_i \mid x_i; \theta)]^{1-d_i} \\ &= \prod_{i=1}^{n} \lambda(t_i \mid x_i; \theta)^{d_i} S(t_i \mid x_i; \theta)3 \end{aligned} \tag{1}$$

where

$$\lambda(t; x) = \lim_{\Delta t \downarrow 0} \frac{P(t \leq T \leq t + \Delta t \mid T > t, x)}{\Delta t}$$

and

$$S(t;x) = \exp\left[-\int_0^t \lambda(s;x)ds\right] = \exp\{-\Lambda(t;x)\}$$

are the hazard and the survival functions.

Using the integrated hazard function $\Lambda(t_i \mid x_i;\theta)$, we see that:

$$\begin{aligned}
\log L &= \sum_{i=1}^{n}\{d_i \log[f(t_i \mid x_i;\theta)] + (1-d_i)\log[1-F(t_i \mid x_i;\theta)]\} \\
&= \sum_{i=1}^{n}\{d_i \log\lambda(t_i \mid x_i;\theta) - \Lambda(t_i \mid x_i;\theta)\} \qquad (2)
\end{aligned}$$

For the grouped data, we divide the time line into J+1 intervals $(0,\ \tau_1]$, $(\tau_1,\ \tau_2]$,..., $(\tau_{J-1,}\ \tau_J]$, $(\tau_J,\ \infty)$. Let c_j be a binary censorship indicator, which is equals to one if the duration is censored in interval j, and zero otherwise, and y_j be a binary indicator equal to one if the duration ends in the j-th interval and zero otherwise. Note that $c_j = 1$ implies $c_{j+1} = 1$ and $c_{J+1} \equiv 1$. Also, $y_j = 1$ implies $y_{J+1} = 1$. If $c_j = 1$, we adopt by convention that $y_j \equiv 1$.

Following Wooldridge (2002), only two combinations of y_j, y_{j-1} and c_j yield probabilities that are not identically equal to zero or one, which are:

$$\begin{aligned}
P(y_j &= 1 \mid y_{j-1} = 0, x, c_j = 0) = 1 - \exp\left[-\int_{\tau_{j-1}}^{\tau_j} \lambda(s;x,\theta)ds\right] \\
&\equiv 1 - \alpha_j(x,\theta)
\end{aligned}$$

and

$$P(y_j = 0 \mid y_{j-1} = 0, x, c_j = 0) = \alpha_j(x,\theta)$$

Then, if for observation i, an uncensored exit occurs in j_i, the likelihood is:

$$L_i = \left[\prod_{h=1}^{j_i - 1} \alpha_h(x_i, \theta) \right] [1 - \alpha_j(x_i, \theta)] \tag{3}$$

where $\alpha_j(x, \theta) \equiv \exp\left[-\int_{\tau_{j-1}}^{\tau_j} \lambda(s; x, \theta) ds \right]$.

If the duration is censored in interval j_i, the likelihood is only the first term on the right hand side of equation (3).

In the case of time-varying covariates that are constant within each time interval, the (partial) likelihood is:

$$L_i = \left[\prod_{h=1}^{ji-1} \alpha_h(x_{ih}, \theta) \right] [1 - \alpha_{j_i}(x_{i,j_i}, \theta)] \tag{3'}$$

In the paper, we implement CLE (Conditional Likelihood Estimation) using exponential and piecewise-constant exponential (PCE) hazard functions in eq. (3').

6 Results

We first present (Figure 1) baseline estimations of the unconditional survival functions (Kaplan-Meier estimator) for the true spells of the banks (considering the effective date they started business) and for spells beginning in July 1994 (left censored data).

The two curves have very distinct behavior, with the one on the left a lot steeper than the one on the right (left censored data). This is an indication that ignoring the left censoring may distort the survival function estimations.

In order to investigate the issue of continuous *vis-a-vis* discrete data, the survival functions were also estimated using daily instead of monthly data. They behave very similarly, indicating that they do not depend on the level of aggregation.

We performed non-parametric rank tests (of survival time) for the equality of survival functions among the four types of banks considered. Visual inspection of the survival functions indicated that foreign banks had a distinct behavior. We use the log-rank, the Fleming-Harrington and the Peto-Peto-Prentice tests (Neumann, 1997).

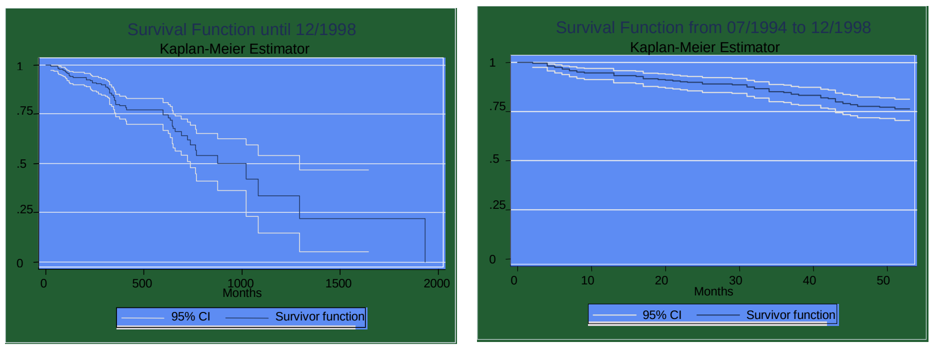


Figure 1: Empirical Survival Functions - Monthly data

The log-rank test is more appropriate under the assumption that the hazard functions are proportional among groups, if they are not the same. The Fleming - Harrington is a generalization of the first one but we can give different weights to the events, depending on the point in time they happen. Because one of the applications of our paper is to verify the presence of contagion, we give higher weights to the events that occur more towards the beginning of the analyzed period, when the Proer was implemented. The Peto-Peto-Prentice test is appropriate when we assume that the hazard functions are affected by differences in the censoring structure among the banks. All three tests reject the null hypothesis that all four types of banks have the same survival function. However, the null cannot be rejected when comparing only state-owned (type 1), private national (type 2) and private national with foreign capital (type 3) banks, as you can see in Appendix A.2 to the log-rank test. We obtain similar results when considering only the banks which collect demand deposits.

Table IV shows average survival times by type of bank, using data with the actual birth dates of the banks and the left censored data (starting in July 1994). The restricted mean is the area below the KM survival function from July 1994 to

December 1998. The extended mean is obtained by taking the KM survival function to zero using an exponential curve, and then computing the total area under the curve.

Table IV: Survival Time – Restricted and Extended Means (in months)

		Restricted Mean		Extended Mean	
Type	Number	Actual Birth Date	Beginning July 1994	Actual Birth Date	Beginning July 1994
State-owned	30	967.18	44.20(*)	967.18	146.53
Private National	165	859.32	44.93(*)	859.32	152.02
Foreign-owned	47	1601.86(*)	52.95(*)	59946.92	1935.04
Priv. Nat. w/Foreign	31	708.08(*)	50.56(*)	2668.89	288.91
total	273	1003.83	46.86(*)	1003.83	196.69

(*) The greatest time observed in our analysis is censored, indicating that the average is underestimated.

The previous results corroborate the idea that foreign-owned banks have a distinct survival behavior, and therefore should not be analyzed together with the other type of banks. Also, the issue of left censored data should not be ignored. If we consider the actual birth date, the state-owned banks seem to have a higher survival time than the private national ones, and this result disappears if we censor our data in July 1994.

In the Appendix A.2 we can see several microeconomics variables the have different means (t-statistic) among survivors and failed banks. The upper side of the Table "Descriptive Statistics" shows the variables employed in the models and the lower side those rejected.

6.1 Conditional Models

Because we are concerned with the colinearity problem that might be present in these kinds of models, we start our model selection process by performing a factorial analysis on the data in order to keep the variables strongly associated with the main factors and achieve an initial reduction in the number of bank-level covariates.[8] As you can see in Appendix A.2, the factorial analysis retains 11 factors. The proportion of the total variance explained by the factors is low. Therefore, we further use

[8] The results for the factorial analysis are available from the authors upon request.

the explanatory and forecasting accuracy of the variables as a selection criterion. All estimates use a robust var-cov matrix based on efficient-score residuals. The observations are likely non-independent, given that we are dealing with covariates that vary in time.

We estimate four model specifications – A, B, C and D. Model A is an exponential model with constant hazard baseline function. It includes bank-level indicators (micro) and macroeconomic variables (IPI and Selic[9]). Model B is a piecewise-exponential model (with bank-level variabels), in which the hazard baseline functions vary in each interval considered (0,6], (6,12], (12,18], (18,24], (24,30], (30,36], (36,42], (42,48], (48,53].[10] Model C is an exponential model that differs from model A in the macroeconomic and contagion variables included: Mres – ratio of total imports to international reserves (liquidity concept), and Vacre – monthly percentage change of loans.[11] Finally, in model D we include only microeconomic variables for comparison with the previous literature.

The microeconomic variables which are significant in all estimated models are: 1) recovery of the administrative expenses through service's income (r205), an indicator of efficiency that has a negative sign decreasing the conditional probability of failure; 2) ratio of atypical assets to total assets (a103), which indicates fraud risk and it impacts positively the probability of failure; 3) operational margin (monthly average in a semester) (r305), with a positive sign, meaning that a higher spread increases the chances of failure; 4) leverage ratio (c204) and 5) ratio of non-performing loans to total loan (a201) both are indicators of credit risk and have a positive sign; 6) loan reserve coverage which reduces the probability of failure and works as a buffer to absorb shocks; 7) ratio of other liabilities to liabilities (c107) that is a measure of a possible deterioration of the bank situation and has a positive impact on failure.

The variable general solvency (l104) is not significant in any of the regressions, a result that is not surprising, given that this variable only shows a mismatch between

[9] See the Appendix A.1 for a description of the variables and expected effects.

[10] The intervals are measured in months starting in July 1994 and ending in December 1998. The estimates are robust to the length of the intervals.

[11] See the Appendix A.1 for a description of the variables and expected effects.

assets and liabilities. None of the liquidity variables are significant either, which also was not surprising given that the liquidity indicators from the INDCON system do not seem to measure liquidity well. The asset variable, which would be a measure of economies of scale and portfolio diversification, is not significant. In addition, we include a variable for the bank age at the beginning of the estimation period and it is not significant in any model, evidencing that the exponential specification is actually reasonable.

Table V shows the estimates for models A and D. We report the hazard ratio coefficients which measure the proportional effect in the hazard function from absolute changes in the covariates. The variables IPI (industrial production indicator) and Selic rate[12] are lagged for 6 months in model A. They both have positive signs, increasing the probability of a bank failure. A high interest rate increases the vulnerability of banks to shocks, while an increase in IPI could lead to lending booms, associated with economic and credit growth, and also to higher vulnerability. The sign and magnitude of the coefficients in model D are similar to the other estimated models, but its predictive power is lower as will be shown later. The main difference with the previous models is that the variable "evolution of typical assets operations" is only significant at 10%. It could be indicating lending booms and therefore would be associated with production levels and interest rate. However, it has a negative impact on the conditional probability of bank failure[13, 14].

[12] The Special System of Custody and Settlement of Federal Securities overnight rate (Selic), expressed in annual terms, is the average rate weighted by the volume of one-day operations backed by federal government securities, carried out at Selic system through repurchase agreements.

[13] Our results are compatible with Rocha (1999). Using a non-time varying dataset, she finds that "leverage ratio", "ratio of non-performing loans to total loans", "operational margin", and "ratio of the total funding to typical assets" are significant. In our model specification D, including only banks that collect demand deposits, all but "ratio of the total funding to typical assets" are significant as well. However, the results of Janot (2001) are substantially different, given that he finds the "ratio of liquid assets to typical assets", the "ratio of loans funded by the foreign market to liabilities", and the "ratio of administrative cost to adjusted total assets" as significant.

[14] Even though the variables "evolution of typical assets operations (e202)", "ratio of administrative cost to average assets (r409)" and "return on adjusted total assets (r206)" are not significant, we keep them for comparison with other studies, but our results are not affected by their exclusion.

Table V: Summary of Results for Models A (exponential model, bank-level and macroeconomic variables) and D (exponential model and bank-level variables)

	Model A			Model D		
Variables	*Hazard ratio.*	s.e. Robust	P>|z|	*Hazard ratio*	s.e. Robust	P>|z|
IPI-lag6**	1.0375	0.0172	0.027	-	-	-
Selic-lag6**	1.0014	0.0006	0.024	-	-	-
Recovery Adm. Expenses**	0.9899	0.0045	0.025	0.9904	0.0038	0.013
Atypical assets/ total assets ***	1.0334	0.0078	0.000	1.0349	0.0080	0.000
Operational Margin***	1.0005	0.0001	0.000	1.0005	0.0001	0.000
Leverage ratio***	1.0002	0.0001	0.000	1.0002	0.0001	0.000
Non-performing/ total loans ***	1.0318	0.0053	0.000	1.0333	0.0051	0.000
Evol. typical assets operat. *[1/]	0.9999	0.0001	0.243	0.9999	0.0001	0.086
Loan reserve coverage***	0.9677	0.0085	0.000	0.9651	0.0087	0.000
Adm. Cost/ average assets	1.0752	0.0878	0.374	1.0639	0.0966	0.495
Other liabilities/ liabilities.***	1.0003	0.0001	0.000	1.0003	0.0001	0.000
Return on adjusted total assets	0.9798	0.0178	0.262	0.9844	0.0205	0.453
Real assets	1.0000	0.0000	0.185	1.0000	0.0000	0.205

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively.
[1/]Significant at 10% only for Model D.

The results for models B (PCE model with bank-level variabels) and C (exponential model, contagion, macro and bank-level variables) are in Appendix A.2, and there are some interesting findings. The coefficients of the microeconomic variables in the piecewise-exponential model B have signs and magnitudes that are similar to the other models. The only time interval that has a significant hazard baseline function at 10% is the one from July 1996 to December 1996, and the conditional probability of failure is smaller than in any other period. An interesting result in Model C is that the variable " import/ international reserve ratio" increases the probability of failure in the banking system.

We estimate other parameterizations of the baseline hazard function for models A, C and D: Weibull, Log-logistic, Lognormal, Gompertz, and generalized Gamma[15] (Appendix A.2). We also estimate the non-parametric Cox model using only bank-level variables. Based on the AIC and BIC, the exponential model is in general better specified, and whenever one of these criteria pointed to some other specification, the predictive capability of the exponential model was always better.

Figure 2 shows the estimated survival functions to model A (exponential model, including micro and macro variables) for the banks that fail and for the ones that do not fail. Because we have a survival function for each bank, we calculate the average probability of survival for each time period (1, 2,. . . , T), for each group (failed and non-failed). We notice that the survival dynamics is substantially different for the

[15]There is no equivalence to model B (piecewise-exponential) for these other parameterizations.

two groups. The survival function for the failed banks is always below the one for the non-failed banks, but they separate after a 30-month period, in December 1996 after Proer implementation.

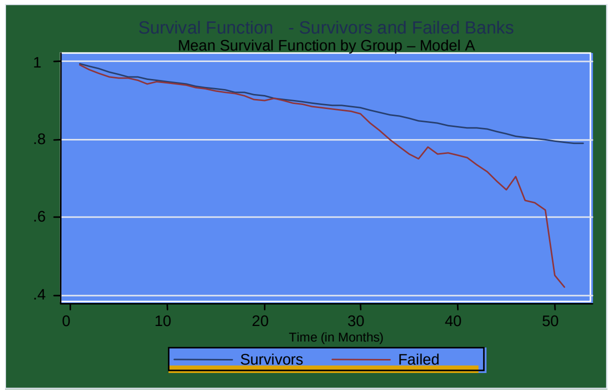
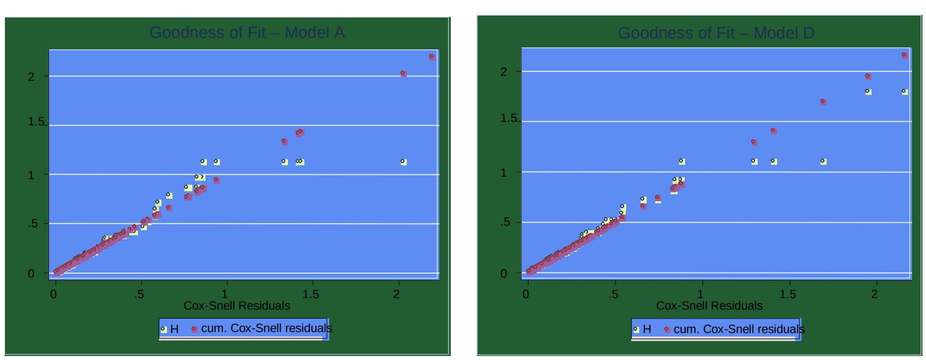


Figure 2: Estimated In-Sample Survival Functions

In order to verify the model's goodness of fit, we plot the predicted Cox-snell residuals (Newmann, 1997). If the model represents a good fit, the residuals should have approximately an exponential distribution with unit parameter. We treat the residuals as a time variable and plot them against the accumulated empirical hazard distribution. A good fit would result in a straight line with slope equal to one. Figure 3 presents these plots for models A and D.[16] All exponential and PCE models seem to be well adjusted. The right tail of the distribution presents higher dispersion because of the reduction in the sample size caused by failure and censoring.



[16] The plots of residuals for the other models are available from the authors upon request.

Figure 3: Cox-snell residuals

Figure 4 shows Martingale residuals versus A201 covariate (ratio of non - performing loans to total loans) to Model A. Plots of those residuals are useful in assessing whether the functional form of the covariate is adequate. As we can see, as the smooth curve is linear around zero, no transformation is necessary. The same is true to the other covariates and models.

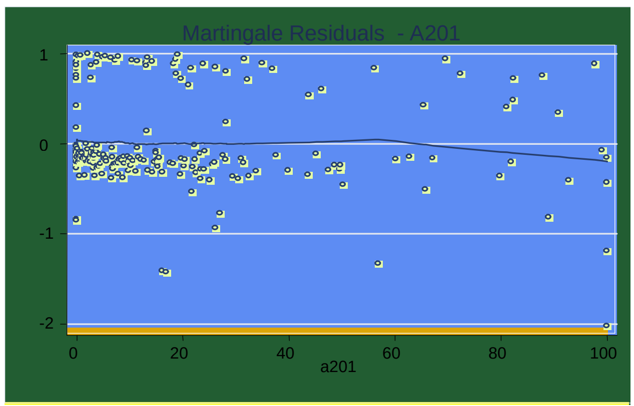


Figure 4: Martingale residuals - Model A

6.2 Forecasting Bank Failure

6.2.1 In-Sample Forecasting

Most studies about bank fragility make in-sample forecasts for certain time intervals. Actually, since most studies assume fixed covariates, the forecasted survival function depends directly on the chosen hazard baseline function, which varies in time. The forecast for intervals is used when one does not have new information available in each period to distinguish the individuals (banks), but this does not happen when panel data is used.

Using the estimated models to classify banks as failed and non-failed, for each time horizon, in and out of sample, is not trivial. The estimated survival probabilities should be compared to some critical (cutoff) value. Typically, the proportion of banks that fail and do not fail in the sample is used to determine this cutoff.[17] This

[17] See for example Dabós and Escudero (2000) and Lane *et al.* (1986).

approach has some drawbacks when the covariates vary in time or even when the data is censored (banks leave or enter the sample during the period), depending on how the failures are distributed in time. If we do not adjust the sample for the censored banks, we would overestimate the proportion of failures. In this sense, the model would say less often that a bank fails, diminishing the probability of type II error and increasing the type I error.

Because of the use of panel data, we are able to forecast the probability of bank failure in each month. We calculate the proportion of failures and non-failures, month by month, correcting for censoring which also includes the banks that are born in the period. The proportion of banks that fail in the first period is given by the ratio of number of failures in the first period to the sum of failures and censored banks after the first period. The same reasoning is applied to the subsequent periods. However, these proportions are the ones used for the Kaplan-Meier estimates. Therefore, our comparisons are between the estimated survival function and the proportion of failures corrected month by month.

The null "hypothesis" in our analysis is a bank failure, and we are interested in type I error (the model does not predict a bank failure when it actually happens), but also in type II error (the model predicts a failure when it does not happen). From the regulator point of view, type I errors should be given a higher weight in his objective function because it involves higher costs to resolve. However, type II errors also imply in costs, given that the regulator has scarce resources and has to prioritize a group of banks to supervise.

Characterizing a prediction as type II error depends on the period and time horizon of interest. Some type II errors represent banks that fail at sometime in the near future, and therefore could be considered a model success. The in-sample forecasts for all model specifications are presented in Table VI.

The first cell in Table VI indicates that model A forecasts correctly the month in which the failure occurs 73% of the time, during the considered period. Considering the banks that actually fail during the period, but taking only the ones for which the relationship between the events forecasted as a failure and the events not forecasted as failure is above the percentage cutoff for type II error, the type I error decreases to 3%. In this case, the model forecasts correctly 97% of the time in a 53-month time horizon.[18]

Table VI: In-Sample Forecasts from 07/1994 to 12/1998

Forecast Errors	Model A	Model B	Model C	Model D
Type I Error	0.27	0.29	0.30	0.38
Type I Error in 53 Months	0.03	0.03	0.03	0.03
Type II Error	0.30	0.31	0.32	0.26
Type II Error for d=1	0.54	0.56	0.58	0.44

Note: d=1 indicate the banks that fail at sometime of the considered period, but not in the specific month.

Since type II errors could be of interest (prediction of a failure when it dos not happen), this percentage, for banks that fail in the period, but not in a specific month, is higher (0.54 instead of 0.30) than for the banks that do not fail, i.e., the model predicts correctly that the banks which eventually fail had problems before hand. This makes it possible for the regulator to act ex-ante, reducing the costs of resolving a bank failure, including the costs of rediscount lending from the Central Bank.

Model D (only includes microeconomic variables) is the one with the worst forecasting power, given that its type I error is greater than any other model's. On the other hand, model D has the lowest probability of type II error, but it cannot distinguish very well the failed from the non-failed banks, as the difference between the two kinds of type II error is the smallest.

6.2.2 Out-of-Sample Forecasting

It would be ideal to use the estimated models for July 1994 to December 1998 to predict the subsequent years. However, the INDCON system was interrupted after

[18] For the banks that do not fail, using the same cutoff value and the same methodology, the percentage of type II error (around 0.30) is similar to the one obtained for the considered period.

1999, making it impossible to perform forecasts after this year. We decide to re-estimate the models using the July 1994 to December 1997 data and simulate the forecast for January to December of 1998.

The first issue to be discussed here is the cutoff value for the survival probability. Some authors (see Whalen, 1991; and Dabós and Escudero, 2000) adopt the same cutoff used for the in-sample forecast, or they calculate another cutoff taking into account only the banks that fail during the time period outside the sample. We make use of the Kaplan-Meier (KM) estimates for the period until 1997 and we construct new probabilities taking into account only the failures that happen in 1998.[19]

Table VII: Out-of-Sample Forecasts from 01/1998 to 12/1998

Forecast Errors	Model A	Model B	Model C	Model D
Type I Error in the month	0.33	0.40	0.40	0.33
Type I Error in 12 Months	0.17	0.17	0.25	0.33
Type II Error	0.30	0.34	0.28	0.32
Type II Error for d=1	0.40	0.40	0.37	0.43

Note: d=1 indicate the banks that fail at sometime of the considered period, but not in the specific month.

Table VII presents the out-of-sample forecasts. Models A and D forecast correctly the month of a failure in 67% of the cases. Models A and B make the best forecast if we consider a one year period, 83% of the cases. Note that a one-year period forecast represents an upper bound for the out-of-sample forecast error. The predictions for a two-year period should be better and it would improve for longer periods of time.

6.3 Comparison of Bank Failure Models

In order to compare our results with previous duration models for bank failure in Brazil, we estimate a model including only microeconomic variables and cross-section data from July 1994. Table VIII shows the results. There are only four significant

[19]The results are only slightly different than if we use the KM for the period until 1998 or if we consider the survival function for period until 1997.

variables in this model, and all except "evolution of typical assets operations" are also significant in our panel data models with micro, macro and contagion variables. The forecast accuracy of this model is a lot worse that of our models. For the in-sample forecast, the type I error for a 53-month period is 0.21, predicting a failure in 79% of the cases, while it is 0.03 for our model A, predicting a failure in 97% of the cases. The type II error is 0.42 and it is 0.30 for our model A.

Table VIII: Cross-Sectional Model– Covariates from July 1994

Variables	*Hazard Ratio*	s.e. Robust	P>|z|
Recovery Adm. Expenses	0.9922	0.0075	0.300
Atypical assets/ total assets* **	1.0467	0.0130	0.000
Operational Margin	1.0102	0.0149	0.491
Leverage ratio*	1.0001	0.0001	0.068
Non-performing/ total loans	1.0191	0.0186	0.299
Evol. typical assets operations*	1.0002	0.0001	0.091
Loan reserve coverage	0.9978	0.0247	0.928
Adm. Cost/ average assets	1.1610	0.1166	0.137
Other liabilities/ tot liabilities* **	0.9694	0.0114	0.008
Return on adjusted tot assets	0.8524	0.0966	0.159
Final real assets	1.0000	1.24E-10	0.582

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively.

7 Applications

7.1 Mean and Median Survival Time

The duration models developed in this paper can be applied to obtain the estimated (in-sample) time of bank failures. Using each conditional model we estimate the mean and median survival times of individual banks for each month of the 1994-1998 period. The median survival time is defined as the time, t, for which $\hat{S}(t) = 0.5$ while the mean survival time is defined as:

$$Tmean = \int_0^\infty \hat{S}(t)dt,$$

where $\hat{S}(t)$ is the estimated (in-sample) survival function.

Figure 5 reports the mean and median survival times according to Model A by bank category: 0 represents the banks that survived through December 1998 and 1 the banks that failed in some period until December 1998. There is a concentration of short survival times for failed banks. As one would expect, the surviving banks exhibit long survival time very often. A striking result is that the failed banks that display long survival time do so only in specific months and, surprisingly, just before the bankruptcy event[20].

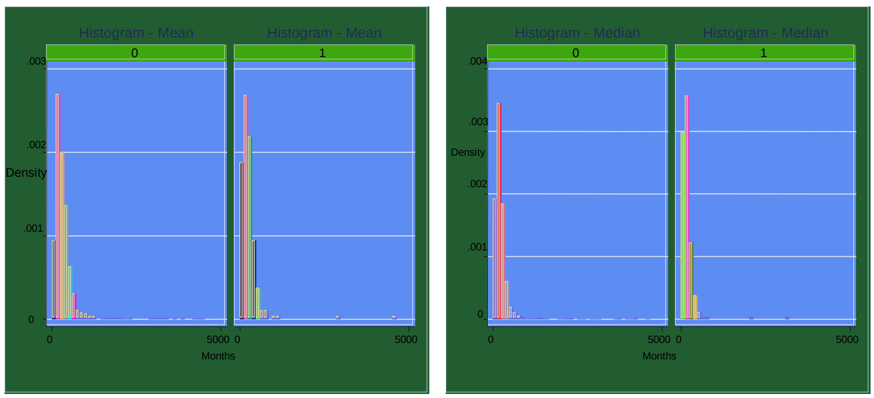


Figure 5: Mean and Median Survival Times - Model A - by Category

Besides making bank-level surveillance of the banking system possible, the expected time to failure allows the regulator to oversee the survival time path and to detect outliers so that it becomes possible to take remedial action. In addition the estimated survival times are comparable among all banks, making any segmentation useless.

7.2 Financial Fragility Index

The methodology proposed in this paper can be extended to provide an indicator of system-wide financial fragility. We build a financial fragility index (IFF) based on

[20] A possible explanation is that when a bank is near to fail it tends to hidden information of its account system.

the estimated (in-sample) conditional probability of failure of each individual bank for each month. The index is given by:

$$IFF_t = \sum_i p_{it}\alpha_{it}$$

where p_{it} is the conditional probability of failure, "t" indexes month, "i" indexes bank and α_{it} is the ratio of each bank's assets to the total assets of the banking system.

Figure 6 displays the IFF based on Models A (micro and macro covariates) and D (only micro covariates) estimations from July 1994 to December 1998. The IFF follows a similar path for both models, except for the time interval between 35 and 40 months when it is declining for Model A and increasing for Model D. Model A presents a local maximum around 35 months, time of Banco Bamerindus failure. Both models indicate a high degree of banking fragility soon before the adoption of the floating exchange rate regime (around the 50^{th} month).

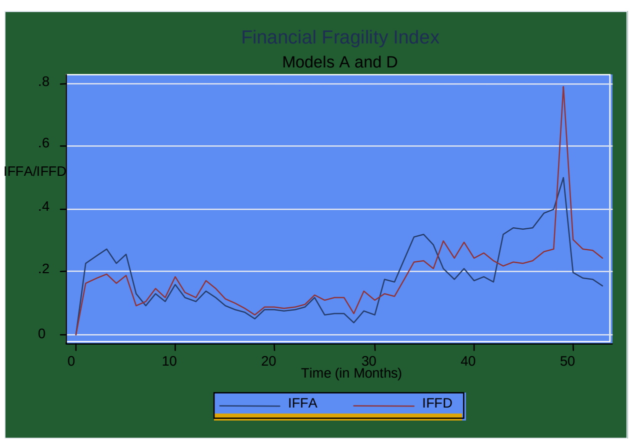


Figure 6: Financial Fragility Index

8 Contagion

In this section, we approach the question of the likelihood that banks failed during the Brazilian banking crisis because of contagion in the banking system. Our case study is the Proer. There was a debate during the institution of Proer about whether the Central Bank should grant subsidized loans to the banks after the December 1995 crisis. The prevalent argument was that the increased systemic risk would make *ex-ante* solvent banks fail without that liquidity support.

In our case it is difficult to analyze the effectiveness of Proer in avoiding contagion, since a counterfactual (bank failure without Proer) does not exist. Because it is a universal program (all banks can benefit from it) there is no control group to perform an evaluation of the program. However, if we assume that contagion would happen, we can verify if Proer was efficient in stopping it[21]. Also, we would like to look for evidence that contagion would actually take place without Proer.

We divide our sample of banks in three groups: banks that failed until November 1995 (before Proer) – group 1, banks that fail during Proer – group 2, and banks that survived through December 1998 – group 0. We then compare *ex-ante* attributes of the groups, testing for differences across groups in means and medians of: i) the estimated probability of failure of banks; ii) the monthly real demand deposits growth.

Testing if group 2 banks are on average as strong as survivors (in terms of probability of failure) amounts to say that solvent banks could have failed during Proer. In addition, if group 2 banks are at least as strong as group 1 banks, we would say that there is evidence in favor of the null hypothesis that bank failures were a continuation of the same process and that Proer may not have reduced systemic risk.

Table IX indicates that banks that failed during Proer and survivor banks have different (mean and median) monthly real demand deposits growth, but banks that failed before Proer and survivors have not. This is evidence that before Proer depositors were not able to distinguish between solvent and insolvent banks and that Proer was effective in avoiding bank runs.

[21]Here, we refer to contagion by asymmetric information as in De Bandt and Hartmann (2000).

Table IX: Tests for Differences in Mean and Median:

Monthly Real Demand Deposits Growth

Group	Mean[1/]	Median
0	0,0328	0,0063
1	0,0086	-0,0059
2	0,0123	-0,0048
Statistics t and χ^2		
0 e 1	0,5425	0,2215
0 e 2	1,8693*	13,8876***
1 e 2	-0,0803	0,0096

[1/] Bartlett's test was applied to confirm if the two-sample data have equal variances. If unequal the test was carried on using the Satterthwaite approximation.

The tests for differences in the conditional probability of failure are presented in Table X. The mean and median probabilities of failure are significantly different for all three groups of banks. The survivors have the lowest probability of failure when compared to any of the other groups. The banks that fail during the Proer seem to be stronger than the ones that fail before, which could be an indication that solvent banks break during the Proer.

Table X: Tests for Differences in Mean and Median
Monthly Conditional Probability of Failure – Model A

Group	Mean	Median
0	0,0054	0,0036
1	0,0149	0,0063
2	0,0093	0,0042
Statistics t e χ^2		
0 e 1	-3,7069***	64,1114***
0 e 2	-5,0346***	29,2685***
1 e 2	2,2430 **	39,9466***

[1/] Bartlett's test was applied to confirm if the two-sample data have equal variances. If unequal the test was carried on using the Satterthwaite approximation.

Based on the demand deposits growth rate it seems that depositors could distinguish between solvent and insolvent banks during the Proer, and this may have contributed to avoid bank runs and contagion. However, as we reject the hypothesis of equality in the conditional probability of failure among groups, we need some caution in interpreting the results in terms of contagion.

9 Conclusion

Based on empirical duration models we estimate conditional probabilities of failure for all Brazilian banks, except foreign-owned ones, that existed in July 1994 or were born between this month and December 1998. We also aggregate all conditional probabilities of failure in a single index (IFF) – Financial Fragility Index – that gives a general measure of crisis risk.

Our analysis finds that foreign banks have a very particular survival behavior, and therefore should be studied separately. The bank-level covariates in our conditional models were significantly related to the probability of failure, however, none of the liquidity indicators were relevant.

This study has the following main contributions. First, it adds contagion and macroeconomic variables to the traditional models based upon accounting data. These macro variables are in fact significant in some models and contribute to increase the predictive power of these duration models.

Second, it uses panel data. The introduction of time-varying variables increases enormously the predictive power of the models relatively to similar specified cross-section models. Some of our models are able to predict the exact month a failure occurs 73% of the time (in-sample forecast). If we are only concerned about failure and not the exact month, the model is correct 97% of the time.

Third, the study discusses the effectiveness of the program Proer in reducing bank runs and contagion. Even though it is not possible to formally test the hypothesis that Proer avoided contagion, we find indications that Proer was efficient in separating solvent from insolvent banks *ex-ante*, minimizing the failure of sound banks.

Fourth, the problem of left censoring in duration models data was addressed. The non-consideration of the actual date of birth of banks can bias and decrease the forecasting accuracy of the models.

One final contribution is the demonstration that bank-level indicators are not necessarily poor predictors of bank failure. Our innovation is the use of a broader dataset.

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A Appendix

A.1 Description of the Variables

Bank-Level Indicators

Indicator	What the Variables Measure	Survival Time: Expected Sign
A101 - ratio of liquid assets to typical assets	Liquidity risk	_/+. High ratio may indicate that the bank has difficulties to participate in the interbank market. On the other hand, it may measure bank's ability to deal with deposit withdrawals.
A102 - ratio of assets to adjusted total assets	Fraud and market risks	+
A103 - ratio of atypical assets to total assets	Fraud Risk	_
A106 - ratio of real state loans to total loans	Market risk	_. Commercial real state loans tend to be risky because they typically have long maturation periods.
A108 - ratio of foreign exchange operations to typical asset operations	Market risk	_. Negative if the ratio indicates high concentration of foreign exchange operations.
A201 - ratio of non-performing loans to total loans	Credit risk	_
A202 - financial assets reserve coverage	Credit risk	+
A203 - loan reserve coverage	Credit risk	_/+ . Growing trend may indicate deterioration of the bank's loans quality. High level of reserves may represent a cushion to absorb shocks.
A301 - ratio of the total funding to typical assets	Mismatching between assets and liabilities	_
A302 - ratio of the non-interest-bearing deposits to typical assets	Liquidity risk	_
A303 - ratio of interest-bearing deposits to total asset operations	Liquidity risk	_/+. It depends on the deposit being more or less volatile during crises.
C102 – ratio of loans funded by the domestic market to liabilities	Credit risk	_/+. It depends on the business cycle.
C104 – ratio of loans funded by the foreign market to liabilities	It should be composed with it above.	_ /+. It depends on the business cycle.

Bank-Level Indicators (cont.)

Indicator	**What the Variables Measure**	**Survival Time: Expected Sign**
C107 - ratio of other liabilities to total liabilities.	Credit risk	_
C204 - leverage ratio	Credit risk	_
E202 - evolution of typical assets operations	To verify lending booms	_/+ . Negative if it indicates lending booms.
L104 - solvency	Solvency	+
R102 - monthly average return on equity in the semester	Solvency	+
R201 - net margin	Efficiency	+
R205 - recovery of the administrative expenses through service's income	Efficiency	+
R206 – return on adjusted total assets	Efficiency of the investment or increase of credit risk if loans becomes higher	_/+. High yields may indicate that the bank is taking risky loans. Low yield may indicate that that risk is not priced properly.
R301 - operational margin (difference between loan yield and deposit interest rate) *	Spread	_
R305 - operational margin (monthly average in the semester)	Spread	_
R308 - monthly average yield on operational assets in the semester	Profitability	_ /+ . It depends on the state of the banking cycle because risky projects can be very profitable at first.
R401 - interest income earned by term depositors	Credit risk	_
R403 - ratio of administrative cost to adjusted total assets	Efficiency	_/+. It depends on the bank's profile (if retailer or wholesaler)
R405 – total funding cost	Credit risk	_
R406 - ratio of salaries and employee benefits to managerial expenses	Efficiency	_
R409 - ratio of administrative cost to average assets	Efficiency.	_

* In developed countries, the sign would usually be positive because it would mean that the bank is efficient. In emerging countries, high spreads may mean that the bank is "gambling for the resurrection" as Rojas-Suárez (2001) displays: high spreads show that the bank is making risky loans.

Macroeconomic Covariates

Variables	Description	Survival Time: Expected Sign
IPCA	Consumer Price Index	_
IPI	Industrial Production Indicator (2002 = 100).	_/+. Negative if it lags lending booms.
Selic	Selic rate accumulated in the month per year and deflated by IPCA	_ /+. Negative if it is related to potential interest rate shock.
Embi	Average spread over US Treasury of Brazilian sovereign bonds calculated by J.P. Morgan	_
Mres	Ratio of total imports to international reserves (liquidity concept)	_ / +
M1res and M2res	Ratio of means of payment - M1 (average in the working days of the month) and M2 (stock at the end of month) to international reserves (liquidity concept), respectively	_

Contagion Covariates

Indicator	What the Variables Measure	Survival Time: Expected Sign
Crisco **	Ratio of risk 2 loans (level H) to total loans	_. Potential bank herding behavior or deposit runs.
Crgdp	Ratio of total loans (in USD) to monthly GDP (in USD).	_/+ . If the ratio is very high, it may indicate regulatory forbearance.
Varcre	Percentual change of loan per month	_. It may indicate lending booms.

Specific Covariates

Indicator	What the Variables Measure	Survival Time: Expected Sign
ativoreal (real assets)	Total assets deflated by IPCA.	+. Economies of scale and portfolio diversification.
Vardvlag3 and Vardvmean	Monthly changing of demand deposits.	+ . Higher demand deposit means more creditworthiness.

** Risk 2 loans are loans with past due more than 60 days and without enough collateral and for all loans with past due 180 days or more.

A.2 Results

A.2.1 Equality of Survival Functions

Log-rank

Type	Observed events	Expected events
1	9	6.62
2	44	33.62
3	1	11
4	5	7.76
Total	59	59

chi2(3) = 14,25

Pr>chi2 = 0,0026

Log-rank

Type	Observed events	Expected events
1	9	7.99
2	44	40.64
4	5	9.37
Total	58	58

chi2(2) = 2,47

Pr>chi2 = 0,2913

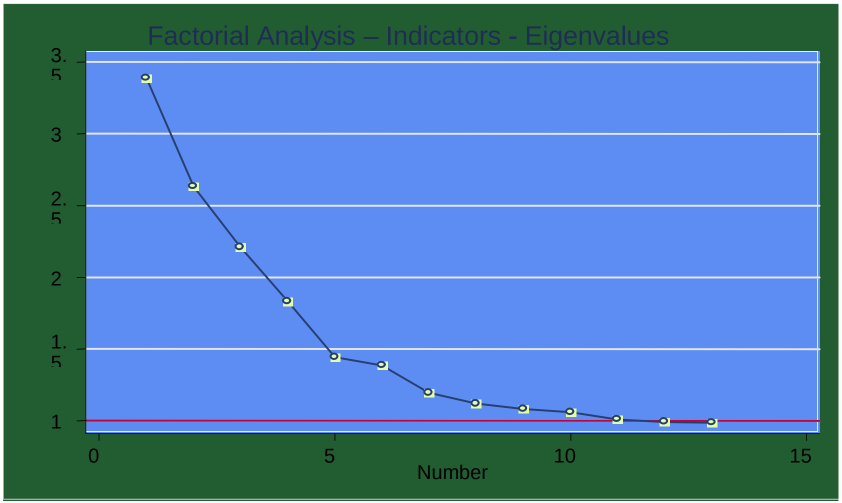
A.2.2 Descriptive Statistics

Desciptive statistics and test for equality of mean

Variable	Mean		Median		Standard-error (mean)	
	d=0	d=1	d=0	d=1	d=0	d=1
r205	29.12	35.81	8.81	6.84	1.044	7.790
a103*	6.45	7.50	3.01	4.50	0.108	0.262
r305***	-114.06	0.98	0.57	0.81	10.785	0.195
c204***	853.62	1282.46	520.37	551.80	14.006	60.791
a201	13.10	13.27	6.00	5.69	0.199	0.502
e202***	5.20	35.84	6.18	0.59	9.471	7.754
a203***	9.00	6.94	3.27	2.16	0.173	0.347
r409***	0.84	1.24	0.59	0.84	0.008	0.040
c107**	21.44	73.21	7.81	8.68	2.513	19.820
r206***	-0.19	-0.42	0.11	0.03	0.036	0.096
ativorealfim***	2.10E+08	1.40E+08	5.70E+06	2.20E+06	1.58E+07	1.78E+07
a101	20.86	-6.78	40.14	36.83	5.042	18.816
a102***	89.17	85.58	93.21	90.45	0.135	0.349
a106***	5.43	3.24	0.00	0.00	0.162	0.220
a108	10.90	7.34	2.06	0.23	0.174	0.340
a202	3.38	2.67	0.20	0.22	0.114	0.179
a301***	79.56	85.61	85.32	89.53	0.474	0.750
a302***	3.88	6.83	0.80	0.86	0.089	0.388
a303	141.23	224.08	77.47	87.49	8.208	29.422
c102***	62.25	70.51	68.79	76.04	0.283	0.666
c104***	17.28	9.83	5.32	0.18	0.245	0.416
l104***	255.55	189.73	120.61	120.74	7.148	12.438
r102	-0.36	-0.35	0.92	0.58	0.295	0.166
r201***	-125.33	-488.24	5.77	1.42	60.971	153.448
r301***	-153.27	-45.30	0.61	0.83	12.456	17.513
r308	7.94	3.78	2.78	2.99	1.496	0.200
r401***	150.83	4.16	0.00	-0.32	12.242	1.447
r403***	0.98	1.30	0.60	0.80	0.020	0.046
r405***	27.94	2.62	-1.06	-1.22	5.089	1.448
r406	6.13	-16.35	51.87	50.86	12.007	40.914

Obs_1: d=0 for banks that did not fail and d=1 otherwise.
Obs_2: * statistically significant to 0,10; ** statistically significant to 0,05; *** statistically significant to 0,01.

A.2.3 Factorial Analysis



Proportion of total variance

Factor	Proportion	Accumulated
1	0.117	0.117
2	0.091	0.208
3	0.076	0.284
4	0.063	0.347
5	0.050	0.397
6	0.048	0.445
7	0.041	0.486
8	0.039	0.524
9	0.037	0.562
10	0.037	0.598
11	0.035	0.633

A.2.4 Models B and D

Summary of Results for Models B and D

	Model B			**Model C**		
Variables	*Hazard ratio.*	s.e. Robust	P>|z|	*Hazard ratio*	s.e. Robust	P>|z|
e2	0.61123	0.32539	0.355			
e3	0.88446	0.43497	0.803			
e4	0.51569	0.28879	0.237			
e5*	0.22861	0.17885	0.059			
e6	0.83231	0.41070	0.710			
e7	0.81028	0.41939	0.684			
e8	1.14667	0.57368	0.784			
e9	0.20208	0.20743	0.119			
varcre2**				1.02919	0.01159	0.011
mres2***				2.9E+8	2.0E+09	0.006
Recovery Adm. Expenses**	0.98906	0.00535	0.042	0.99021	0.00452	0.031
Atypical assets/ total assets ***	1.03252	0.00782	0.000	1.03423	0.00766	0.000
Operational Margin***	1.00045	0.0001	0.000	1.00045	0.00010	0.000
Leverage ratio***	1.0002	0.00005	0.000	1.0002	0.00005	0.000
Non-performing/ total loans ***	1.03274	0.00531	0.000	1.03368	0.00493	0.000
Evol. typical assets operat. *[1/]	0.99995	0.00005	0.336	0.99996	0.00004	0.324
Loan reserve coverage***	0.96639	0.00921	0.000	0.96586	0.00869	0.000
Adm. Cost/ average assets	1.11309	0.09027	0.186	1.09195	0.09507	0.312
Other liabilities/ liabilities.***	1.00032	0.00005	0.000	1.00032	0.00005	0.000
Return on adjusted total assets	0.97571	0.01905	0.208	0.97804	0.01909	0.255
Real assets	1.00000	0.00000	0.182	1.00000	4.4E-10	0.182

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively.

A.2.5 Model and Distribution Selection

Criteria AIC e BIC to model selection

Model	df	AIC	BIC
A	14	300.46	400.23
B	20	307.55	450.08
C	14	299.20	398.96
D	12	302.27	387.78

Criteria AIC e BIC to distribution selection

Distribution	Model A		Model C		Model D	
Criteria	AIC	BIC	AIC	BIC	AIC	BIC
Exponential	300.47	400.23	299.20	398.96	302.27	387.78
Weibull	301.62	408.51	297.90	404.79	304.26	396.90
Log-logistic	302.35	409.24	295.76	402.65	304.46	397.10
Lognormal	300.11	407.00	295.13	402.02	304.10	396.74
Gompertz	299.13	406.03	300.68	407.57	303.99	396.63
Gammma Gen.	298.90	412.92	295.73	409.75	302.86	402.63

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