BANKRUPTCY PREDICTION IN BRAZIL: A TWO-STAGE MODEL EMPLOYING ACCOUNTING DATA

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RESUMO

Para tentar medir e prever a "saúde financeira" de empresas, pode-se usar os chamados modelos de previsão de insolvência, construídos com apoio em técnicas estatísticas e aplicados para analisar índices econômico-financeiros selecionados, obtidos a partir dos demonstrativos contábeis.
A partir da metade dos anos 90, questões tais como o aparecimento de novas técnicas de modelagem, a crescente importância da gerência do risco de crédito e as condições econômicas vigentes trouxeram de volta o interesse pela análise e previsão da insolvência de empresas.
O objetivo deste artigo é descrever um método para elaboração de modelos de previsão de insolvência, fundamentado em técnicas estatísticas, e ilustrá-lo através de uma aplicação empírica a uma amostra de empresas comerciais e industriais brasileiras, empregando dados para o período de 1996 a 2000.

PALABRAS CHAVES: Previsão de insolvência, análise discriminante, efeito tesoura.

ABSTRACT

It may happen that firms collapse irrespective of their financial statements being published in a regular basis and being prepared according to professional accounting standards and statutory requirements. The relationship between accounting data and business failure therefore deserves ongoing and expert attention. Bankruptcy prediction refers to the search for applicable models or procedures allowing to anticipate convincing signals of future problems.This paper proposes an empirical model for bankruptcy prediction that proceeds in two-stages: the first seeks to select appropriate predictors; the second employs discriminant analysis to classify successful and bankrupt firms. Empirical information has been collected from accounting data published by the Brazilian equivalent of SEC and refers to the period 1996 / 2000. Considering comparable figures reported in the literature, retained models obtain quite good hit ratios. For the selected time period, accounting data may be considered a convenient empirical support to predict bankruptcy in the Brazilian context.

KEY WORDS: Bankruptcy prediction, discriminant analysis, "scissors effect".

1. INTRODUCCIÓN

It is not possible to be completely sure about the future results of human decisions made in complex systems under changing environmental conditions. This is especially true as long as business decisions are concerned. Management science models offer a reliable approach to minimizing that uncertainty. The development and use of several models and techniques can be of great help to understanding, managing and controlling the consequences stemming from business failure.

In spite of its long history in terms of the specialized literature (Fitzpatrick 1932, Winakor & Smith, 1935), the study of business failure supported by accounting indicators took impulse in the seventies (Blum 1974, Deakin 1972, Edmister 1972, Johnson 1970, Kanitz 1978), soon after pioneering work by Beaver (1967) and Altman (1968). In a comprehensive survey, Altman (1984) reviewed a large number of works, both published and non published, that had appeared outside the United States up to the early eighties; about a decade later he updated and enlarged that survey (Altman & Narayanan, 1997).

In Brazil, the analysis of firm insolvency with forecasting objectives underwent a significant progress throughout the 1980s (Bragança & Bragança, 1984; Kasznar, 1986), following the way opened up by Kanitz (1978) and Altman *et al*. (1979).

Insolvency prediction models may be applied in a variety of business situations. For instance, banks use those models to analyze credit risks and to make loan decisions. Even though such models are seldom employed as the unique approach to most daily decisions about granting or not the loan, they have an important role concerning periodic revisions. Those models can also serve as a supporting tool for practicing accountants, e. g. as an aid for auditors to evaluate their clients' reported performance (Zavgren, 1989).

From the mid 1990s on the emergence of new modeling techniques and the growing importance of risk credit management, as well as the prevailing economic conditions, brought about renewed interest toward the analysis and prediction of insolvency (Altman, Marco & Varetto, 1994; Brockert *et al*., 1997; Eisenbeis, 1997; Lennox, 1999; Matias & Siqueira, 1996; Santos, 1996). Some authors investigated whether failure prediction models are transferable across countries (Ooghe & Balcaen, 2002)., while others adopted a comparative approach (Hunter & Isachenkova, 2000, Laitinen & Kankaanpää, 1999; Mossman *et al*., 1998; Ooghe *et al*., 1999). Industry-related aspects of bankruptcy prediction have also been studied (Platt, 1989; Platt & Platt, 1991). Recently, Balcaen & Ooghe (2004) completed a very comprehensive and updated survey where traditional statistical models have been scrutinized from numerous viewpoints.

This article describes an empirical approach to help build models for insolvency prediction based on statistical techniques (see Taffler, 1984), and illustrates the approach by applying it to a sample of Brazilian commercial and industrial firms, using data for the period 1996-2000.

Previous authors (e. g., Shirata, 1998) call attention to the fact that, in most studies related to insolvency prediction, variable selection, even when mentioned, is not always clearly discussed, if at all. The approach proposed in this article depicts model building as a two-stage process wherein predictor variables selection, the first stage, is also statistically treated (see also Sanvicente & Minardi, 1998).

2. METHOD

In this section the main methodological steps for data collection and for the analysis of results are indicated.

2.1 RESEARCH DESIGN AND DATA COLLECTION

For convenience reasons in terms of data availability, it was decided to use the register of Brazilian publicly traded companies, originated and distributed by *CVM- Comissão de Valores Mobiliários*, the Brazilian equivalent of the American SEC. This directory contains, among other, comprehensive accounting information on registered companies. Indicators to be used for statistical estimations were selected from the specialized literature.

To distinguish between failure states two a priori groups of companies were defined. Firms in the group of “problematic” companies were identified, according to the CVM register, as having already formally petitioned for supervised liquidation, or that were subjected to legal reorganization (concordatárias), or endured widely recognized, out-of-court manifestation of “problems” (see also Altman & Narayanan, 1997, p. 37). Hereinafter these “problematic” firms will be referred to as “insolvent” or “bankrupt”.

To compose the group of “successful” firms a convenience sample was designed comprising about three solvent companies for each insolvent already selected. Business sector and size (total capital) were also taken into account to obtain “similar” observations, so that the two groups obeyed respectively the same sectoral composition and, within each sector, had approximately the same size. A final group of 76 companies was obtained. Appendices A and B list the sectoral affiliations of each firm in the two groups.

Time period was chosen as the 1996-2000 interval. During that period available information would be, at the same time, more recent and, supposedly, free from direct influence of a national economic plan (*Plano Real*). For each firm and each accounting indicator three yearly figures were retained as they related to the year when the firm filed for bankruptcy and the two immediately preceding years.

Data collection was eased through the use of *SABE-Sistema de Análise de Balanços Empresariais*, a commercial software tool available in Brazil. The main sources for accounting indicators were the Balance Sheet and the Operational Income Statement. Therefrom data were collected corresponding to 36 (thirty-six) indicators for the period of 1994 – 2000, and included liquidity ratios, capital structure, flow of funds, profitability and market indicators.

Information on flows of funds included not only traditional indicators (such as Net Working Capital), but also a specific ratio aimed at capturing the so-called “scissors effect”, upon believing that financial distress precedes bankruptcy. The “scissors effect” is defined as the ratio “working capital *less* operating working capital” to “total assets”. According to Assaf Netto & Silva (1997, p. 19), the occurrence of the "scissors effect" indicates financial threats to the extent that the company is experiencing, for successive periods, an increase in the need to finance working capital that is greater than the difference “working assets less working liabilities”. In this case the numerator in the “scissors effect” is more and more negative (see also Kane *et al*., 2000).

2.2 STATISTICAL MODEL AND DATA ANALYSIS

Whenever the study of corporate performance is approached by combining a large amount of quantitative information about several attributes, it is often appropriate to make use of some kind of selection procedure in order to identify the " main" variables of interest - for instance, those variables that "influence most", or that are " more reliable ", or possessing any other "virtues”.

In particular, when separation and classification of companies in terms of “success or failure” is concerned, it is also advisable to apply statistical techniques that may serve, first, to determine such "main variables" and, second, to “correctly” classify a priori a given company as “successful” or not. Accordingly, these are the two most important tasks in any exercise of bankruptcy prediction.

This paper presents a two-stage prediction model. In the first stage, the selection step, the initial set of variables is statistically scrutinized to provide a working set of variables that will be used, in the second stage, for prediction purposes. Multivariate statistics helps select well-performing candidates for each step.

According to Shirata (1998), in many studies about insolvency prediction variable selection has not been clearly discussed and relies on implicit or “intuitive” criteria whereby it is often difficult to understand how the group of variables has been obtained. In this paper it is argued that there is an adequate albeit simple form of selecting the variables that will compose the forecasting model. In the first, selective stage Discriminant Analysis and Logistic Regression supported variable selection and provided two working lists of selected variables. The final list consisted of precisely those variables that belonged to both working lists. Hopefully this procedure will confer some "robustness " to the selected list of 16 predictors.

Taking the preceding list as a starting point, the prediction model followed from the application of stepwise Discriminant Analysis. Since the initial list had already undergone a double test of relevance in terms of group separation, likely statistical defects of the stepwise approach have been traded against its predictive virtues, to be discussed now.

In order to avoid that the forecasting model would consist of contemporary (or current) variables alone, in which case the very idea of prediction might loose practical sense, three observations are used for each indicator - one for the year when the company filed for or was declared bankrupt, and one for the first and second year immediately preceding the event. Accordingly it may happen that “contemporaneous” observations will be excluded from the final specification for the predictive equation, excluding tardy and hence useless effects for prediction purposes.

2.3 RESULTS

In this section two kinds of results are presented. The selection of variables is explained first, followed by the results of the modeling stage that comprise the analysis of both the separation power of the selected variables and the predictive power of the retained equations. In addition, descriptive results are included to help visualize and compare the behavior of some indicators within each group of companies.

First Stage – Selected predictors and their behavior along time

Among the variables selected in turn by Discriminant Analysis and by Logistic Regression, precisely 16 indicators belonged simultaneously to the two groups; they are shown in Table 1. The smallest F value equaled 4,173 and the largest significance level was 0,045 (less than 5%). These variables composed the initial list where to start the search for a final predictive equation.

Table 2 shows the evolution of some indicators during the 3-year period, for the group of insolvent companies. The average Quick Ratio is deteriorating along the period. In addition, the deviation patterns are decreasing in the same period, pointing to a growing homogeneity of behavior within the insolvent group. The most significant variation occurs between T-1 and T (18,93%), showing a worsening financial health in that group. This finding suggests the lack of positive results in managing firms’ liabilities in the short run,

In what the variable Current Ratio (LC) is concerned, figures behave differently: averages are deteriorating from year to year, whereas the deviation pattern fluctuates.

Table 1 – Selected variables and their mnemonics

NAMES	MNEMONICS *
1. Net Operating Income / Total Assets	$ROAT_0$
2. Return on assets ratio	$RLAT_0$
3. "Scissors Effect"	$STAT_1$
4. Return on assets ratio	$RLAT_1$
5. Gross margin	MB_2
6. Quick ratio	LS_0
7. Current ratio	LC_0
8. "Scissors Effect"	$STAT_0$
9. Current ratio	LC_1
10. Net Operating Income / Total Assets	$ROAT_1$
11. Quick ratio	LS_1
12. "Scissors Effect"	$STAT_2$
13. Quick ratio	LS_2
14. Return on assets ratio	$RLAT_2$
15. Net margin	ML_2
16. Debt to assets ratio	$ETAT_1$

* Note - subscripts indicate the year wrt bankruptcy filing: T_0 = same year; T_1 = one year earlier; T_2 = two years earlier; see text.

Table 2 - Evolution of selected indicators for insolvent companies

	Year T-2			**Year T-1**			**Year T**		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
LS	0,5815	0,5819	100,07%	0,4876	0,5784	118,62%	0,3695	0,4863	131,61%
LC	0,7457	0,5977	80,15%	0,6600	0,6458	97,85%	0,4947	0,5246	106,04%
STAT	-0,1886	0,3777	200,27%	-0,2173	0,4854	223,38%	0,3658	0,4638	126,79%
ROAT	-0,1098	0,3093	281,72%	-0,2545	0,5583	219,37%	-0,2993	0,3992	133,38%
RLAT	-0,1288	0,3034	235,56%	-0,2165	0,5206	240,46%	-0,2728	0,4146	151,98%

Note – Mean = arithmetic; SD = standard deviation; CV = coefficient of variation (SD/Mean) in %

In comparison to Quick Ratio, it can be concluded that most of the insolvent companies presented a relative increase in inventories, maybe due to bad purchases or, more likely, to bad sales results. Again regarding inventories, it may be noticed that, during the period, the overall market underwent relevant transformations. Probably, insolvent companies may have failed to adapt to the new sales configurations quickly and/or effectively enough.

The evolution of the "scissors effect" variable (STAT) is compatible with a situation of pre-insolvency. A company in that situation endures an extreme difficulty to manage cash, possibly the occurrence of multiple commitments leading to the sacrifice of operational activities in the attempt to meet very short term liabilities.

For the two ratios relating to Profitability – namely, Return on Assets (RLAT) and Net Operating Income to Total Assets (ROAT) - averages decreased consistently throughout the period, meaning that, in the sample used here, companies steadily lost profitability. The worst change occurred from T-2 to T-1, corresponding to a 132 % decrease in ROAT and suggesting a worse operational and, consequently, financial inefficiency, leading the company to sharper insolvency.

In the case of liquidity ratios, the coefficient of variation increased along the period within the insolvent group, indicating the instability of their financial management in the short term. In the case of profitability ratios, the coefficient of variation evidenced a clear fluctuation.

The variation in Returns on assets (RLAT) underwent a neat movement of growth followed by decrease. It must be recalled that averages are becoming more and more negative along the periods. The time path describing the variation in STAT keeps similarity with RLAT. The opposite happened to ROAT variation, for which there were just regular decreases, suggesting the common impossibility to generate profitable operations

Table 3 exhibits the behavior of four indicators within the group of solvent companies. The figures for both Quick and Current Ratios don't reveal any special feature, except for the values of the coefficient of variation. The comparison of these values with those found for insolvent companies (Table 2) shows that the former values are almost always greater, indicating the larger variability of the selected indicators within the insolvent group.

The inverse is true with respect to STAT, ROAT and RLAT. In fact these indicators showed much more variation in the solvent case; at the same time, they are much less negative than in the insolvent case.

A tentative explanation for those differences might be sought in the behavior of liquidity, whose means are declining all over the periods for insolvent companies. With their liquidity in danger, the search of reasonable profitability is abandoned, becoming a secondary goal as a result of the accelerating insolvency process.

Table 3 - Evolution of selected indicators for solvent companies

	Year T – 2			Year T – 1			Year T		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
LS	0,8735	0,7334	83,96%	0,8385	0,6203	73,98%	0,9053	0,7294	80,57%
LC	1,2586	1,2246	97,30%	1,2289	0,7868	64,02%	1,2915	0,9708	75,17%
STAT	0,0042	0,3105	7410,50%	-0,0064	0,2307	3599,06%	-0,0235	0,1826	777,02%
ROAT	0,0040	0,1748	4353,67%	-0,0070	0,1649	2365,85%	-0,0024	0,0889	3719,67%

Note – Mean = arithmetic; SD = standard deviation; CV = coefficient of variation (SD/Mean) in %

Second Stage – the forecasting model

The predictive results to be presented hereinafter appear as three different models, depending on which kind of time lags have been considered when stepwise discriminant analysis was applied to generate the predictive equations.

The rationale for distinguishing those three cases is that, in order for the prediction exercise to make sense, preference must be given to models requesting data that would be available before the occurrence of "problems". In what follows, contemporaneous equations are nonetheless considered and analyzed.

When three years were considered for inclusion in the predictive model, the stepwise procedure selected only contemporaneous indicators. The final form of the canonical, standardized equation is:

$$Y = 1{,}083\ ROAT0 - 0{,}293\ LS0 - 0{,}686\ RLAT0 + 0{,}569\ LC0 + 0{,}578\ STAT0.$$

Out of five variables two, namely LS0 and RLAT0, present negative signs. Considering the threshold locus, this means that the larger their values (in other words, the better the financial status), the nearer is insolvency, a clear inconsistency. A possible explanation for the negative sign is the high correlation among variables in the equation (e.g., LS0 correlates high with LC0, and RLAT0 with ROAT0). This is a recurrent problem in multivariate analysis. No attempt was made to eliminate correlated variables any further. Recall that the objective, in this stage, is to get a "good" equation in a forecasting sense.

Table 4 contains the predictive results. It can be seen that, out of 21 insolvent companies, the estimated discriminant function above correctly classifies 16 as insolvent and, incorrectly, 5 as solvent, yielding a hit ratio of about 76,2%. Out of 55 solvent companies, 52 were correctly classified against 3 incorrect ones, corresponding to a hit ratio of 88,2% for the solvent group.

Together, the 3-year model yielded an overall hit ratio amounting to 88,2% of successful classifications of the sampled companies. However, the so-called Type I error – that of classifying an endangered firm as a continuing entity (Altman & Narayanan, 1997, p. 39) – is admittedly quite high. According to Hair *et al*. (1998, p. 259), predictive accuracy is biased upward when the total sample is used.

Table 4 - Classification Matrix for the 3-year equation

Original membership	**Predicted as Insolvent**	**Predicted as Solvent**	**Total**
Insolvent	16	5	21
Insolvent (%)	76,2	23,8	100
Solvents	5	51	55
Solvents (%)	7,3	92,7	100
Correct classification of total sample (%)		88,2	

When only variables corresponding to the two past years preceding the failure event were considered, the final model resulting from the application of stepwise discriminant analysis can be written as the following standardized equation:

$$Y = 3{,}895\ ROAT1 - 3{,}593\ RLAT1 + 0752\ STAT1\ .$$

As it was the case before, this equation contains only information pertaining to the most recent period. Also the sign of RLAT is negative, and the same comments apply.

Using the estimated discriminant function, the classification matrix can be computed and appears in Table 5. The upward biased hit ratio didn't alter but the Type I error is very high.

When split sampling was applied to the preceding two equations, no significant change was observed in the hit ratio as they kept quite close to the preceding values of 88,2% and 81,6%, respectively.

Table 5 - Classification Matrix for the 2-year equation

Original membership	**Predicted as Insolvent**	**Predicted as Solvent**	**Total**
Insolvent	12	9	21
Insolvent (%)	57,1	42,9	100
Solvent	5	50	55
Solvent (%)	9,1	90,9	100
Correct classification in total sample (%)		81,6	

When only variables corresponding to the single oldest year preceding the failure event was considered, the final equation supplied by the application of stepwise discriminant analysis can be written in the following standardized form:

$$Y = -0{,}509\ MB2 + 0{,}472\ ML2 + 0{,}718\ STAT2 + 0{,}326\ RLAT2 + 0{,}069\ LS2\ .$$

The resulting classification is summarized in the Table 6. Note that, for this equation, cross validation brought about new values for the proportion correctly classified, as shown in the last row in that Table. Again, Type I error is very high.

Table 6 - Classification Matrix for the 1-year equation

Original membership	**Predicted as Insolvent**	**Predicted as Solvent**	**Total**
Insolvent	9	12	21
Insolvent (%)	42,9	51,7	100
Solvent	2	53	55
Solvent (%)	3,6	96,4	100
Correct classification of total sample (%)		81,6	
Correct classification of splitted sample (%)		78,9	

Summing up, results are always better (in terms of correct a posteriori classification) when contemporaneous information is allowed to enter the equation. This is obviously not an interesting specification for practical prediction purposes. When current information is dismissed (as it should be for practical reasons), resulting hit ratios are still quite good as they exceed 80%, an adequate figure *vis à vis* published results.

In all three cases hit ratios are biased upward. In addition, the error of incorrectly classifying “bad” companies as “good” ones was high to very high in the three cases. This calls for correction and improvement in the proposed specifications. Two possibilities come to mind. First, use the “complete” lists of variables in each case, avoiding the stepwise method and allowing selection to be made on logical grounds. Recall that the hit ratio increases with the number of variables. The “complete” list would provide 16 variables for 3 periods, 11 indicators for 2-year equation and 5 for one year. Second, one might reduce the initial specification of 16 variables by stepwise discriminant analysis and then repeat the resulting equation for the 2 and 1 year cases, adjusting only for consistency reasons; this is similar to a model used since 1979 by Altman (Altman & Narayanan, 1997, p. 39; Altman *et al*., 1979) for validation purposes.

Whenever both are allowed, newer information dominates (and even excludes) older ones. Notwithstanding the preceding comments, it may be argued that, according to this dominance, the equation including T1 and T2 , meaning two and three years backward, should be preferred. That choice is nonetheless dependent on the timely availability of necessary accounting data (see, however, the alert by Mossman *et al*., 1998).

3 DISCUSSION AND CONCLUSION

Predictive models are just a special though not exclusive type of tool for business risk assessment. The application of discriminant analysis is one among several forms of a priori company classification. Often any such models must be strengthened by the experience summarized into business analysts’ subjective evaluations. In the present paper accounting data serve as the only source of empirical information.

Models developed here consider the use of accounting data related to three periods, T, T-1 and T-2, where T is the (contemporaneous) year when bankruptcy was filed for. Of course, any model including contemporaneous information, either from accounting sources or else, is clearly uninteresting and hardly applicable in practical terms. However, in the three-year equation estimated here, all five variables are dated in year T.

It may be useful for auditors and business analysts to anticipate insolvency problems. In spite of their recognized limitations, predictive models could be incorporated to analytical procedures to help estimate failure probabilities and, for that matter, to avoid collapsing into insolvency states.

The models developed in this study present some differences in relation to previous work. Firstly, they can be viewed as an empirical approach to estimating the so-called “scissors effect”. In this study that variable appeared in all three discriminant equations and can then be considered as a relevant bankruptcy predictor (Horta, 2001, chapter 4).

Another difference concerns the selected time period. In fact, this paper can help throw some light on the business impacts of *Plano Real* in terms of *post facto* consequences since the insolvency predictors selected here depart from published literature in Brazil.

The third difference relates to the proposed two-stage model. In this study, two statistical techniques – namely, discriminant analysis and logistic regression - were simultaneously used to select predictive indicators; from this first stage a robust list of 16 variables was selected to be used in the specification of an *a priori* classification equation in the second stage.

Another aspect deserving mention is departure from parity sampling. Irrespective of recency, previous work often employed a paired sample of failed/non-failed firms. In this paper a more realistic relative proportion was adopted so that an excessive influence of insolvent firms would be avoided, as it is the case in real world.situations.

A particularly interesting result concerns the meaning of many variables present in the final equations. In all three equations the indicators serving to classify companies are admittedly of a different accounting nature in comparison to previous empirical research in the Brazilian context, e. g. "profitability" or the "scissors effect". The decreased importance of both debt and financial leverage indicators for insolvency prediction is also attested through their almost complete absence in the estimated equations.

These results are welcome as they correspond to the considerable changes occurred in the Brazilian economy in terms of increased openness and competitiveness, as well as the strengthening of firms operating under smaller profitability margins. In previous periods, markup and inflation were high and consequently financial managers prioritized short-term results; therefore liquidity indicators were preeminent in models of bankruptcy prediction. No doubt, new managerial priorities responded to those changes in economic conditions and, in what concerns the companies selected for this study, they are reflected in the kind of discriminant variables appearing in the final equations.

An additional interpretation of the noteworthy presence of profitability ratios as discriminant variables lies in the increased quality of accounting data in Brazil, as they offer today much more reliability than before, when accounting information was often disposed of or dismissed for bankruptcy prediction purposes. In this study correct predictions amounted to some 80% or more, attesting that accounting ratios provide a high information content even in prediction applications.

Misclassifications relating to Type I errors still deserve attention and improvement. At any rate, statistical techniques performed well in the exercises developed here. The combination of discriminant analysis and logistic regression provided an adequate selection of predictors and discriminant analysis served for prediction purposes as well.

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