Explaining time to bank failure in Colombia during the financial crisis of the late 1990s

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Abstract

This paper identifies the main bank specific determinants of time to failure during the financial crisis in Colombia using duration analysis. Using partial likelihood estimation, it shows that the process of failure of financial institutions during that period was not a merely random process; instead, it can be explained by differences in financial health and prudence existing across institutions. Among the relevant indicators that explain bank failure, the capitalization ratio appears to be the most significant one. Increases in this ratio lead to a reduction in the hazard rate of failure at any given moment in time. Of special relevance, this ratio exhibits a non-linear component. Other important variables explaining bank failure dynamics are profitability of assets and the ratio of non-performing loans to total loans. Leverage appears to affect the hazard rate also, but with lower statistical significance.

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1 Introduction

During the late 1990s and early 2000s, Colombia's financial system experienced a period of financial stress, characterized by the failure of several banks and other financial institutions, as well as by the severe deterioration of the whole system's financial health. The capitalization ratio of the system fell dramatically, as did profitability and liquidity. As a consequence of the crisis, the number of institutions[1], 110 in June 1998, dropped to only 57 in December 2001, after failures, merges and acquisitions. Total assets of the financial system experienced a real contraction of more than 20 percent during the same period, making that episode of financial stress the deepest financial crisis experienced by the country in the last one hundred years.

The literature on the financial crisis of Colombia has concentrated in explaining its causes and consequences (see, for instance, Arias et Al (1999), Arbeláez et Al. (2003), Carrasquilla and Zárate (2002), Parra and Salazar (2000), Uribe and Vargas (2002), Urrutia (1999) and Villar et Al (2005)) There have been no micro-level studies of the role of specific financial variables in determining failure and time to failure of banks. This paper uses duration models to explain and predict failures of financial institutions in Colombia.

In economics, duration models have been used largely in labor economics applications (two references are Kiefer (1988) and Lancaster (1990)). The application of these models to explain bank failure is less wide. Lane et Al (1986), Weelock and Wilson (1995), and Whalen (1991), use duration models to explain bank failure in the United States. Some other studies have used duration models to explain time to failure after particular episodes of financial stress in under-developed countries.

[1]The financial system here includes commercial banks, financial companies, and financial companies specialized in commercial leasing. Financial cooperatives and special public financial institutions are not included here.

For example, Gonzalez-Hermosillo et Al (1996) use them to explain bank failure after the Mexican crisis of 1994, and Carree (2003) does a hazard rate analysis of Russian commercial banks in the period 1994-1997.

Although all these studies study the importance of bank specific financial variables in determining time to failure during times of financial stress, none of them emphasizes the role played by the capitalization ratio in this process. There are theoretical as well as practical reasons to consider that the capitalization ratio plays a special role for financial institutions. The literature on capital crunch (see, for example, Peek and Rosengren (1995), Estrella et Al (2000), and Van den Heuvel (2004)) shows that, under capital regulations, this ratio is important for financial institutions when they are taking decisions on portfolio composition. In the practical world, following the Basel accord (Basel Committee on Banking Supervision, 2004), financial institutions and supervisors now follow closely the capital ratio of the institutions they regulate, and impose minimum requirements. Thus, there are reasons to believe that capitalization plays a special role for financial institutions in determining their portfolio decisions, their overall financial health, and thus the degree of trouble that they might experience in episodes of financial stress.

This paper studies the time to failure of financial institutions during the recent period of financial crisis in Colombia. From the point of view of the econometrician, this is an informative sample, as there are enough failures to identify and measure significant financial variables. It shows how, together with other financial variables, capitalization determined significantly and nonlinearly the hazard of failing during the crisis.

Section II briefly describes what happened during the episode of financial crisis in Colombia. Section III presents the description of the data. Section IV presents the techniques used to construct a model for the failure of financial institutions. Section V presents the results of the estimation, as well as empirical tests to check the validity of the model. Finally, Section VI concludes.

2 The financial crisis in Colombia

During the 1980s, Colombia's financial system was subject to elevated reserve requirements and forced investments, and to strong constraints on foreign investment, as well as on the types of operations that intermediaries could do and on interest rates[2]. Additionally, a process of bank nationalization was held during that decade. In contrast, at the beginning of the 1990s, a program of financial liberalization was implemented. The process was supported by the laws 45 of 1990 and 9 of 1991, which eased the conditions for the entrance of foreign investment to Colombia, promoted more competition in the financial system, and gave financial institutions more liberty in the management of financial operations and interest rates (see Banrep (2002)).

As a result, the ratio of intermediated assets (loans plus bonds) to GDP increased from 31 percent in 1990 to 47 percent in 1996. The number of financial institutions increased significantly, the participation of the assets of foreign banks in the total assets of the system increased, and most of the government-owned financial institutions were privatized.

As a consequence of the growth in the financial system and of the economic expansion that took place during the first half of the 1990s, between 1991 and 1997 Colombia registered a credit boom without precedent. The ratio of loans to GDP and the price of assets (financial and real) grew steadily, as well as the number of intermediaries. But, as is often the case during the processes of quick expansion of credit after processes of financial liberalization[3], the quality of loans of financial institutions decreased, and this elevated the financial fragility of the economy[4].

[2]These were requirements imposed by the *Superintendencia Bancaria*, which at the time of the crisis was the regulator of the financial system in Colombia.

[3]For example, Carree (2003) argues that the process of bank liquidation that occurred in Russia during the period 1995-1998 (the Central Bank of Russia withdrew about 1000 bank licenses during that period), can be explained by the period of ease in financial regulation policies that took place during the early 1990s.

[4]During the ascendant part of the cycle, the fragilities of the financial system were not very visible. Most of the financial intermediaries obtained high profitability levels, in many occasions coming from the higher levels of risk undertaken by them, as well as by low levels of provisions. When the downturn began, financial fragility became evident as loans damaged, deteriorating the

Between 1998 and 1999 a sudden capital reversion occurred, followed by a steep fall in the terms of trade, which led to a reduction in the aggregate level of expenditure. This has been identified as the main cause of both the financial crisis and the economic recession experienced in Colombia recently (Villar et Al (2005)). Internal demand fell, especially during 1999, as well as output, while interest rates increased to historically high levels. However, as Parra and Salazar (2000) argue, monetary policy played also a role in increasing the vulnerability of the system, when in June 1998, the Central Bank while defending the exchange rate band added extra pressure on interest rates. The average interest rate on ninety-days CDT's[5] increased more that 500 basis points in one month, while the average interest rate on loans increased almost 1000 basis points in the same period of time. From that moment on, a sharp deterioration of the financial health of the intermediaries began. Loan quality decreased - i.e., the rate of non-performing loans to total loans for the system increased from 7.9% in June 1998 to 16% by the end of 1999-, and the losses of financial institutions, which had very low levels of provisions, led to a reduction of capital and a worsening of capitalization. The reduction in the capitalization ratio was common for all the institutions, but was asymmetric, doing more damage to those that had low capitalization levels before the crisis. Most of those institutions were liquidated, either forced by the Superintendencia Bancaria (hereafter Superbancaria, the financial system's supervisor) or voluntarily. Others merged, or were absorbed by other financial institutions.

The period of financial stress generated a reduction in the size of the financial intermediation industry of Colombia and a change in asset composition of the financial system. In terms of size, the ratio of intermediated assets to GDP reduced to 38 percent in 2000. In terms of asset composition, the participation of loans in the asset of banks reduced, giving space to the acquisition of more securities, showing that financial institutions became more conservative in their lending policies, in order to maintain higher capitalization levels. Similarly, the ratio of provisions to loans of surviving institutions grew steadily. As a consequence, concentration of the

financial systems' capital.

[5]Mainly time deposits issued by financial institutions to finance their positions in assets.

financial system increased, mainly due to the processes of liquidation, and mergers and acquisitions of institutions that took place during the period of stress.

3 Description of the data

In June 1998 there were 110 institutions in the financial system of Colombia, excluding financial cooperatives and special public financial institutions. From those institutions considered here as the financial system, 39 were commercial banks, 43 were financial companies, and the remaining 28 were financial companies specialized in commercial leasing. Three and a half years later, the financial system was constituted by only 57 institutions: 27 commercial banks, 19 financial companies, and 11 financial companies specialized in commercial leasing.

Although there are some differences between commercial banks and financial companies, basically regarding liability composition[6], in practical terms both types of institutions serve very similar purposes and compete in the issuance of loans and deposits. However, financial companies specialized in commercial leasing are quite different, in the sense that they have different purposes than the other intermediaries mentioned before, and their activities and portfolio composition are also very different. Therefore, for the purpose of this paper, data are collected only from commercial banks and financial companies.

Since we are interested in explaining time to failure during the financial crisis, the period of observation is the 42 months elapsed from June 1998, the moment in which the crisis began, and December 2001, when the system started its period of recovery. Financial data as of June 1998 was collected for each of the financial institutions considered for the empirical analysis. Following previous studies and theoretical expectations, the following financial ratios were considered in the expla-

[6] The main difference can be found in demand deposits: while commercial banks can issue checking accounts, financial companies cannot. Nevertheless, they can issue saving deposits and time deposits. Another difference is the required amount of initial capital: the minimum required capital to constitute a bank is almost three times as big as that needed to constitute a financial company. Nevertheless, initial capital requirements are small vis-à-vis the size of the intermediaries once they are operating, and the differences observed in the capitalization ratio between the groups of commercial banks and financial companies are relatively small.

nation of time to failure: capitalization (CAP), defined as the ratio of equity to assets; leverage (LEV), defined as the ratio of total liabilities to equity; liquidity (LIQ), calculated as the ratio of liquid assets net of liquid liabilities to deposits; management efficiency (EFF), approximated by the ratio of operating expenses to total liabilities; provisions (PROV), defined as total provisions over total loans; profitability of assets (PROF), given by the ratio of annualized profits to average annual assets; loan participation (LOAN), given by total loans over total assets; and non-performing loans (NPL), defined as non-performing loans over total loans.

This paper emphasizes the special role played by the capitalization ratio, identifying a non-linear impact of this ratio on time to bank failure in Colombia. To account for a non-linear component of capitalization, a variable called CAPL was included. This variable results from the multiplication of CAP by an indicator function that takes the value 1 if CAP is less or equal to 13.4 percent (the sample mean) and 0 otherwise. Other cutoff values were also considered, without changing the thrust of the results[7].

These financial indicators are proxies of the variables traditionally considered in the CAMEL model[8]. The data set used to construct the variables consists of information of the balance sheets that financial institutions have to report to the Superbancaria. Table 1 shows a summary of the indicators for both groups of intermediaries in June 1998.

[7] The cutoff value of 13.4 percent is the mean and so gives us enough observations on either side to identify a potential nonlinear effect. Some experimentation with other values did not give substantially different results. Moving to 8% (minimum capital ratio under Basel I) did not give enough lower observations to identify a significant nonlinear effect.

[8] CAMEL stands for: capitalization, assets, management, earnings, liquidity. CAMEL models are used to study the financial institutions' default risk.

Table 1: Summary of the financial ratios used in the empirical analysis (In percentage). Mean values for all indicators.

Indicator	Commercial Banks	Others	Total
CAP	13.4	13.4	13.4
LEV	650	640	646
LIQ	6.2	0.2	3.8
EFF	0.5	0.4	0.5
PROV	3.0	1.5	2.3
PROF	0.6	0.4	0.5
LOAN	61.0	72.9	66.2
NPL	7.4	8.4	7.9

Note that both banks and other institutions had identical aggregate indicators for capitalization, and very similar aggregate indicators for leverage, management efficiency and profitability of assets, in June 1998. Some differences can be seen in asset composition, though, as banks appeared to have more liquid portfolios than other institutions. Particularly, the ratio of loans to assets for the aggregate of banks was lower than that of other institutions, while the former also had a higher liquidity ratio. Additionally, banks had a slightly lower ratio of non-performing loans[9], and a higher ratio of provisions to total loans. However, Table 1 is constructed for the aggregate of each group, and heterogeneity can be observed within each group.

Regarding failure, from the group of banks 12 failures were observed between June 1998 and December 2001, representing a failure rate of 31 percent; meanwhile, 16 institutions of the group of non-banks failed during the same period, representing

[9] The differences in asset composition between banks and other institutions seem to have reduced after the period of financial crisis. Both banks and non-banks have tended to have more liquid portfolios, and to have higher provisions. This can probably be explained by the systematic default of banks that took higher risks in the period of credit boom before the crisis, and by more conservative lending policies taken by surviving banks that tend to account better for risks that derivate from the lending business.

a failure rate of 37 percent[10]. Failure rates of both groups of intermediaries appear to be fairly similar. In the next section formal tests are done to show that both groups have the same survivor function.

4 Duration models to study bank failure

We use a duration or hazard function model to study the time to failure of financial institutions. This approach generalizes the more common binary response (logit or probit) approach by modeling not only the occurrence of failure but the time to failure - allowing finer measurement of the effect of different variables on failure. Thus, duration models applied to this problem can provide answers to questions that are relevant for both financial supervisors and financial institutions, such as: after the occurrence of a negative shock, what is the probability that a bank fails in the following months given it has survived up to that moment?; or, what is the predicted time to failure for a bank of some given characteristics? A model capable of answering those questions at low cost can be very useful as an early warning model, to identify potential vulnerabilities of the financial system, and could be used by supervisors as an alternative to the costly site visits that they make periodically to financial institutions considered at risk.

Most of the papers that apply these models to explain time to bank failure use the semiparametric proportional hazards model of Cox (1972); an exception is the work of Carree (2003), who uses several parametric models to explain bank failure in Russia. The proportional hazards model is the most frequently used, because it does not make assumptions about the particular functional form of the baseline

[10] In this paper, failure is considered as the event in which an institution is liquidated, either by the decision of the regulator (forced failure) or by the decision of the institution's managers ("voluntary" failure). The moment in which the bank fails is defined as the month in which the institution is liquidated formally; that is, the moment at which the institution stops reporting its balances to the Superbancaria. Even when this is not a exact measure of the moment in which a bank fails, it appears to be the best possible approximation, and the fact that the balance sheets of financial institutions are reported on a monthly frequency, rather than a quarterly frequency as in other countries makes this measure more accurate. Institutions that merged of were acquiesced by other(s) are not considered as a failure here, even when their financial indicators at the moment of merge or acquisition showed significant deterioration.

hazard, and because estimated hazard functions of bank failure in many cases are non-monotonic, thus reducing the number of parametric models that can be used.

This section presents a brief description of duration models, making emphasis in the proportional hazards model, which is used in the empirical analysis of the paper. A relevant reference in the use of duration models in economics can be found in Kiefer (1988).

4.1 Survival functions and hazard functions

In duration models, the dependent variable is duration, the time that takes a system to change from one state to another. In the case of bank failure, duration is the time that it takes for a bank to fail after the occurrence of a negative shock that affects the financial system.

In theory, duration T is a non-negative, continuous random variable. However, in practice duration is usually represented by an integer number of months, for example. When T can take a large number of integer values, it is conventional to model duration as being continuous (Davidson and MacKinnon (2004)).

Duration can be represented by its density function $f(t)$ or its cumulative distribution function $F(t)$, where $F(t) = \Pr ob(T \leq t)$, for a given t. The survival function, which is an alternative way of representing duration, is given by $S(t) = 1 - F(t) = \Pr ob(T > t)$. In words, the survival function represents the probability that the duration of an event is larger that a given t. Now, the probability that a state ends between period t and $t + \Delta t$, given that it has lasted up to time t, is given by

$$\Pr ob(t < T \leq t + \Delta t) = \frac{F(t + \Delta t) - F(t)}{S(t)} \qquad (1)$$

This is the conditional probability that the state ends in a short time after t, provided it has reached time t. For example, in the case of bank failure it is the probability that a bank changes of state from operating to not operating (i.e. fails) in a short time after time t, conditional on the fact that the bank was still operating at time t.

The hazard function $\lambda(t)$, which is another way of characterizing the distribution of T, results from considering the limit when $\Delta t \to 0$ of equation (1). This function gives the instantaneous probability rate that a change of state occurs, given that it has not happened up to moment t. The cumulative hazard function $\Lambda(t)$ is the integral of the hazard function. The relation between the hazard function, the cumulative hazard function and the survival function is given by equation (2)

$$\Lambda(t) = \int_{u=0}^{t} \lambda(u)du = -\log[S(t)] \qquad (2)$$

Some empirical studies use parametric models for duration. Some commonly used distributions are the exponential, the Weibull and the Gompertz. The exponential or the Weibull implies that the hazard function is monotonic. In the case of the Weibull, the hazard rate is assumed to either decrease, increase or remain constant in time, while in the case of the exponential –which is a particular case of the Weibull- the hazard rate is assumed to be constant in time. Therefore, the use of these distributions for studying economic phenomena such as bank failure is quite limited, as it is natural to think that the hazard of failure after a negative shock behaves non-monotonically –increase up to a certain point, and then decrease. The Gompertz distribution allows non-monotonic hazard rates, but is not particularly flexible.

Therefore, before assuming a particular form, it is useful to estimate the hazard and survival functions nonparametrically. This is especially important to do when there is no previous literature on the study of a particular case, as the process of financial institution failure in Colombia.

One way of estimating the survival function is by using the Kaplan-Meier nonparametric estimator, which is very useful as it takes into account censored data. Suppose that bank failure is observed at different moments in time, $t_1, t_2, ..., t_m$, and that d_i banks fail at time t_i[11] For $t \geq t_i$,

[11] Note that in continuous time there should be no ties in time of failure among banks. Nevertheless, in practice ties are observed.

$$\hat{S}(t) = \prod_{t_i \leq t} \left[1 - \frac{d_i}{N_i}\right] \qquad (3)$$

where N_i represents the total number of banks that were still operating at time t_i.

The failure patern of banks and of other financial institutions during the financial crisis of Colombia was similar in terms of percentage of institutions failing. That suggests that the survival functions of both groups might be similar. Table 2 shows summary data about the dynamics of financial institutions failure. Figure 1 shows the estimated survival function for both groups of intermediaries. These look similar. In order to corroborate that intuition, formal tests of equality of the survival functions were done. Table 3 shows the results of these tests.

Table 3: Test for equality of the survivor functions

$Ho:$ Both groups have equal survival functions

$Test$	$\chi^2(1)$	$Prob > \chi^2$
$Log - rank$	0.45	0.5039
$Wicoxon$	0.41	0.5238

As can be observed from Table 3, there is no evidence to reject the null hypothesis of equality of the survival functions of both groups. Therefore, in the rest of the paper we treat all the institutions as one group. The Kaplan-Meier survival function for the whole group of institutions is shown in Figure 2.

In order to estimate the hazard function, it is first required to obtain an estimation of the cumulative hazard function. The Nelson-Aalen non-parametric estimator is "natural" for this purpose. Equation (4) shows how to compute this estimator. For $t \geq t_i$

$$\hat{\Lambda}(t) = \sum_{t_i \leq t} \frac{d_i}{N_i} \qquad (4)$$

The hazard function can be estimated as a kernel smooth of the estimated hazard contributions[12] $\Delta\hat{\Lambda}(t_i) = \hat{\Lambda}(t_i) - \hat{\Lambda}(t_{i-1})$, as

[12]The kernel smoothed estimator of $\lambda(t)$ is a weighted average of these "crude" estimates over

$$\hat{\lambda}(t) = \frac{1}{b}\sum_{i=1}^{D} K\left(\frac{t-t_i}{b}\right)\Delta\hat{\Lambda}(t_i) \qquad (5)$$

where $K()$ represents the kernel function, b is the bandwidth, and the summation is in the total number of failures D that is observed (see Klein and Moeschberger (2003)).

Figure 3 shows the estimated smoothed hazard function for the group of financial institutions. Note how the hazard rate of failure is clearly non-monotonic. Initially it increases sharply up to approximately month 10, then decreases up to month 25, then increases a little and finally decreases from month 30 on. The form of the estimated hazard function shows that the most commonly used parametric models for the distribution of duration do not seem to be appropriate for modeling the baseline hazard of bank failure in Colombia during the period of financial stress.

4.2 Proportional hazards

Our objective is to understand how bank specific variables affected the conditional probability of failure and time to failure after the shocks that initiated the financial crisis in Colombia. In ordinary regression models, explanatory variables affect the dependent variable by moving its mean around. However, in duration models it is not straightforward to see how explanatory variables affect duration, and the interpretation of the coefficients in these types of models depends on the particular specification of the model. But there are two widely used special cases in which the coefficients can be given a partial derivative interpretation: the proportional hazards model and the accelerated lifetime model (see Kiefer (1988)).

Following the previous literature on the application of duration models to bank failure (see, for instance, Lane et Al (1986) and Whalen (1991 and 2005)), this paper

event times close to t. How close the events are is determined by b, the bandwidth, so that events lying in the interval [t-b, t+b] are included in the weighted average. The bandwidth is usually chosen to minimize the measured mean squared error, or to produce a desired level of smoothness. The kernel function determines the weights given to points at a distance from t. For the case of this study, the chosen kernel was the asymmetric Epanechnikov kernel, which gives progressively heavier weights to points closer to t.

estimates a proportional hazards model in which no parametric form is assumed for the baseline hazard function. As it is shown in Section V, this assumption seems to be an appropriate one for the problem of interest.

Under the proportional hazards specification, explanatory variables affect the hazard rate in a proportional way. Specifically, the hazard rate can be written as

$$\lambda(t, x, \beta, \lambda_0) = \phi(x, \beta)\lambda_0(t) \qquad (6)$$

where λ_0 is the baseline hazard. Note that the effect of time on the hazard rate is captured completely through the baseline hazard. One common specification for the function ϕ, which is followed in this paper, is $\phi(x, \beta) = \exp(x'\beta)$, where x is a vector of covariates and β is the corresponding vector of parameters to be estimated. Under this specification

$$\frac{\partial \log[\lambda(\cdot)]}{\partial x_k} = \beta_k$$

for all k. Therefore, the coefficients can be interpreted as the constant, proportional effect of the corresponding covariate on the conditional probability of completing a spell. In the particular case of bank failure, completing a spell is associated with the moment in which a bank is liquidated.

4.3 Estimation technique

In the case of specifications which model the baseline hazard explicitly by making use of a particular parametric model, estimation is done by the method of maximum likelihood. When the baseline hazard is not explicitly modeled, the estimation method to follow is partial likelihood estimation, which was developed by Cox (1972). The key point of the method is the observation that the ratio of the hazards for any two individuals i and j depends on the covariates, but does not depend on duration:

$$\frac{\lambda(t, x_i, \beta, \lambda_0)}{\lambda(t, x_j, \beta, \lambda_0)} = \frac{\exp(x_i'\beta)}{\exp(x_j'\beta)} \qquad (7)$$

Suppose there are n observations and there is no censoring. If there are no ties, durations can be ordered from the shortest to the longest, $t_1 < t_2 < ... < t_n$. Note that the index denotes both the observation and the moment of time in which the duration for that particular observation ends. The contribution to the partial likelihood function of any observation j is given by

$$\frac{\exp(x_j'\beta)}{\sum_{i=j}^{n}\exp(x_i'\beta)} \tag{8}$$

i.e., the ratio of the hazard of the individual whose spell ended at duration t_j to the sum of the hazards of the individual whose spells were still in progress at the instant before t_j. The likelihood can then be written as

$$L(\beta) = \prod_{i=1}^{n}\frac{\exp(x_j'\beta)}{\sum_{j=1}^{n}\exp(x_i'\beta)}$$

Thus, the log-likelihood function is

$$\ell(\beta) = \sum_{i=1}^{n}\left[x_i'\beta - \sum_{j=i}^{n}x_j'\beta\right] \tag{9}$$

By maximizing equation (9) with respect to β, estimators of the unknown parameter values are obtained. Therefore, the intuition behind partial likelihood estimation is that, even without knowing the baseline hazard, only the order of durations provides information about the unknown coefficients which are the object of estimation.

When there is censoring, like in most empirical applications, the censored spells will contribute to the log-likelihood function by entering only in the denominator of the uncensored observations. Censored observation will not enter the numerator of the log-likelihood function at all.

Ties in durations can be handled by several different methods. In this paper, ties are handled by applying the Breslow method[13].

[13] As it was mentioned before, in continuous time ties are not expected. For the case of bank

5 Estimation results

The model was estimated using the partial likelihood method proposed by Cox (1972), as it was said before. Results of the estimation are presented in Table 4, which shows the values of the estimated coefficients[14] and their standard errors.

One first important conclusion from Table 4 is that the null hypothesis that none of the indicators included in the model is important in explaining the behavior of duration is clearly rejected. This provides evidence that supports the idea that failure of financial institutions during the period of financial stress was not a merely random process; instead, it can be explained by differences in financial health and prudence existing across institutions.

Regarding the role played by individual indicators, it can be seen that the one which resulted more significant in explaining the hazard rate is the capitalization ratio. The sign of the coefficient is negative, implying that an increase in the capitalization ratio for a given bank results in a reduction of its probability of failing at every moment of time, everything else constant. This result is very important, in the sense that it tells both the institutions and their supervisors that the evolution of this ratio should be followed in time.

failure, there should not be two banks which failed at exactly the same time. Nevertheless, given that the moment of failure here is considered the month in which the bank liquidates, ties are possible, and in fact they occur. Suppose we have 4 individuals a_1, a_2, a_3, a_4, in the risk pool and in a certain moment a_1 and a_2 fail. The Breslow method says that, given it is unknown which of the failures preceded the other, the largest risk pool will be used for both failures. In other words, this method assumes that a_1 failed from the risk pool a_1, a_2, a_3, a_4, and a_2 also failed from the risk pool a_1, a_2, a_3, a_4. The Breslow method is an approximation of the exact marginal likelihood, and is used when there are no many ties at a given point in time.

[14]Note that here coefficients instead of hazard ratios are shown, in order to make interpretation simpler.

Table 4: Partial likelihood estimation results

$Variable$	$Coefficient$	$Std.Err.$
CAP	-.0841*	.0315
CAPL	-.1320	.0642
LEV	.0011***	.0006
LIQ	.0048	.0294
EFF	-.0969	.1199
PROV	-.0375	.1574
PROF	-.0233**	.0108
LOAN	-.0231	.0223
NPL	.1004**	.0500

Total number of institutios: 82

Total number of failures: 28

Log-likelihood= -98.841

$LR\chi^2(9) = 23.39$

$\Pr ob > \chi^2 = 0.0054$

* Statistically significant at the 1 percent level

** Statistically significant at the 5 percent level

*** Statistically significant at the 10 percent level

Similarly important is the fact that the variable CAPL affects the hazard rate significantly and with the expected negative sign. This provides evidence in favor of a non-linear effect of the capitalization ratio on the probability of failure[15]. Therefore, improvements in this ratio are more important for poorly capitalized banks than for banks with better capitalization levels. This result can be explained intuitively. It can be expected that there is a capitalization level over which a bank no longer benefits from a further increase, and, on the contrary, could loose profitable

[15] Recall IND1 is constructed as the product of the capitalization ratio and an indicator function that takes value 1 if the institution is below the average capitalization ratio of the system, and 0 otherwise. Thus, the total effect of capitalization for a bank whose capitalization ratio is over the mean is given by IND1, and for an institution whose capitalization ratio is below the mean is given by the sum of IND1 and IND1A.

lending opportunities.

Another important variable in explaining the hazard rate is profitability of assets (PROF). The sign is also negative, indicating that, ceteris paribus, increases in profitability reduce the risk of failure of a bank. This is a natural result, and reinforces the importance of banking capital, as when profits are increasing equity is also increasing –provided not all profits are being distributed to share holders.

Finally, non-performing loans (NPL) affect also significantly the hazard rate. Note that the sign of the coefficient is positive, indicating that an increase in this ratio implies an increase in the risk of failure of a given bank, everything else constant. In a lower degree, hedging (LEV) also affects the hazard rate, and the coefficient has the expected sign.

The results presented in Table 4 are good. Nevertheless, they rely on the proportional hazards assumption. Therefore, it is important to test whether this assumption is a sensible one in the context studied here. One alternative to do is by implementing a test known as the *Schoenfeld's residuals test*. The idea is that the proportional hazards assumption implies that the effect of the covariates on the hazard function is constant over time.

5.1 Testing the proportional hazards assumption

Testing the hypothesis that the effects of the covariates do not vary over time is equivalent to testing for a zero slope in a generalized linear regression of the scaled Schoenfeld residuals on functions of time. The null hypothesis of the test is that the slope is zero. A rejection of the null hypothesis indicates that the proportional hazards assumption is not an adequate one. It is a conventional practice to do a test of each covariate as well as a global test. The results of this test are shown in Table 5.

Table 5: Test of proportional hazards assumption

$Ho:$ Slope is zero

$Covariate$	rho	χ^2	$Deg.freed.$	Prob>χ^2
CAP	.0790	.36	1	.5487
CAPL	-.1865	1.44	1	.2297
LEV	-.0966	.47	1	.4930
LIQ	-.0064	.00	1	.9703
EFF	-.0367	.03	1	.8653
PROV	-.0836	.93	1	.3338
PROF	-.0659	.09	1	.7582
LOAN	-.1166	1.21	1	.2716
NPL	-.0434	.15	1	.6952
Global test		11.58	9	.2381

The results of the test show that the null hypothesis of a zero slope cannot be rejected either for the individual cases or for the global test. This provides evidence that supports the idea that the proportional hazards assumption is adequate in the context of the model of bank failure.

After estimating a duration model by the partial likelihood method it is possible to obtain the estimated hazard and survival functions. Figure 4 shows the estimated survival function evaluated at the mean values of all the predictors When comparing the fitted function with that estimated using non-parametrical methods, it can be observed that they are quite similar.

6 Conclusions

This paper identifies the main bank specific determinants of time to failure during the financial crisis in Colombia using duration analysis. Using partial likelihood estimation, it shows that the process of failure of financial institutions during that period was not a merely random process; instead, it can be explained by differences in financial health and prudence existing across institutions.

Among the relevant indicators that explain bank failure, the capitalization ratio appears to be the most significant one. Increases in this ratio lead to a reduction in the hazard rate of failure at any given moment in time. Of special relevance, this ratio exhibits a non-linear component, implying that the impact of increases in this variable is more important for less capitalized banks. This result, which appears to be intuitive and appealing, agrees with the literature on capital crunch that suggests that banks' capital is crucial for real decisions taken by banks, such as portfolio choices.

One implication of this important finding is that managers and supervisors should pay close attention to capital requirements, in order to maintain financial soundness.

Other important variables explaining bank failure dynamics are profitability of assets and the ratio of non-performing loans to total loans. Leverage appears to affect the hazard rate also, but with lower statistical significance.

The estimation procedure assumes the proportional hazards assumption holds. This assumption implies that explanatory variables affect the hazard rate in a proportional way. Proportional hazards models are frequently used in related literature given the convenient interpretation of the estimated coefficients that they allow. As the validity of the results relies upon the appropriateness of the proportional hazards assumption, tests of its adequacy are made. The results show that there is no evidence to reject the appropriateness of this assumption.

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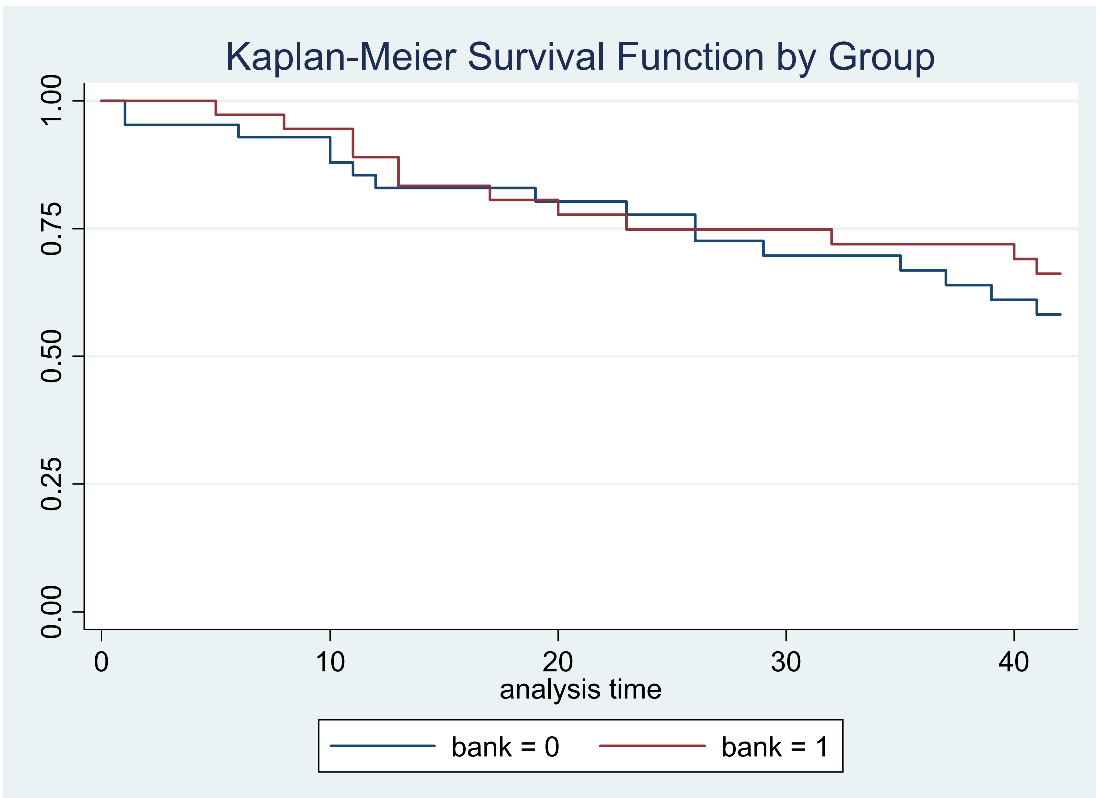
Kaplan-Meier Survival Function by Group
0.00
0.25
0.50
0.75
1.00
0
10
20
30
40
analysis time
bank = 0
bank = 1

Figure 1:

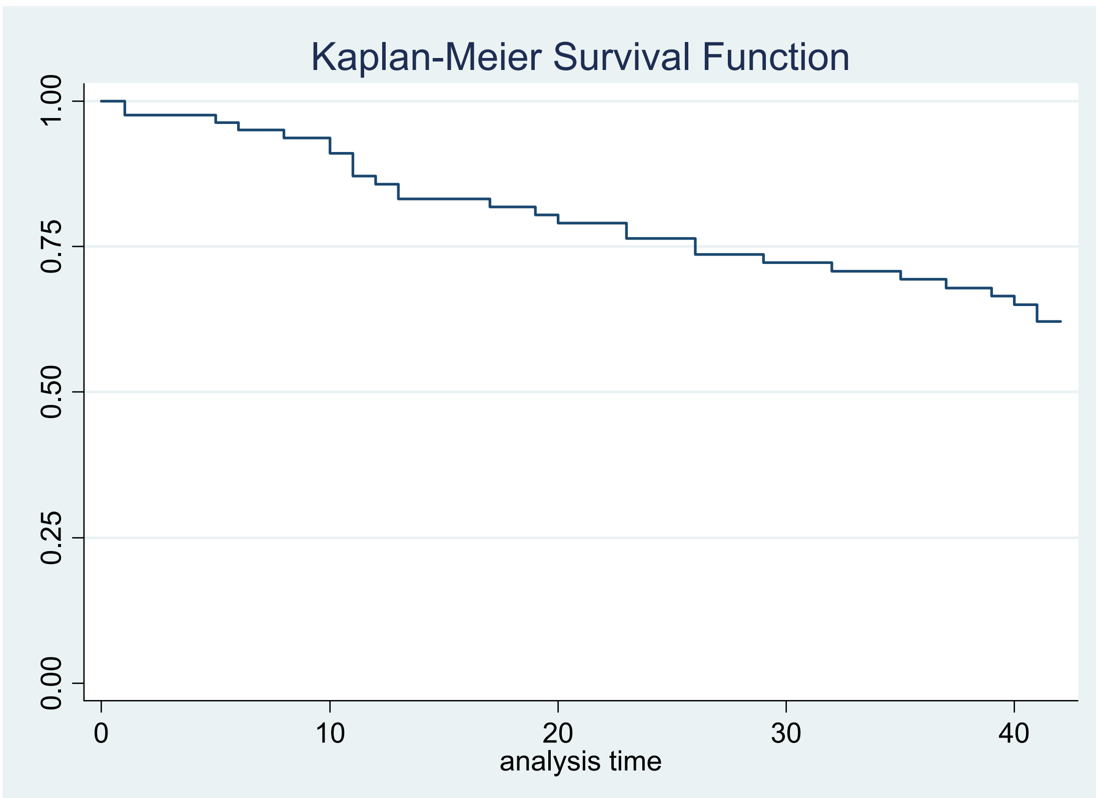
Kaplan-Meier Survival Function
1.00
0.75
0.50
0.25
0.00
0
10
20
30
40
analysis time

Figure 2:

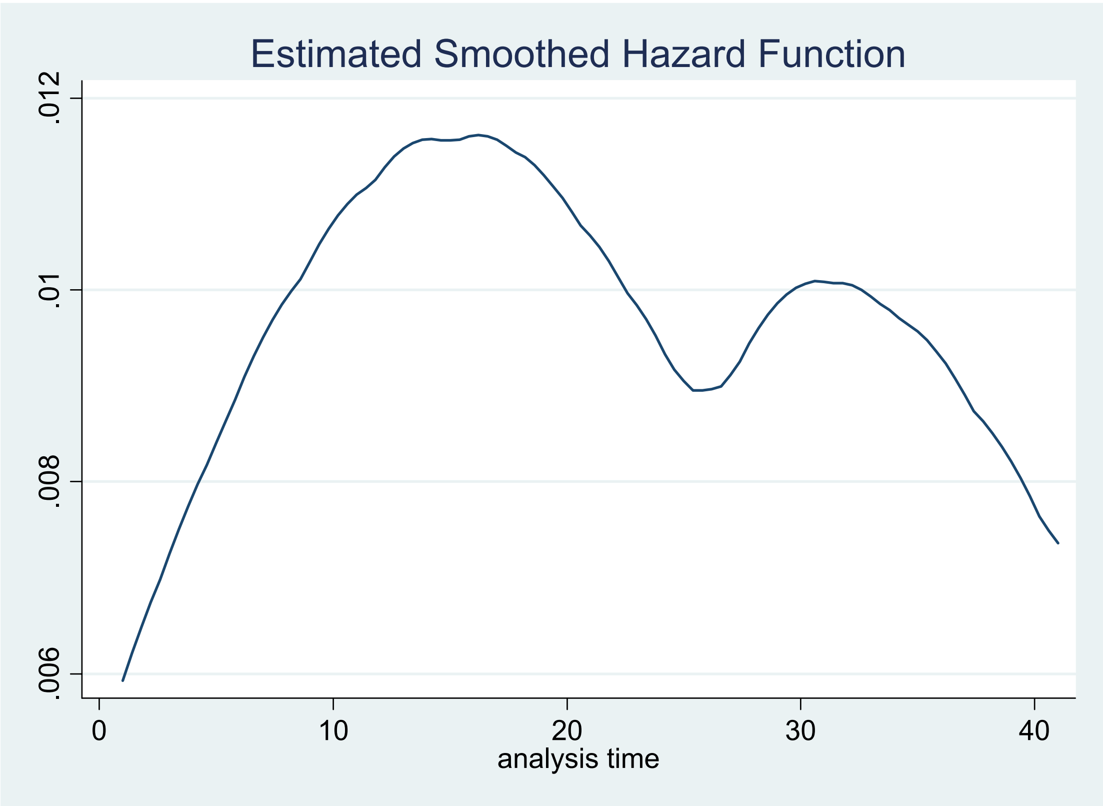
Estimated Smoothed Hazard Function
.006
.008
.01
.012
0
10
20
30
40
analysis time

Figure 3:

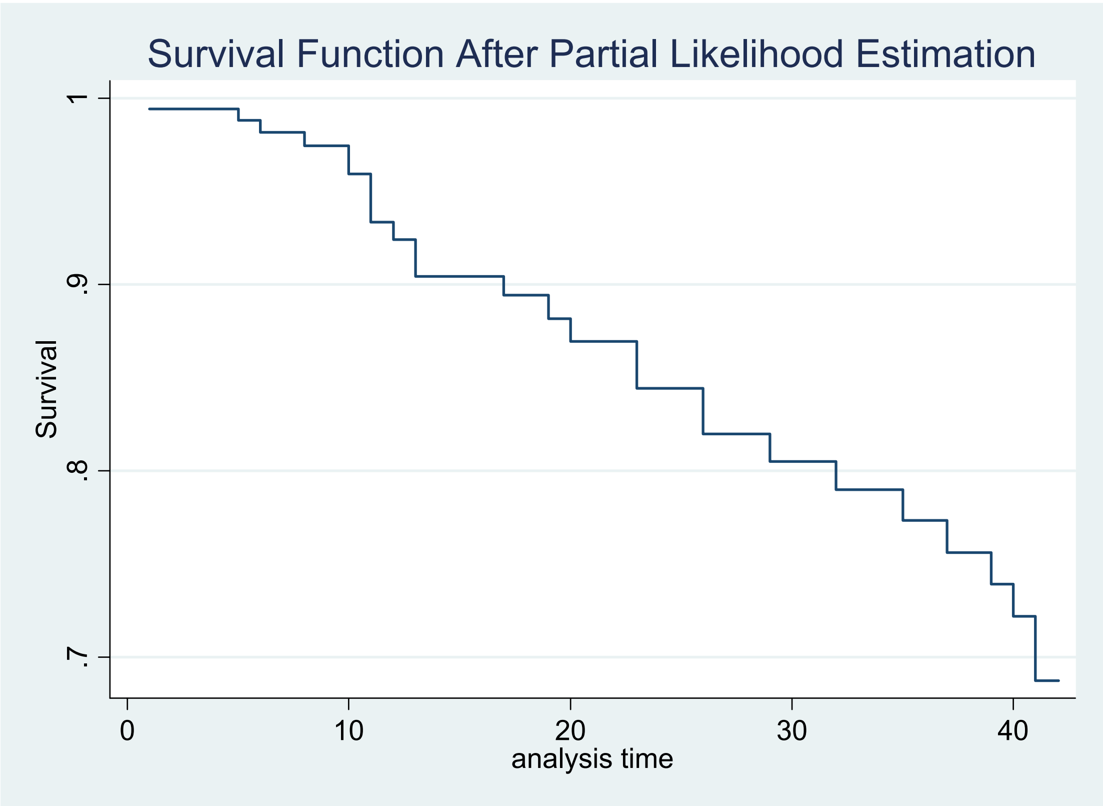
Survival Function After Partial Likelihood Estimation
Survival
1
.9
.8
.7
0
10
20
30
40
analysis time

Figure 4:

TABLE 2

Time	Beg. Total	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf.	Int.]
bank=0							
1	43	2	1	0.9535	0.0321	0.8266	0.9882
6	40	1	0	0.9297	0.0392	0.7975	0.9768
7	39	0	2	0.9297	0.0392	0.7975	0.9768
10	37	2	0	0.8794	0.0507	0.7339	0.9480
11	35	1	0	0.8543	0.0551	0.7037	0.9318
12	34	1	0	0.8291	0.0589	0.6743	0.9148
17	33	0	1	0.8291	0.0589	0.6743	0.9148
19	32	1	0	0.8032	0.0625	0.6443	0.8965
23	31	1	0	0.7773	0.0657	0.6151	0.8776
26	30	2	1	0.7255	0.0708	0.5586	0.8379
28	27	0	1	0.7255	0.0708	0.5586	0.8379
29	26	1	0	0.6976	0.0733	0.5282	0.8161
33	25	0	1	0.6976	0.0733	0.5282	0.8161
35	24	1	0	0.6685	0.0758	0.4969	0.7931
37	23	1	0	0.6395	0.0779	0.4664	0.7694
39	22	1	0	0.6104	0.0796	0.4367	0.7452
41	21	1	0	0.5813	0.0809	0.4077	0.7204
42	20	0	20	0.5813	0.0809	0.4077	0.7204
bank=1							
3	39	0	2	1.0000	.	.	.
5	37	1	0	0.9730	0.0267	0.8232	0.9961
6	36	0	1	0.9730	0.0267	0.8232	0.9961
8	35	1	0	0.9452	0.0377	0.7980	0.9860
11	34	2	0	0.8896	0.0521	0.7319	0.9571
13	32	2	0	0.8340	0.0619	0.6672	0.9218
17	30	1	0	0.8062	0.0658	0.6359	0.9025
18	29	0	1	0.8062	0.0658	0.6359	0.9025
20	28	1	0	0.7774	0.0695	0.6036	0.8820
23	27	1	0	0.7486	0.0726	0.5722	0.8606
32	26	1	0	0.7198	0.0753	0.5415	0.8384
40	25	1	0	0.6910	0.0776	0.5115	0.8157
41	24	1	0	0.6622	0.0795	0.4821	0.7923
42	23	0	23	0.6622	0.0795	0.4821	0.7923