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Explaining and Predicting Bank Failure in Argentina Using Duration Models

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Abstract

This paper studies the role played by several financial and economic indicators in determining the process of bank failure in Argentina after the Mexican crisis known as the “tequila effect”. Due to the relative scarcity of previous studies, this paper priorizes the use of semiparametric and non-parametric methods which allow us to measure the effect of explanatory variables in the process of bank failure together with duration dependence effects. The dynamic of bank failures can be fairly characterized by observable factors, which discards the possibility that it had been governed by contagion processes solely. The non-monotonocity of the implicit hazard rate suggests that there were contagion effects, and that they had a strong influence in the first 200 days of the crisis.

Resumen

En este artículo se estudia el papel jugado por varios indicadores financieros que pueden determinar el proceso de quiebras de bancos en Argentina luego de la crisis Mexicana conocida como “efecto tequila”. Frente a la relativa escasez de resultados previos, este estudio prioriza el uso de métodos semiparamétricos y no-paramétricos, los cuales posibilitan medir la influencia de las variables relevantes que determinan la caída de bancos junto a efectos de “duration dependence”. La dinámica de la caída de bancos puede ser razonablemente caracterizada por un conjunto de factores observables, lo cual descarta la posibilidad de que la misma haya sido gobernada exclusivamente por procesos de contagio en donde la situación financiera de los bancos no juegue ningún papel. La no monotonicidad de la función de riesgo sugiere que existieron efectos de contagio y que los mismos tuvieron una fuerte influencia en los primeros 200 días de la crisis.

1 Introduction

In 20 December 1994, the day in which the Mexican devaluation that originated the bank crisis known as "tequila effect" occurred, 206 financial institutions existed in Argentina. In August 1995 this number had fallen to 156, as a consequence of the financial reorganization after the crisis.

The fall in the financial entities number (defined as banks, financial companies, saving and loan mortgage companies, and loan companies), was about 25%. In September 1997, only 143 entities existed.

This "mortality" pattern of financial entities in Argentina is a very interesting fact to study using duration models, which are helpful tools in explaining and predicting not only the "death" probability, but also how this probability develops over time, which economic variables affect it, and when the potential failure will occur. These methods, generally applied in biological and medical ciencies, allow us to predict a patient's survival time (or that of a bank), who has been submitted to an initial event (a surgical operation in the patient's case, or deposits withdraws or the bank crisis stress in case of a financial institution), given the bank's (patient's) characteristics. These techniques proved useful in the analysis of marriage duration, time between sons birth, time of new technologies adoption, products duration, wars duration, jobs duration, resolution of legal processes, time of students' graduation, etc.

The use of duration models to explain and predict financial entities' failures is relatively recent. Cole and Gunther (1995), González-Hermosillo, Pazarbasioglu and Billings (1996), Lane, Looney and Wansley (1986), Weelock and Wilson (1995) and Whalen (1991) have produced results in this direction using different duration techniques to analyze bank failures. For the Argentinean case, Anastasi et al. (1998) present a parametric approximation to the bank failure problem.

This article studies the role played by many financial indicators which can influence the bank failure process in Argentina. Due to the scarcity of previous work on the Argentinean case, this paper priorizes the use of semiparametric and non-parametric methods, which allow us to measure the effect of relevant variables that determine the bank failures together with duration dependence effects, without the need of arbitrary and possibly not realistic assumptions.

Dabós (1998) analyzed bank failure probabilities for the Argentine case using a sample of cooperative banks. In this paper, these previous results are extended using a broader sample, and not only the failure probability is analyzed, but also its *timing*. The model can be used to explain the observed failures conditional a set of observable bank characteristics. Additionally, the possibility of using the estimated model as an early alarm tool to predict the failure risk is explored.

2 The bank failure process in Argentina.

Two groups of banks were considered for the analysis: cooperative, and private national banks. Public and foreign banks were not considered, because of their special characteristics. Non-bank entities were not considered either, because the analysis is constrained to banks.

In December 20th 1994 there were 64 private national banks, as a result of taking out public and cooperative banks, local offices of international entities, and other 4 banks that, because of their special characteristics, were not included, out of the total financial entities sample. These last 4 banks are: MBA Banco de Inversión S.A., Cofirene Banco de Inversión, Banco Federal Argentino and the Banco Caja de Ahorro S.A. From these 64 private national banks considered, only 3 (Crédito Comercial S.A., Extrader S.A. and Multicrédito S.A.) had problems before the crisis had ended (that is, before 146 days passed, or from 20 December 1994 to 15 May 1995).

Between May 15th 1995 (end of the crisis), and December 20th 1995, another 11 banks disappeared from the financial system. So, 14 banks disappeared in one year from the beginning of the "Tequila" crisis. Between December 20th 1995 and December 20th 1996, 8 private national banks disappeared. In 25 September 1997, from the 64 banks initially considered, only 40 were still operating. In total, the number of disappeared cooperative banks from December 1994 to September 1997 was 24.

Looking at the cooperative banks, from the 38 existing entities in December 1994, 6 disappeared before the crisis ended. Among the remaining ones, another 23 were out of the market before 20 December 1995 (one year after the Mexican crisis began). Between 20 December 1995, and 20 December 1996, two more cooperative banks disappeared. Only six cooperative banks were operating in 25 September 1997. In total, 32 cooperative banks disappeared between December 20th 1994 and September 25th 1997.

September 25th 1997 is the last day considered, because it includes a sufficiently long period, and it coincides with the date and the information supplied by the Banco Central de la República Argentina about bank failures that we use. Choosing the correct period for the analysis is not a trivial task, because it involves a trade-off between homogeneity and sample accuracy. Once a period is chosen for the analysis, for those banks that did not fail in that period, it is not possible to know if they will in the future, so a longer period would let us study banks' survival with more detail. On the other hand, a longer period, would force us to given account of a more heterogeneous time span, possibly includying structural changes, which, although interesting, are not the subject of this investigation.

Private national banks, and cooperative banks are listed in the Appendix, together with the date in which they disappeared, the reason of their disappearance and their life time in days, from 20 December 1994 to 25 September 1997.

Table 1: Bank failures in each group

Bank Types	Operating for 20/12/94	Disappeared:				Operating for 25/9/97
		Before 15/5/95	Between 15/5/95 and 20/12/95	Between 20/12/95 and 20/12/96	Between 20/12/96 and 25/9/97	
Cooperative	38	6	23	2	1	6
Private National	64	3	11	8	2	40

Table 2: Banks by duration time, for each group.

Duration in days since 20 December 1994.

Duration	146	365	731	1010
Cooperative	32	9	7	6
Private National	61	50	42	40

3 The duration model applied to the bank failure process.

During the bank crisis generated by the "tequila effect" many banks faced the following scenario. Suppose that a bank begins to loose deposits, so all it's efforts will be aimed to continue operating. Suppose now that after a week, the bank is still loosing deposits and operating. A very interesting question that managers, directors, and control authorities would like to answer at that moment is what is the failure probability for the next week, period, or instant, considering that the bank is still operating. Another interesting question is which is the estimated time until it fails, given the bank's characteristics.

Duration models allow us to handle these questions in a parsimonious and informative way. In this section we briefly discuss the duration model and the particular estimation and inference strategies adopted in this paper.[2].

In general terms, the variable of interes in this type of models is the time it takes a system to change from one state to the another. Generally, such change is associated with an event (finding a job, a firm's bankrupt, the solution of a labor conflict, a product disappearance of the market, etc.), which indicates the ending of an event whose duration we try to model. This random variable is called a *duration*, it takes positive values, and we will call it T.

If the duration is understood as a continuous random variable that takes positive values, its probability distribution can be characterized by any of the following three functions:

1. Distribution Function: $F(t) = Prob(T < t)$
2. Survival Function: $S(t) = Prob(T > t) = 1 - F(t)$
3. Density Function: $f(t) = dF(t)/dt = - dS(t) / dt$

As mentioned before, a quantity of interest will be the probability that the event ends in an interval beginning at t and considering that it has not finished until that moment. Such conditional probability will be:

$$h(t, \Delta) = \text{Prob}\,[\, t \leq T \leq t+\Delta \mid T \geq t \,]$$

[2] A detailed presentation of the duration model exceeds the scope of this paper. Kalbfleisch and Prentice (1980), Klein and Moeschberger (1997), Miller (1981) and Parmar and Machin (1996), among others, are recognised studies with special reference to medical, and biological problems. Lancaster (1990) presents a detailed analysis on the duration models with emphasis in labour economics applications. A recent synthesis with economic applications is Neumann (1997). The usual example where this technique is used is the unemployment duration analysis. Kiefer(1988) is a very useful summery.

The *hazard rate* is defined as:

$$h(t) = \lim_{\Delta \to 0} \; h(t, \Delta) / \Delta$$

and it represents the instant probability that the event concludes at t, conditional on the fact that it lasted up to t. Intuitively, the hazard rate approximates the probability of bank failure for the next moment, given that the bank is still operating at t. The relationship between the hazard rate and the previous functions is given by:

$$S(t) = \exp(-\int_0^t h(s)ds)$$

so it is possible to get any of the 3 previous functions from this one, so the hazard rate can also be used to characterize the duration.

A duration model is a model for the random variable *T*, based on any of the functions that characterize it, as previously described. As is usual in the literature, the analysis is mainly centered on the survival function *S(t)* and on the hazard function *h(t).* It is also important to consider the *cummulative hazard function*:

$$\Lambda(t) = \int_0^t h(t)dt = -\log S(t)$$

which will be useful to describe estimators used in the empirical section.

As a first step, it is interesting to analyze the unconditional distribution of T, that is, momentarily ignoring the possibility of using explanatory variables. At this stage, it is cautious to rely on non-parametric methods, which, as mentioned in the Introduction, avoid the risk of using unrealistic assumptions, while being informative about the basic features of the duration process.

The rest of this section shortly describes the estimation and inference techniques used in this paper. The survival function will be estimated using the standard Kaplan-Meier non-parametric estimator. Suppose that failures occur at the moments t_1, t_2, . . ., t_d and that at period t_i ; d_i banks fail. Let Y_i be the number of banks that are operating at period t_i. The Kaplan-Meier estimator of *S(t)* for $t_1 < t$ is:

$$S_{KM}(t) = \prod_{t_i \leq t} \left[1 - \frac{d_i}{Y_i} \right]$$

and $S_{KM}(t) = 1$ if $t < t_1$. The survival functions are estimated for both bank groups separately. To test the hypothesis of similarity between survival functions of both groups, we use a log-rank test and a Wilcoxon test, which is standard practice in the literature (see Klein and Moechberger 1996, pp. 191-200, for more details).

Estimation of the hazard function is a more delicate matter than that of the survival. We use a an asymmetric kernel smoothing method similar to the one described in Klein and Moeschberger (1997, pp. 152-163.). Basically, raw estimations where calculated on the hazard function based on the Nelson-Aaleen's cummulative hazard function estimator:

$$\Lambda_{NA}(t) = \sum_{t_i \leq t} d_i \ / \ Y_i$$

for $t_1 \leq t$, and 0 for $t \leq t_1$. The raw hazard function estimates are non zero at the moments where bank failures are observed, and correspond to:

$$h_{NA}(t_i) = \Lambda_{NA}(t_i) - \Lambda_{NA}(t_{i-1})$$

The final estimation corresponds to a kernel smoothed version based on:

$$\hat{h}(t) = b^{-1}\sum_{i=1}^{D} K\left(\frac{t-t_i}{b}\right) h_{NA}(t_i)$$

where *b* is the bandwidth and *k( )* the kernel function. We use the Epanichnikov's kernel with a correction at the extremes. This correction is necessary because negative durations are not observed, and therefore near to 0 it is necessary to use an asymmetric kernel.

The incorporation of explanatory variables is not trivial, and depends on the desired interpretation. A flexible model strategy was chosen, whose optimal properties do not depend on ex-ante theoretical or empirical arbitrary assumptions. We also preferred a simple model specification, that would lead us to simple economic interpretations. Under these considerations, the semiparametric character of Cox's *proportional hazard model* seems to be a good balance between analytical simplicity and functional flexibility.

Under this model, explanatory variables affect the hazard rate in a proportional way. More precisely, the hazard rate is modelled as:

$$h(t \mid x) = h_0(t) \exp(\beta' X)$$

where β is a p vector of coefficients and X is vector of p explanatory variables. The $h_0(t)$ function is called the *baseline hazard function*.

It is important to note that the baseline hazard controls the hazard rate's time behavior since the hazard rate depends on time only through the baseline hazard rate. The second factor introduces the effect of explanatory variables in a multiplicative way. Therefore, the coefficients in this representation can be interpreted as semielasticities of the hazard rates with respect to marginal changes in the explanatory variables.

$$\partial \ln h(y|X) / \partial X_k = \beta_k$$

with k = 1, ... , p.

The parameters of this model (the β coefficients) will be estimated using Cox's partial likelihood technique (Cox, 1972). The proportional hazard assumption implies that the effect of explanatory variables on the hazard function is constant over time, and works by moving the baseline hazard rate up or down in a proportional way. This assumption can be formally evaluated following the procedure proposed by Harrell (1986), based on Shoenfeld's (1982) residuals. In very general terms, under the proportional hazard's assumption, Shoenfeld's residuals should not be related with the elapsed time. Harrell (1986) proposes to use the correlation between these residuals and the time ranks as a proportional hazard's null hypothesis test[3].

4 Bank failure process empirical analysis in Argentina.

4.1 Basic characteristics of the bank duration process

As a first approximation, a descriptive analysis of the main bank duration process characteristics was performed, leaving momentarily aside the possibility of including explanatory variables to enrich the analysis. Table 1 shows some basic statistics of the bank' s duration time and of the seven indicators that will later be used as explanatory variables. These statistics where calculated for both bank groups, separately.

[3] This methodology comes from Splus (Statistics Guide, pp. 662).

Table 3: Descriptive statistics for groups of banks

Variable.	Mean.	Std. Dev.	Min.	Max.
a) Cooperative banks (38 banks).				
t3	288.11	225.96	57.00	731.00
ind1	17.14	8.10	8.38	50.18
ind2	5.74	2.24	0.99	10.93
ind3	22.37	8.19	8.62	55.17
ind4	11.47	14.90	0.15	91.24
ind5	16.33	5.21	7.57	27.78
ind6	66.93	44.96	8.30	178.40
ind7	1.33	17.72	-62.30	17.90
b) Private banks (64 banks).				
t3	585.95	226.27	37.00	731.00
ind1	17.58	15.41	4.43	95.10
ind2	7.09	4.22	0.05	21.56
ind3	32.80	22.27	4.81	120.30
ind4	15.88	31.68	-10.90	213.20
ind5	11.41	13.77	0.94	84.68
ind6	58.35	69.80	-1.38	442.00
ind7	4.86	11.88	-36.90	27.13

Of the 38 cooperative banks in the sample, 31 banks failed and 9 survived. During the period we are studying, the average duration of the whole sample in this category was 288 days, while the average duration for the banks that failed was 188 days. In the case of private bank, of the 64 banks in the sample, 22 failed, and 42 survived. The average duration of all the banks in this group was 585 days, and the average for those that failed was 309 days.

As mentioned in the previous section, the duration distribution can be characterized in several ways. Figure 1, shows graphically the estimation of the survival function estimation for all the banks in the sample as a single group, based on the Kaplan-Meier[4] method. Figure 2 shows these estimations for both bank groups separately. Table 4 presents a brief description of the bank failure dynamics. For each bank group, each row in the table shows the period in which the failure occurred, together with the information used to construct the previously mentioned figures. These results suggest that bank mortality dynamics was notoriously different if it's a cooperative or a private bank. This observation is further validated by the survival function similarity tests shown in table 5. In the same table results for the log- rank and Wilcoxon tests are presented. Both statistics reject the null hypothesis of similarity between survival functions of both groups.

Two interesting effects can be observed. First, private banks' survival function is significantly higher than cooperative banks' function: *at every moment of the crisis it is more probable to have a cooperative bank failure than a private bank failure*. Second, the survival function for private banks decreases slower than that of cooperative banks, which shows a strong acceleration approximately 200 days after the Tequila crisis began.

[4]The general estimations where made in Stata 5.0. The proportional hazard tests where made in Splus 4.0. The smoothing processes where also made in Splus 4.0, and are available on request to the authors.

Table 4: The bank failure dynamics.

Time (t). (in days).	Banks in t.	Total Fails.	Survival Function	Standard Error.	95% Confidence Interval.	
Cooperative banks (type=0).						
57	38	2	0.9474	0.0362	0.8056	0.9866
71	36	1	0.9211	0.0437	0.7749	0.9738
104	35	1	0.8947	0.0498	0.7434	0.9591
133	34	1	0.8684	0.0548	0.7123	0.9430
139	33	1	0.8421	0.0592	0.6819	0.9258
147	32	6	0.6842	0.0754	0.5115	0.8067
154	26	1	0.6579	0.0770	0.4848	0.7849
191	25	1	0.6316	0.0783	0.4586	0.7627
192	24	2	0.5789	0.0801	0.4075	0.7169
195	22	7	0.3947	0.0793	0.2418	0.5441
224	15	2	0.3421	0.0770	0.1983	0.4911
239	13	3	0.2632	0.0714	0.1369	0.4081
283	10	1	0.2368	0.0690	0.1176	0.3794
378	9	1	0.2105	0.0661	0.0989	0.3501
468	8	1	0.1842	0.0629	0.0811	0.3201
731	7	0	0.1842	0.0629	0.0811	0.3201
Private banks (type=1).						
37	64	1	0.9844	0.0155	0.8942	0.9978
85	63	1	0.9688	0.0217	0.8808	0.9921
133	62	1	0.9531	0.0264	0.8617	0.9846
143	61	1	0.9375	0.0303	0.8420	0.9761
155	60	1	0.9219	0.0335	0.8224	0.9667
163	59	1	0.9062	0.0364	0.8032	0.9568
182	58	1	0.8906	0.0390	0.7842	0.9463
210	57	1	0.8750	0.0413	0.7656	0.9354
224	56	1	0.8594	0.0435	0.7472	0.9242
240	55	1	0.8438	0.0454	0.7291	0.9127
253	54	1	0.8281	0.0472	0.7112	0.9009
265	53	1	0.8125	0.0488	0.6935	0.8889
346	52	1	0.7969	0.0503	0.6760	0.8766
349	51	1	0.7812	0.0517	0.6588	0.8641
352	50	1	0.7656	0.0530	0.6417	0.8515
408	49	1	0.7500	0.0541	0.6248	0.8387
437	48	1	0.7344	0.0552	0.6080	0.8257
468	47	1	0.7188	0.0562	0.5914	0.8125
529	46	1	0.7031	0.0571	0.5749	0.7992
559	45	2	0.6719	0.0587	0.5424	0.7722
702	43	1	0.6562	0.0594	0.5264	0.7584
731	42	0	0.6562	0.0594	0.5264	0.7584

Figure 1: Estimated survival function for all the banks as one group.

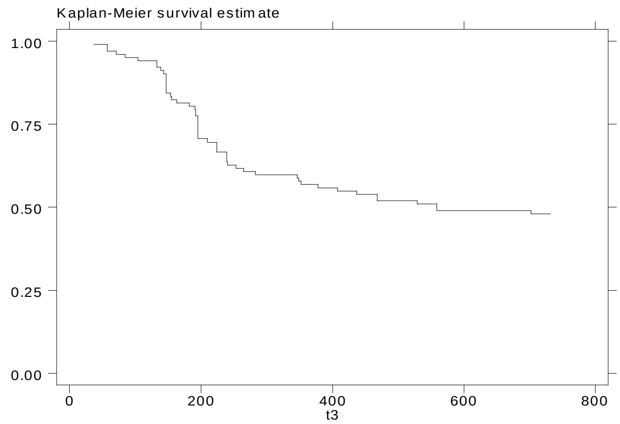


Figure 2: Estimated survival functions for private and cooperative banks separately.

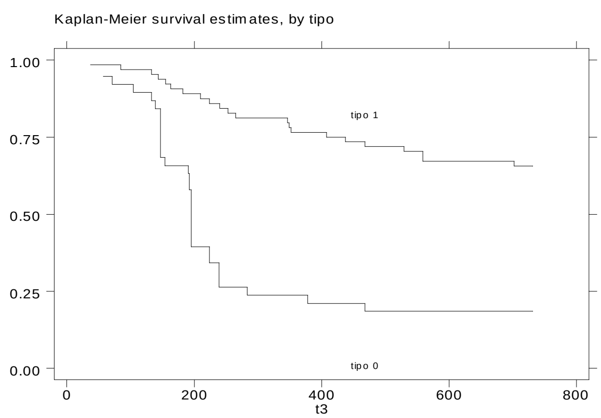


Table 5: Tests of equality of survival functions

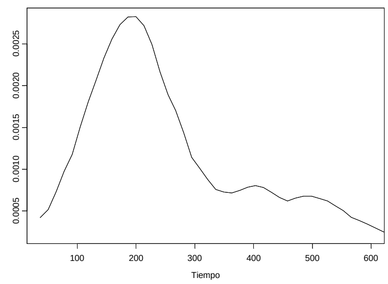
	Chi2(1)	Pr>Chi2
Log-Rank	32.43	0.0000
Wilcoxon	32.65	0.0000

Ho: Both survivorship functions are equal.
Ha: Different bank groups have different functions.

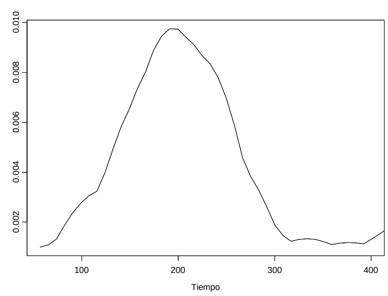
Figure 3 shows the hazard function estimation results using the smoothing method described in the previous section, for the sample as one group, and for cooperative and private banks separately. As was mentioned in Section 3, the hazard rate measures, at each moment, the instant probability that a bank fails, given that is was active until moment. So this function can be interpreted as a failure risk indicator for the banks that are still operating. The results clearly show a phenomenon suggested by the survival functions estimated before. From the beginning of the crisis, bank failure risk increases monotonically and rapidly until approximately 200 days after the crisis began, and then it begins falling.

Figure 3: Hazard Functions.

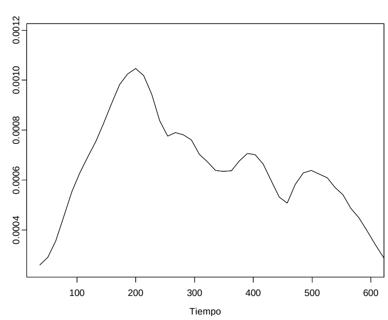
1) Hazard function estimations for all the banks, as one group.



2) Hazard function estimation for cooperative banks.



3) Hazard function estimation for private banks.



This possible non-monotonicity of the hazard rates narrows the number of possible parametric models that could be chosen to represent the bank failure dynamics.

For example, the Weibull or exponential models have monotonic or constant hazard rate functions, which are not compatible with the results shown in this section.

4.2 A conditional model for banks duration.

This section will study the possibility of using the banks' financial performance indicators as explanatory factors of the survival dynamics. In this paper we use the structure of explanatory variables considered in Dabós (1998) in his bank failure probability analysis. The following coefficients are considered as indicators of the banks' situation (in November 1994):

1) Net worth / Assets (IND1)
2) Liabilities / Net worth (IND2)
3) Immediate liquidity = (Liquid assets + Government securities)/ Deposits (IND3)
4) Structural liquidity (Net worth – Lock up capital) / Liabilities (IND4)
5) Administration expenses / Liabilities (IND5)
6) Irregular portfolio – Provisions / Net worth (IND6)
7) Rentability / Net worth (ROE) (IND7)

These indicators follows the traditional school in the analysis of financial entities default risk, looking at the principal variables to be considered in the C.A.M.E.L. model (Capitalization, Assets, Management, Earnings, Liquidity). 1 and 2 are capitalization indicators (C), 6 is an asset quality indicator (A), 7 is a rentability indicator (E), and 3 and 4 are liquidity indicators (L). 5, an efficiency estimator, would be an approximation for (M) management. In the Statistical Appendix the indicators values are shown for all the banks.

Considering the results in the previous section, to run the estimations, the effect of the indicators was allowed to change by bank group. 14 explanatory variables were included, which correspond to the 7 previously mentioned indicators and slope dummy variables per bank group. The *indk* (k=1,......,7) variables correspond to the X_k indicator while *ink* takes values equal to *indk* for private banks and 0 for the rest of them, so that the coefficients of this last group of variables are interpreted as differential effects by bank type. Under these considerations, Cox's model is specified as:

$$h(t \mid X) = h_0(t)\exp\left\{\sum_{k=1}^{7}(\beta_k X_k + \gamma_k DX_k)\right\}$$

where D is an indicator with value 1 if the bank is private and 0 if it is cooperative, and according to the definition, X_k = *indk*, and DX_k = *ink*. The effect of the k-th on the hazard rate can be evaluated as:

$$\frac{\partial \ln h(t \mid X)}{\partial X_k} = \beta_k + \gamma_k D$$

so that the semi-elasticity of the hazard rate with respect to the k-th indicator is β_k for cooperative banks, and $\beta_k + \gamma_k$ for private banks.

Estimation results for this model are shown in Table 7, where the corresponding columns show the estimated coefficients, their standard deviations, the z statistic corresponding to the null hypothesis that the coefficient is equal to 0, the p-values, and a 95% confidence interval.

In general terms, the global fit is acceptable, and many variables are significantly different from 0. The χ^2 statistic corresponding to the test of the null hypothesis that none of the explanatory variables is significantly different from 0, is notoriously higher to the critical values commonly accepted. This result suggests that it is incorrect to say that the bank failure process was caused by random, non-systematic factors, and that, on the contrary, it is significantly influenced and explained by financial and economic observable factors. This result agrees with those obtained by

Schumacher (1996) in a bank failure multinomial model, and also confirms those suggested by Dabós (1998) who, maybe because of a strong collinearity between the explanatory variables, found that only one indicator is relevant to explain the bank failure process.

Dabós (1998) uses as explanatory variable an binary indicator equal to 1 if the bank failed during certain period, and 0 if it didn't. Therefore, as Doksum and Gasko (1990) remark, the binary model is a censored version of the duration model, where the explained variable is the time elapsed until default. This suggests that the higher variability considered by the allowed for a better identification of the factors that explain the development of the bank crisis.

The null hypothesis that all the *ink* variable (k=1,......,7) coefficients are all equal to 0 is also rejected. This suggests that, as we expected, it is important to separate among bank types.

Looking at the individual effect, at first place, the capitalization measure given by the indicator 1 (Net worth / Assets), is not significantly different from 0 for both groups, that is, it's effect is null for cooperative and private banks.

The capitalization effect, measured by the leverage level as Indicator 2 (Liabilities/ Net worth), is significantly different from 0, and with the correct sign. A marginal increase in its level, increases the default risk in approximately 23% for both cooperative and private national banks.

Indicator 3 (Liquid Assets +Government Securities / Deposits) has the correct sign, given that an instant liquidity marginal increase reduces the default risk in approximately 6% for both groups.

The structural liquidity measured by Indicator 4 (Net worth – Lock Up Capital / Liabilities) has no effect at all in both groups.

Up to now, a capitalization measure and a liquidity one, have the expected effect that theory suggests, and resulted important in determining a bank’s default risk, for both type of banks.

Indicator 5, (Administrative Expenses/ Liabilities) presents a positive effect on the default risk in private national banks. A marginal increase in it, increases the default risk in 20% in private national banks, and has no effect in cooperative banks.

The expected effect for the portfolio situation measured by Indicator 6 (Irregular portfolio- Provisions / Net worth) has the expected sign in cooperative banks but not for private national banks. If Indicator 6 increases marginally, the default risk in cooperative banks increases 1%, and decreases 0,5% in private national banks. Maybe because of possibly present identification problems Indicator 6 does not appear as an important variable to explain the banks default risk.

Finally, the greater the rentability (ROE), the lower the default risk (-4%), but only for private national banks. The rentability effect is not important at all in cooperative banks.

Table 7: Cox's model estimation.

Variable	Coefficient	Std. Err.	Z	P>|z|	95% Confidence interval.	
ind1	0.1037	0.0667	1.5530	0.1200	-0.0271	0.2345
ind2	0.2358	0.1373	1.7170	0.0860	-0.0333	0.5050
ind3	-0.0613	0.0270	-2.2660	0.0230	-0.1143	-0.0083
ind4	-0.0301	0.0377	-0.7980	0.4250	-0.1040	0.0438
ind5	-0.0300	0.0406	-0.7400	0.4600	-0.1096	0.0495
ind6	0.0119	0.0070	1.6950	0.0900	-0.0019	0.0257
ind7	0.0166	0.0129	1.2820	0.2000	-0.0088	0.0419
in1	-0.0915	0.0705	-1.2980	0.1940	-0.2297	0.0467
in2	-0.1272	0.1342	-0.9470	0.3430	-0.3903	0.1359
in3	0.0038	0.0382	0.0990	0.9210	-0.0712	0.0787
in4	-0.0316	0.0500	-0.6310	0.5280	-0.1297	0.0665
in5	0.1965	0.0727	2.7040	0.0070	0.0541	0.3390
in6	-0.0174	0.0081	-2.1470	0.0320	-0.0333	-0.0015

in7	-0.0423	0.0222	-1.9050	0.0570	-0.0858	0.0012
Total banks = 102			Log likelihood		-199.3553	
Total defaults = 53			Chi2(14)		59.3100	
			Prob > chi2		0.0000	

Proportional hazards assumption evaluation.

The proportional hazards assumption causes that the explanatory variables effect be constant over time, that is, a marginal change in any of the explanatory variables has just one effect on the hazard function: a vertical shift along time. To test if the proportional hazards assumption is valid, Harrell's test was used, based on Schoenfeld's (1982) residuals. Intuitively, a model is estimated allowing Cox' s model β coefficients to change over time. Under the proportional hazards assumption these coefficients should be constant, and therefore, under the null hypothesis, the graph showing those coefficients estimations along time should approximate a horizontal line. The Harrell's test can be interpreted as a test in which the coefficients are constant[5]. This is confirmed by the tests results, which, for a 95% confidence interval, suggest not to reject the constant coefficients null hypothesis in any of the cases. In general terms, the obtained results suggest that the proportional hazards assumption is not bounding for the studied case.

Table 8: Proportional hazards hypothesis test.

	rho	Chisq	p
ind1	-0.120	0.909	0.340

[5] These coefficients' estimations are not shown because of space reasons (but are available through the authors). The coefficients' estimation graphs along time, for each specification variable, do not show oscillation that would suggest that these are not constant, in any of the studied cases.

ind2	0.001	0.000	0.991
ind3	0.018	0.012	0.911
ind4	0.092	0.268	0.605
ind5	0.193	1.987	0.159
ind6	-0.080	0.426	0.514
ind7	-0.096	0.494	0.482
in1	0.066	0.239	0.625
in2	-0.050	0.173	0.678
in3	0.059	0.170	0.680
in4	0.004	0.001	0.974
in5	-0.105	0.755	0.385
in6	0.147	1.275	0.259
in7	0.092	0.402	0.526
GLOBAL		10.340	0.737

4.2 Model's predictive capacity analysis.

As an additional exercise, it is interesting to test the estimated model's predictive capacity. Computed predictions resulted similar to those presented by Whalen (1991). For each period t, it is possible to obtain the survivorship estimated probability *S(t|X)*, using the relation we described in section 3, between the hazard rate and the survivorship function, applied to the Cox's proportional hazard's model:

$$\hat{S}(t \mid X) = \hat{S}_0(t)^{\exp(\hat{\beta}' X)}$$

where:

$$\hat{S}_0(t) = \exp\left\{-\int_0^t \hat{h}_0(u)du\right\}$$

where $h_0(\ )$ is the previously estimated baseline hazard function, and $\hat{\beta}$ is the coefficients' vector estimated by Cox's model. Using these formulas, for any period t^*, it is possible to find the probability that a bank had survived until that period given its financial characteristics (the X vector). Then, the probability that a bank had survived until that period is predicted, if the estimated probability of doing so is higher to a pre-established cut value S^*.

This exercise is done bank by bank, and then the survivorship predictions are compared with the observed ones. According to this analysis, there can be two possible classification mistakes: predicting that a bank would survive until t* when it didn't, or predicting that the bank would not survive until t*, when it did.

Table 9 presents the resultant classifications out of the previously described analysis. Predictions where made taking three reference periods: 365, 547 and 731 days. The proportion of banks that had survived until the reference period was taken as cut value, as usually done.

Table 9: Cox's model predictions.

	Predicted values		
	0	1	Total
365-days predictions.			
0	34	10	44
1	14	44	58
Total	48	54	102
547-days predictions.			
0	38	12	50

1	11	41	52
Total	49	53	102
731-days predictions.			
0	41	12	53
1	9	40	49
Total	50	52	102

The columns correspond to predicted values and the rows to observed values. For example, for the 365-day predictions, 34 banks failed before 365 days, and the model correctly predicted that. 44 banks that survived more than 365 days are correctly classified by the model. On the other side, 10 banks are classified in the survival group, while they failed before 365 days, and 14 banks were incorrectly classified in the default group while they survived during the reference period.

In general terms, the model's prediction capacity is more than acceptable, with a correct classification rate of around 80%. The predictive performance does not seem to change with the prediction horizon, though a small improvement is observed.

A second prediction exercise was to calculate survivorship functions for the different bank groups. That is, the predicted survivorship probabilities where calculated for three bank groups classified according to their observed performance. Following Wallen's (1991) classification, banks can be separated in 1) seriously ill, 2) ill, and 3) sane. The first ones correspond to the group that failed before 365 days, the second ones correspond to those that failed between 365 and 547 days, and the last ones to those that didn' t failed. For each bank group the survivorship function was calculated, using the financial indicators' averages. This average values are shown intable 11.

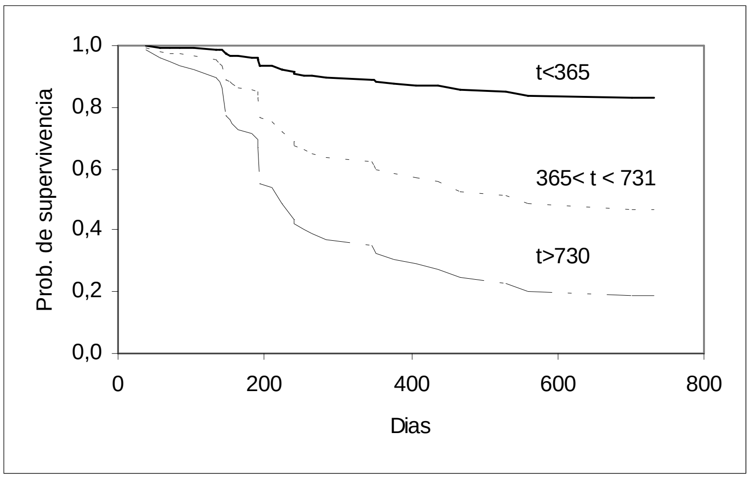
Tabla 11: Explanatory variables' average values for the different bank groups.

Failure	ind1	ind2	ind3	ind4	ind5	ind6	ind7
<365	15,033	6,773	21,073	7,944	14,748	85,231	0,017

365< t< 547	22,616	6,271	37,301	20,237	21,243	46,090	3,361
t> 730	18,603	6,483	34,415	18,791	10,417	43,119	6,753

Results are shown graphically in figure 4.

Figure 4: Survivorship functions predicted for different bank groups.



These results show that the bank dynamics are notoriously different according to the banks' financial performance. The survivorship probabilities decrease slowly until approximately 150 days after the crisis began. After 200 days, they show a strong risk acceleration for banks with worse conditions, and then they continue to fall slowly. The probabilities, for all the banks, seem to be stabilized at the 400 days from the beginning of the crises.

5 Conclusions.

This paper presents improvements in many directions on the study of the bank crisis dynamics in Argentina. First, it allows getting a clear description of the way in which the facts that ended in the default of a considerable number of bank institutions developed, been consequence of the events that happened after the Mexican crisis. Second, since the time to default is included as a variable in the duration model we used, it was possible to clearly identify important factors in the bank failure process. This is an advantage on the binary models, which, though their good predictable capacity for the Argentinean case in Dabós (1998), have problems to separate the individual effect of the explanatory variables.

The used model seems to be a good balance between flexibility and parsimony. The Cox's model semiparametric characteristic allowed us to estimate the parameters without laying on restrictive or unreal structures about the failure dynamics, as it happens with parametric models which are based on specific functional structures. This paper supplies original evidence about the functional structure of the hazard rate function, which presents a clear non-monotonic structure. Although it is based on a relatively small number of observations, the used methodology could provide interesting information about the non-parametric estimation of that function. This is an interesting point for future research.

The dynamic of bank failures can be fairly characterized by observable factors, which discards the possibility that it had been governed by contagion processes solely, where the bank financial situation does not play any role. It is yes interesting noting that the non-monotonicity of the hazard rate function suggests that there were contagion effects, and that they had a strong influence in the first 200 days of the crisis.

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STATISTICAL APENDIX.

Cooperative Banks.

	BANK.	**Disappearing Date as Cooperative Bank.**	**Modifications (Disappearing Reason).**	**Duration (in days since 20-12-94 to 25-09-97).**
1	ACISO	15 February 1995	Absorbed by Banco Integrado Departamental C.L.	57
2	Aliancoop	3 July 1995	Fusion with other 5 Coop. Banks. Banco Argencoop C.L. creation.	195
3	**Almafuerte**			**1010**
4	Bica	1 August 1995	Became a S.A. (Bica S.A.)	224
5	C.E.S	3 July 1995	Fusion with other 5 Coop. Banks. Banco Argencoop C.L. creation.	195
6	Carlos Pellegrini	29 June 1995	Transferred assets and liabilities. Bank Bisel S.A. creation.	191
7	Coinag	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
8	Cooperativo del Este	30 June 1995	Transferred assets and liabilities to Banco Entre Ríos S.A.	192
9	Nicolás Levalle	16 August 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	239
10	Caseros	29 September 1995	Transferred comercial fund to Banco de la Cuenca del Plata S.A., that changed name for Banco Caseros S.A.	283
11	Coop. De La Plata	8 May 1995	Absorbed by Banco Mayo C.L.	139
12	**Coopesur**	4 March 1997	Revoked.	805
13	**Credicoop**			**1010**
14	**De Balcarce**			**1010**
15	De la Ribera	15 February 1995	Absorbed by Banco Integrado Departamental C.L.	57
16	De las Comunidades	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
17	De los Arroyos	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
18	**De Rio Tercero**			**1010**
19	Del Noroeste	23 May 1995	Absorbed by Banco Cooperativo de Caseros Limitado.	154
20	**Patricios**	1 April 1996	Became a S.A. (Banco Patricios S.A.)	468
21	**Emp. De Tucumán**			**1010**
22	Horizonte	3 July 1995	Fusion with other 5 Coop. Banks. Banco Argencoop C.L. creation.	195

23	Independencia	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
24	Institucional	30 June 1995	Transferred assets and liabilities to Banco Entre Ríos S.A.	192
25	Integrado Departamental	16 August 1995	Revoked.	239
26	Local	3 July 1995	Fusion with other 5 cooperative banks. Banco Argencoop C.L. creation.	195
27	**Mayo**			**1010**
28	Meridional	16 August de 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	239
29	Noar	2 May 1995	Absorbed by Banco Mayo C.L.	133
30	Nordecoop	3 July 1995	Fusion with other 5 cooperative banks. Banco Argencoop C.L. creation.	195
31	Núcleo	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
32	Nueva Era	1 March 1995	Absorbed by Banco El Hogar de Parque Patricios C.L.	71
33	Rural de Sunchales	3 April 1995	Absorbed by Banco Bica.	104
34	San José	16 May 1995	Transferred assets and liabilities. Banco Bisel S.A. creation.	147
35	Sudecor	3 July 1995	Became S.A. (Banco Sudecor Litoral S.A.)	195
36	**B.U.C.I.**	2 January 1996	Became S.A. (B.U.C.I. C.L.)	378
37	Vaf	3 July 1995	Fusion with other 5 cooperative banks. Banco Argencoop C.L. creation.	195
38	Vallemar	1 August 1995	Absorbed by B.U.C.I. C.L.	224

Private National Banks

	BANKS	Disappearance Date (or Problems)	Modifications (Disappearance Reason or Problems)	Duration (in days since 20-12-94 to 25-09-97)
1	Banco Asfin S.A.	1 June 1995	Transferred assets and liabilities. to Banco Velox.	163
2	Banco Austral S.A.	17 August 1995	Revoked.	240
3	Banco Baires S.A.	1 June de 1996	Transferred assets and liabilities to Banco Crédito Provincial S.A.	529
4	Banco Basel S.A.	24 May 1995	Revoked.	155
5	Banco Caudal S.A.	11 September 1995	Transferred assets and liabilities to Banco Mayo C.L.	265
6	Banco Comafi S.A.			1010
7	Banco Comercial de Tres Arroyos S.A.			1010
8	Banco Comercial de Tandil S.A.	1 April 1996	Absorbed by Banco Crédito Pcial. S.A.	468
9	Banco Comercial Israelita S.A.			1010
10	Banco Crédito de Cuyo S.A.			1010
11	Banco Crédito Provincial S.A.			1010
12	Banco de Cnel. Dorrego y Trenque Lauquen S.A.	30 August 1995	Revoked.	253
13	Banco de Crédito Argentino S.A.			1010
14	Banco de Crédito Comercial S.A.	2 May 1995	Transferred comercial fund to Banco Unión Comercial e Industrial C.L.	133
15	Banco de Galicia y Bs. As. S.A.			1010
16	Banco de Junín S.A.	1 February 1996	Absorbed by Banco Crédito Comercial S.A.	408
17	Banco de Caseros S.A.	21 November 1996	Revoked.	702
18	Banco de la Edificadora de Olavarría S.A.			1010

19	Banco de Olavarría S.A.	4 de December 1995	Transferred assets and liabilities to Banco Mayo C.L.	349
20	Banco de Valores S.A.			1010
21	Banco del Buen Ayre S.A.			1010
22	Banco del Fuerte S.A.	7 December 1995	Revoked.	352
23	Banco del Iberá S.A.	12 May 1995	Transferred assets and liabilities to Banco de Corrientes.	143
24	Banco del Sol S.A.			1010
25	Banco del Sud S.A.	1 December 1995	Changed name for Banco Bansud S.A.	1010
26	Banco del Suquía S.A.			1010
27	Banco Exprinter S.A.			1010
28	Banco Extrader S.A.	26 January 1995	Revoked.	37
29	Banco Feigin S.A.	18 July 1995	Revoked.	210
30	Banco Finansur S.A.			1010
31	Banco Florencia S.A.			1010
32	Banco Frances del Rio de la Plata S.A.			1010
33	Banco Interfinanzas S.A.	15 April 1997	Changed name for Banco B.I. Creditanstalt S.A.	1010
34	Banco Israelita de Cordoba S.A.			1010
35	Banco Julio S.A.			1010
36	Banco Liniers Sudamericano S.A.			1010
37	Banco Los Tilos S.A.			1010
38	Banco Macro S.A.			1010
39	Banco Mariva S.A.			1010
40	Banco Mayorista del Plata S.A.			1010
41	Banco Medefin S.A.	27 June de 1996	Changed name for Banco Medefin UNB S.A.	1010
42	Banco Mercantil Argentino S.A.			1010

43	Banco Mercurio S.A.			1010
44	Banco Mildesa S.A.	1 de April de 1997	Absorbed by Banco Rio Negro S.A.	833
45	Banco Monserrat S.A.	1 August 1995	Absorbed by Banco del Suquia S.A.	224
46	Banco Multicredito S.A.	15 March 1995	Revoked.	85
47	Nuevo Banco de Azul S.A.	8 May 1997	Revoked.	870
48	Banco Piano S.A.			1010
49	Banco Platense S.A.	22 May 1997	Revoked.	884
50	Banco Popular Argentino S.A.	1 July 1996	Absorbed by Banco Roberts S.A.	559
51	Banco Popular Financiero S.A.	1 July 1996	Absorbed by Banco Sudecor Litoral S.A.	559
52	Banco Privado de Inversiones S.A.			1010
53	Banco Provencor S.A.	20 June 1995	Transferred comercial fund to Banco Mayo C.L.	182
54	Banco Quilmes S.A.			1010
55	Banco Real S.A.			1010
56	Banco Regional de Cuyo S.A.			1010
57	Banco Republica S.A.			1010
58	Banco Rio de la Plata S.A.			1010
59	Banco Roberts S.A.			1010
60	Banco Roela S.A.			1010
61	Banco Saenz S.A.			1010
62	Banco Shaw S.A.	1 December 1995	Absorbed by Banco del Sud S.A.	346
63	Banco UNB S.A.	1 March 1996	Absorbed by Banco Medefin S.A.	437
64	Banco Velox S.A.			1010

Cooperative Banks.

	BANK	T3	IND1	IND2	IND3	IND4	IND5	IND6	IND7
1	Aciso	57	11,31	7,84	15,13	5,42	14,83	71,7	15,1
2	Aliancoop	195	16,14	5,2	26,76	10,28	25,55	29,6	2,9
3	Almafuerte	731	15,78	5,34	30,39	4,82	9,01	96,6	10,1
4	Bica	224	12,97	6,71	18,95	9,53	13,28	33,3	16
5	C.E.S.	195	22,95	3,36	26,41	14,22	25,3	73,4	3,3
6	Carlos Pellegrini	191	14,71	5,8	29,53	9,47	13,49	17,4	7,9
7	Coinag	147	16,47	5,07	22,59	12,2	13,16	50,4	17,4
8	Cooperativo del Este	192	12,15	7,23	16,17	8,04	13,39	57,1	10,7
9	Nicolas Levalle	239	28,09	2,56	34,37	10,85	22,59	50,2	-6,6
10	Caseros	283	17,76	4,63	22,8	10,28	20	48,6	6,4
11	Coop. de la Plata	139	11,83	7,45	8,62	0,15	9,84	135,3	-32,1
12	Coopesur	731	12,52	6,99	22,88	4,88	20,39	60,3	7,4
13	Credicoop	731	15,06	5,64	31,73	9,27	20,12	8,3	12,9
14	De Balcarse	731	25,65	2,9	23,98	15,42	11,99	23,7	-5,2
15	De la Ribera	57	10,46	8,56	17,89	0,85	14,01	178,4	8,1
16	De las Comunidades	147	29,37	2,4	22,53	25,4	25,12	38,6	0,2
17	De los Arroyos	147	15,58	5,42	22,55	10,24	14,95	36,6	7,3
18	De Río Tercero	731	25,98	2,85	11,84	21,45	20,18	46,3	9,2
19	Del Noroeste	154	10,09	8,91	32,78	4,85	9,1	139	-0,2
20	Patricios	468	11,22	7,91	20,19	2,36	22,06	71,7	7,9
21	Emp. de Tucumán	731	50,18	0,99	55,17	91,24	9,77	44	10,2
22	Horizonte	195	16,73	4,98	17,43	7,93	22,55	77,1	-4,4
23	Independencia	147	16,76	4,97	20,39	9,76	13,47	43,8	-0,8
24	Institucional	192	13,17	6,59	14,82	9,44	13,57	35,2	17,9
25	Integrado Depart.	239	11,86	7,43	13,31	6	11,63	48,3	17,5
26	Local	195	9,43	9,6	22,31	1,19	27,78	177,2	-62,3
27	Mayo	731	12,97	6,71	31,54	3,3	13,87	38,6	1
28	Meridional	239	17,65	4,67	19,41	9,04	17,26	80,9	-4,2
29	Noar	133	10,32	8,69	17,1	4,21	10,1	98	16,2
30	Nordecoop	195	16,33	5,12	14,63	11,8	18,36	34,2	3,05
31	Núcleo	147	31,23	2,2	17,89	31,38	16,12	93,5	3,72
32	Nueva Era	71	15,37	5,51	22,11	6,08	7,57	61,3	4,1
33	Rural de Sunchales	104	13,71	6,29	18,95	6,68	13,25	87,6	-6,7
34	San José	147	28,11	2,56	26,69	22,14	16,5	17,3	5,4
35	Sudecor	195	15,15	5,6	17,02	8,42	14,07	11,2	6,6
36	B.U.C.I.	378	15,6	5,41	16,12	12,07	16,24	37,3	11,1
37	Vaf	195	12,16	7,22	26,6	4,08	19,03	132,5	-5,2
38	Vallemar	224	8,38	10,93	20,57	1,04	20,86	158,8	-61,2

T3= Duration (from 20/12/94 to 20/12/96)

Private National Banks.

	BANK	T3	IND1	IND2	IND3	IND4	IND5	IND6	IND7
1	Asfin S.A.	163	11,37	5,98	20,38	5,58	11,42	64,48	7,09
2	Austral S.A.	240	18,79	4,32	11,05	16,13	15,71	33,1	14,31
3	Baires S.A.	529	18,52	4,39	25,96	16,71	9,94	32,16	3,19
4	Basel S.A.	155	28,35	2,53	37,91	-10,9	9,33	10,31	7,45
5	Caudal S.A.	265	12,61	6,93	15,1	5,44	5,12	101,1	6,81
6	Comafi S.A.	731	6,35	14,74	43,3	5,82	1,97	13,25	14,78
7	Com.Tres Arroyos S.A.	731	16,76	4,96	22,25	13,57	11,72	59,8	0,27
8	Com. de Tandil S.A.	468	14,64	5,83	24,31	1,79	16,31	106,5	-3,25
9	Com. Israelita S.A.	731	11,93	7,38	24,22	9,19	7,68	107,5	10,31
10	Cred. de Cuyo S.A.	731	17,75	4,63	27,6	13,95	12,44	61,26	18,63
11	Credito Pcial S.A.	731	11,87	7,42	42,35	3,51	14,82	20,1	6,03
12	Cnel. Dorrego S.A.	253	4,43	21,56	17,71	-2,23	14,9	442	6,97
13	Credito Argentino S.A.	731	13,67	6,31	32,57	7,59	10,93	43,35	3,11
14	Credito Comercial S.A.	133	12,24	7,17	21,41	7,55	15,36	115,1	-7,47
15	Galicia y Bs. As. S.A.	731	11,27	7,88	28,84	7,48	8,05	38,48	11,9
16	De Junin S.A.	408	15,5	5,45	27,93	10,75	10,1	43,52	4,81
17	Caseros S.A.	702	95,1	0,05	120,3	122,6	84,68	0,16	-4,62
18	De la Ed. de Olav. S.A.	731	13,89	6,2	19,33	7,17	12,24	139,1	14,5
19	De Olavarria S.A.	349	15,58	5,42	16,04	8,61	11,86	82,27	10.19
20	De Valores S.A.	731	10,47	8,54	48,57	6,52	5,64	55,13	0,42
21	Del Buen Ayre S.A.	731	12,39	7,07	20,33	4.99	7,15	37,41	8,31
22	Del Fuerte S.A.	352	9,05	10,05	15,6	-0,4	13,42	290,7	-36,9
23	Del Ibera S.A.	143	16,91	4,91	22,22	14,15	15,91	19,87	7,8
24	Del Sol S.A.	731	26,6	2,76	4,81	16,97	10,5	-0,98	7,03
25	Del Sud S.A.	731	17,97	4,56	31,1	18,5	9,7	22,05	9,56
26	Del Suquia S.A.	731	11,89	7,41	24,1	8,14	9,24	26,9	17,1
27	Exprinter S.A.	731	7,45	12,42	84,57	5,77	1,14	19,34	-5,83
28	Extrader S.A.	37	7,24	12,82	31,32	5,16	3,35	84,13	-16,14
29	Feigin S.A.	210	5,9	15,94	31,21	2,65	4,18	70,95	10,57
30	Finansur S.A.	731	4,69	20,3	23,3	3,14	2,71	25,75	17,03
31	Florencia S.A.	731	9,23	9,83	9,87	4.99	4,85	109	14,25
32	Frances S.A.	731	17,87	4,59	34,3	17,5	7,18	11,6	11.99
33	Interfinanzas S.A.	731	10,44	8,58	91,9	5,17	4,49	27,46	4,95
34	Israelita de Cord. S.A.	731	11,3	7,85	23,3	7,72	10,92	105,8	9,28
35	Julio S.A.	731	29,47	2,39	12,54	13,44	8,69	39,93	5,3
36	Liniers Sud. S.A.	731	7,27	12,74	15,23	4,68	5,39	68,98	23,32
37	Los Tilos S.A.	731	15,01	5,66	25,12	12,11	10,03	139,9	7,89
38	Macro S.A.	731	11,03	8,06	31,79	10,93	2,24	41,05	16,04
39	Mariva S.A.	731	10,7	8,35	60,55	3,85	3,66	30,6	7,38
40	Mayorista del Plata S.A.	731	48,56	1,06	79,8	78,26	10,22	-0,13	-8,31
41	Medefin S.A.	731	8,15	11,26	35,43	7,68	2,78	19,3	4,55
42	Mercurio S.A.	731	76,47	0,31	91,1	213,2	81,5	-0,009	-22,35
43	Mercantil Arg. S.A.	731	13,95	6,16	36,7	2,77	15,64	15,06	-9,75
44	Mildesa S.A.	731	9,1	9,98	29,75	8,43	3,46	6,45	9,05
45	Monserrat S.A.	224	15,45	5,47	24,01	7,02	13,65	132,52	-1,3
46	Multicredito S.A.	85	11,18	7,94	12,72	4,9	8,78	66,05	6,03
47	Nuevo Bco de Azul S.A.	731	13,66	6,32	24,45	2,89	14,45	132,3	-8,64
48	Piano S.A.	731	12,66	6,89	25,88	7,27	2,38	27,14	3,87
49	Platense S.A.	731	16,18	5,18	21,46	8,97	16,12	135,7	19,66
50	Popular Arg. S.A.	559	12,6	6,94	41,02	6,06	12,28	40,93	-13,7

51	Popular Fin. S.A.	559	13,78	6,26	33,63	6,44	16.9	58,37	2.99
52	Privado de Inv. S.A.	731	49,68	1,01	83,02	58,28	9,86	-0,03	-1,98
53	Provencor S.A.	182	14,2	6,05	10,05	7,66	18,08	68,07	25,75
54	Quilmes S.A.	731	9,04	10,06	29,51	2,18	11,8	44,13	-3,96
55	Real S.A.	731	35,38	1,83	47,65	46,72	6,31	-1,38	0,55
56	Reg. de Cuyo S.A.	731	29,94	2,34	22,44	20,2	12,52	11,73	9,76
57	República S.A.	731	10,52	8,51	54,4	7,54	2,03	19,72	-7,6
58	Rio de la Plata S.A.	731	13,18	6,58	32,57	8,57	6,72	8,27	14,25
59	Roberts S.A.	731	11,54	7,66	21,55	9,47	5,65	21,37	13,46
60	Roela S.A.	731	32,18	2,11	31,44	20,82	0,94	18,37	5,23
61	Saenz S.A.	731	32,21	2,1	12,16	43,1	12,45	22,96	27,13
62	Shaw S.A.	346	11,9	7,41	34,16	7,23	11,1	53,03	-26,5
63	UNB S.A.	437	6,58	14,2	26,25	3,35	2,68	24,17	21,83
64	Velox S.A.	731	13,73	6,28	17,65	11,31	6,87	71,34	6,81