Parsimonious Models of Financial Insolvency in Small Companies

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ABSTRACT. This study is an extension of current research on insolvency diagnosis. We intend to demonstrate that in small firms, the relevant information for the preventive diagnosis of insolvency can be synthesised in a model built upon a more reduced number of economic and financial ratios than the ones generally used in this kind of study. Our approach produces parsimonious models that can extract information from publicly available accounting-financial data. We demonstrate that using an extensive exploratory stage that will monitor the effects of correlation between financial variables, we will be able to build relatively stable models with a small set of variables.

The results of the models built by resorting to discriminant analysis and to logistic regression present a similar accuracy to models previously developed. Our models present the advantage of including a small number of variables that can be interpreted in the light of current financial theory and therefore it reduces the number of financial data needed to make an insolvency diagnosis. This is particularly decisive when working in an environment of restricted information availability, which is very common in small companies.

1. Introduction

The possible occurrence of an insolvency situation is a serious threat to the various economic agents holding an interest in the insolvent organisations. The discriminant models based on book values of accounting data can be very efficient screening devices (Altman and Saunders, 1998). In fact, it is not possible to make an exhaustive financial analysis for each small firm that resorts daily to financial institutions for fund-raising purposes. Moreover, as the number of inspected variables increases, it becomes more difficult to make a summary of the critical information, while the firm still has a good response and adjustment capacity (Houghton and Woodliff, 1987).

Nowadays there is a quite widespread acceptance of the capacity of discriminant models built from accounting data to predict insolvency (Altman, 1984). Although, we must be more precise in what sense we refer to prediction of insolvency. In fact, when a prediction is made about the insolvency situation of a firm through a discriminant model, we are, indeed, comparing the characteristics of this firm with those of a group of firms, which become insolvent.

On the other hand, there is no systematic body of knowledge, i.e., a theory, which establishes decisive variables and the causality behind the crisis. We believe that it is not plausible that an insolvency theory could recommend a large set of financial ratios like the ones regularly used in current empirical models.

It is our objective to develop a discriminant model that incorporates a reduced number of variables, because we expect that using a reduced number of variables makes the model less sample specific and easier to build from theoretical considerations.

Our model was developed from the accounting data of firms from the Portuguese Footwear Manufacture sector. This is a quite homogeneous sector structured around small size companies particularly affected by a recession period undergone by the Portuguese economy at the beginning of the decade. According to data obtained from the MOPE Data Base,[1] 1,922 Portuguese firms went bankrupt from 1992 to 1996, while six thousand

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firms faced a bankruptcy process or resorted to the corporate reorganisation plan.[2]

We tried to fit the model to a sectoral sample because one of the problems in developing parsimonious models lies in the industry requirements embodied in the methodology. The growing number of studies about financial distress and bankruptcy developed since Altman (1968) agreed on the difficulties of generalising results for companies of different industry sectors. Initially research on insolvency prediction tried to control for industry effects by matching the firms in the samples by sectors, but authors like Platt and Platt (1990) demonstrate that this kind of adjustment cannot accommodate industry effects on insolvency, which tend to produce instability of coefficients of the discriminant functions. Here we are assuming that the financial strength of a company with a given set of financial ratios depends on the industry to which it belongs.

In this study we demonstrate the capacity of building parsimonious discriminant models that are quite accurate on insolvency prediction of small firms. Our approach mitigates problems of lack of reliable and comprehensive financial information about small companies and allows the inclusion of a small set of variables with stable coefficients that behave consistently with financial theory.

The remainder of the paper is organised as follows. The next section tries to summarise the most relevant research in this field and introduces our definition of insolvency. In the third part we will introduce the sampling techniques and estimation procedures of discriminant models. In the fourth section we present the main results of the model and several kinds of sensitivity analysis. In the final section we present the conclusions.

2. Solvency diagnosis by means of economic and financial indicators

The study of the economic and financial indicators that make it possible to obtain a preventive diagnosis of corporate financial distress underwent a decisive impulse with the works of Altman (1968) and Altman, Haldeman y Narayanan (1977) resorting to multivariate statistical techniques, in particular Linear Discriminant Analysis (LDA). In subsequent years other researchers such as Zavgren (1985) and Zmijewski (1984) resorted to Logistic Regression (LR) and demonstrated that the classification accuracy of the models did not depend on the statistical method used.

Nevertheless, since the seminal works of Altman (1968), research began to concentrate on publicly traded firms and the asset-size was considered an important issue in sample selection. Small firms and very large firms were eliminated from the sample. The latter were eliminated due to the rarity of bankruptcy in this type of firm and for the small firms the argument was the lack of reliable and comprehensive information. However, since the work of Edmister (1972) researchers began to be interested in small sized companies. This author built the first discriminant function for insolvency prediction in small businesses. His seven-variable discriminant model could not work well on validation samples. Some possible causes of those results were pointed out, namely the existence of high levels of multicollinearity between financial ratios, which requires a strict control on the selection of the variables for the models. Keasey and Watson (1986, 1987) continued to recognise difficulties in the extension of this type of models to small firms. Nevertheless, the popularity of bankruptcy prediction models has been disseminated from the United States, overcoming some imperfection of the models. Currently there are countless credit institutions that have been incorporating these models in their risk analysis procedures. Moreover, during the 1980's, Central Balance-Sheets of European Central Banks began to collect small business accounting data and became reliable sources of small company data, which they began to use in their own empirical models (Bardos, 1984, 1991, 1995).

The common pattern that becomes evident in the literature is the difference in the number and type of variables used and the instability of the coefficients of the functions. Watson and Everett (1999) suggested that one of the possible explanations for the differences between models was the influence of the definition of financial failure on the results, which is usually constrained by the availability of data.

In this study we try to outline an efficient strategy for overcoming these deficiencies which tend to produce models that only work well in situations similar to those from which the function was generated (Edmister, 1972).

Since our purpose is to carry out a preventive diagnosis of insolvency situations, it would be advisable to avoid definitions based or legal instruments intended for the reorganisation of insolvent firms and/or for their liquidation. The bankruptcy concept is chiefly of a legal nature, without any specific economic and univocal significance, and mainly dependent on the political options followed at a particular time. Bankruptcy is often the lowest point of this process of economic and financial deterioration, although it is only one of the possible outcomes of the crisis, which, in principle, should ensure that the distribution of the assets of the non-complying firm should be performed in an orderly manner by the creditors. However, the sale of an insolvent firm, its absorption by another firm or even its liquidation by the respective shareholders, are other legal and possibly more frequent alternatives for the situation, not being specific of any type of crisis in particular. In short, insolvency does not necessarily lead to the winding-up of the firm.

Because we are essentially interested in the financial condition of the firms, it was decided to adopt an identification of insolvency similar to a "situation of a firm which can no longer meet its financial obligations, when these become due" (Beaver, 1966). In order to distinguish it from a one-off liquidity distress, the insolvency crisis was identified as a situation of a sustained non-compliance with banking obligations, throughout one whole year. This information was supplied by the Central Balance-Sheet Office of the Banco de Portugal (CBBP) and can be considered a simple and efficient way to assess the solvency deterioration of small firms. Edmister (1972) used a similar criterion of "loss borrower" to the US Small Business Administration (SBA) selecting 42 small firms that had loan defaults.

We adopted this indicator, since we believe that when a small firm begins to have problems with banks it will be considerably difficult to find alternative sources of financing and reverse the insolvency situation. A firm in such position has lost considerable flexibility and has externally issued a powerful indication of risk. Therefore, the solvency concept is associated with some inability to achieve results and/or to generate liquidity permitting the reversal of the non-compliance situation of its financial obligations.

3. Research and methodology and data

3.1. *The sample*

The data used in this research were taken from the Central Balance-Sheet Office of the *Banco de Portugal*. It is a database built from publicly available information (Balance Sheet and Profit and Loss Account), supplied by the participant companies.

This kind of information is currently compiled in the BACH Database (Bank of Harmonised Data of Company Accounts). The BACH is a database managed and distributed by the DG-II of the European Commission, in cooperation with national institutions of the different participant countries, namely the European Committee of European Central Balance-Sheet associated countries. Those researchers interested can use this kind of harmonised data from to more easily reply and test the results of this study in other national and industrial contexts. Moreover, the institutions involved certify the quality of the database in order to avoid biased results (Watson and Everett, 1999).

Sudarsanam and Taffler (1995) surveyed a list of conditions that the ratio method needs to satisfy in order to adequately control for size, time and industry effects but demonstrated empirically that they rarely hold. In order to control for these factors we select for as target group the small firms belonging to the Portuguese Footwear manufacture industry. It is a quite homogeneous sector in terms of production and business cycles structured around a large number of small firms and constitutes one of the main Portuguese industries.

A representative and random sample was considered with accounting data available for three fiscal years prior to 1993, including twenty four cases of firms undergoing a sustained situation of non-compliance with banking obligations in that year. The statistical analysis was built by comparing two samples with the same number of cases for each type of firm and matching them. The sample was paired by selecting, for each firm having experienced a sustained situation of non-compliance with banking obligations during the 1993 fiscal year, one "normal" firm with similar total asset value.[3] The total value of assets is often used as a proxy for size. The sample is paired according to this criterion, in order to diminish the influence on the ratio-crisis relationship introduced by the total value of the assets.

3.2. *The variables*

The first stage of the empirical work consisted of identifying which economic and financial ratios were more affected by the corporate insolvency situation. The selection of the economic and financial ratios was made at two different levels. First, only with a view to its inclusion in the study and, subsequently, to its integration in the models.

Since the beginning of the research, we were aware of the need to reduce the number of possible highly correlated variables, in view of the limited number of observations. But without a proper theory to supply the variables that account for the differences between the normal and insolvent firms, it was difficult to select ratios based only on the statistical properties of the available data.

An initial set of forty-two ratios was selected. The first twenty-nine were already calculated by the Central Balance-Sheet Office of the *Banco de Portugal*[4] and the calculation of the other ratios was based on the frequency with which they arose in other studies.[5]

According to Barnes (1986, 1987), the ratio selection is still a problem without a single answer, since the "information intersects the individual ratios". A large number of variables makes it necessary to establish an operative analysis permitting the selection of a sub-group of variables on which one can focus attention, at the data exploratory stage. Note that there is no optimum criterion allowing the selection of a sub-group of variables without estimating the models, by using all possible combinations, which is materially hard to achieve.

A first impression was obtained by graphically examining the trend of the ratio averages during the 1990–1992 period, for each of the groups, attempting to isolate the indicators with persistent relevant differences and, preferably, diverging trends. To confirm these impressions we continued the analysis of the differences between the average values of the groups, by applying the *t test* to the equality of group means, in an attempt to evaluate the degree of significance of the differences between the distributions of each group of variables.

Since the normality of distributions of the variables was not confirmed by statistical testing of most of the variables,[6] a statistical test was also taken into account, which would not require assumptions on the form of distribution and the *Wilcoxon's W* non-parametric statistic confirmed the results of previous tests.

The graphical analysis of the trend of the group means and the tests for the similarity of univariate statistics allowed us to conclude that, in general, the distribution of ratios of firms considered as normal was more stable than the distribution of the ratios of insolvent firms, which tended to deteriorate as the crisis became closer. Furthermore, not all ratios were equally discriminating in the sense of opposite trends and increasing differences on univariate statistics.

3.3. *Grouping the variables by categories*

After the analysis of a set of univariate statistics of differences between the groups, an extensive exploratory stage was organised in order to gather those ratios into homogeneous categories with an economic and financial meaning.

Although multicollinearity, in the Linear Discriminating Analysis does not give rise to the sort of biases it induces at the regression techniques level, it does give rise to a high instability in the function coefficients. Horrigan (1965) had the intuition that the high multicollinearity between financial ratios could be used as an advantage. It could mean that "only a small number of financial ratios are needed to capture most of the information ratios can provide, but it also means that this number must be selected very carefully" (Horrigan, 1965, p. 561).

Therefore we sustain that this grouping of variables can prevent most of the effects of multicollinearity on the discriminant functions, which translate into an excessive number of variables presented in the discriminant functions with unstable coefficients.

Grouping the ratios into categories is a technique that had already been used by authors such as Courtis (1978) and Pinches, Mingo and Carruthers (1973) or more recently Bardos (1995). Pinches, Mingo and Carruthers (1973) resorted to factorial analysis in order to identify the major independent factors that would structure the financial documents. These would be featured by retaining most of the information contained in the matrix of original data, i.e., explaining most of the data variance. But as Barnes (1987) affirms, the minimisation of the duplication of information cannot be achieved purely by logic; it is mainly an empirical matter in which linear independence is used largely as a statistical criterion.

We have tried to group the ratios by categories with an economic significance by resorting to an analysis of the correlation matrices. Inside these categories, the most discriminating indicator was selected, according to the univariate statistics pointed out above. As we can see in Table I the established categories are more numerous than those which would be obtained by means of a factor analysis, but, generally, they allow us to isolate a sub-group of ratios with great discriminating power in consecutive years.

In the Appendix 1, the ratios are classified by categories. In the categories Degree of Transformation, Productivity, Bank Indebtedness and Operating Financial Weight, contrary to expectations, no ratios were selected with significant discriminating power and therefore these categories are not mentioned in Table I.

3.4. *Discriminant analysis vs. logistic regression*

The attempt at diagnosing insolvency by means of individual ratios is limited, because it is difficult to compile in a single ratio the information contained in major accounting documents. On the other hand, the use of large sets of individual ratios may generate indecision instead of decisions.

Multivariate analysis presents the advantage of considering the variables as a whole, with the purpose of incorporating information on the relationships established among them. In the insolvency prediction literature, Linear Discriminant Analysis (LDA) and Logistic Regression (LR) are the dominant methodologies for building this type of model. Yet the references in the literature to LDA are more numerous. Thus, for comparative reasons, we present more frequently references to discriminant functions in our study.

The LDA methodology consists of preparing a linear function, labelled discriminant function, which shall divide the space of the variables in such a way that the distance between the groups should be the maximum. The LDA assumes that, for each group of firms, the different variables should follow a normal multivariate distribution and that the matrices of variance-covariance should be equal for both groups.

In order to test the hypothesis that covariance matrices are equal, we used *Box's M test* and the results pointed to the rejection of equality. Nonetheless, we continued to use the discriminating linear function, since, according to Klecka

TABLE I
Categories and ratios selected due to their discriminating power in the footwear sector

Categories	Selected ratios
Profitability	Return on total assets
Resources stability	Coverage of capital investment
Indebtedness	Rate of indebtedness
Investment	Rate of investment
Accumulated profitability	Retained earnings/Total assets
Sales turnover	Oper. working capital requirements turnover
Weight of the financial charges	Distribution of income by banks
Self-financing creation	Distribution of income by self-financing
Operating financing	Customer credit period
Liquidity	Current ratio
Coverage by self-financing	Self-financing capacity/Borrowed capital
Activity	GVA growing rate

(1980), there is no clear rule to determine how different the matrices should be, in order for it to be advisable to use the quadratic function; the linear discrimination continues to be considered adequately robust.

Moreover, in order to evaluate the normality problem we carried out the Shapiro-Wilks test of the distributions of each variable at an individual level. As we can observe in Appendix 2, the results of this test show that the normality assumption is only rarely met. Furthermore it should be taken into account that even if the variables, when taken separately, were normally distributed, their joint distribution might not be normal. Therefore, and although LDA seems to be a robust technique, according to Barnes (1982) it is advisable to introduce changes in the ratios or in part of their data, with a view to, at least, reducing that deviation of distributions from normality. Following the example of Bardos (1984), it was decided to adjust the observations with extreme values to a higher limit value, equal to the value up to which 95% of the observations of the data available from the Footwear Sector occur. As a lower limit for the distribution of the variables, the value adopted was that up to which 5% of the observations occur. This process is usually named "windsorising" and has been demonstrated to be preferable to the use of the logarithms of the variables. This last kind of transformation may change the interrelationships among the variables and affects the relative position of the observations in the group (Eisenbeis, 1977).

Logistic Regression (LR) may be an alternative analysis method to LDA, if one cannot assume that the variables are multinormal and homoscedastic in both groups. However, although the virtues of the alternative use of each method are much discussed, according to MacFaden (1976) and Lo (1986), the infringement of the underlying assumptions of the analysis leads to the conclusion that the selection of the most robust technique is not clear. Yet, during the 1980's, there was an increasing use of LR in this type of research. One of the clearest advantages of this type of analysis is that it allows the determination of the level of significance of a particular variable, since Discriminating Analysis does not allow its calculation independently from other variables in the model. Another advantage of LR occurs at the level of the "Normal" or "Insolvent" type predictions, since it makes it possible to establish a probabilistic measure of the insolvency risk between both extremes, which is only indirectly achieved through Discriminating Analysis.

The methodological option for the parallel use of both techniques is intended to test the sensitiveness of the results to the statistical method. If both types of analysis select the same variables when based on different assumptions, there is strong evidence of the relevance of those variables in the population behaviour.

3.5. *The selection of models*

The setting up of the models is an imperfect science, specific to each problem, depending on theoretical considerations and data adjustment. This task becomes more difficult when, as Foster (1986) stressed, not only are the theories on financial distress little developed but also, they are only very rarely taken into account when building models and giving an economic sense to the results. It must always be kept in mind that the use of iterative methods cannot be a substitute for a theory that organises the models *a priori* and gives economic sense to the results.

Another issue raised with respect to the construction of the models is to know if data for one or more consecutive years should be used or if, on the contrary, it should be decided to opt for the construction of a model every year. Most of this sort of studies selected one single model, with the application of LDA to the variables available for the year immediately prior to the crisis. Nevertheless, like Altman, Haldman and Narayanan (1977),[7] we have tried to build distinct models with data from different periods before the crisis as to test the stability of the results.

For the purpose of establishing a model, the selection of the variables to be included in the models cannot be based solely on the compliance of their statistical behaviour with model assumptions; otherwise, the results obtained would have no economic meaning. The selection of variables to be included in the models was thus not only carried out by an iterative method, but was the result of an extensive exploratory stage which organised the ratios around categories, according to their discriminating power, at univariate level.

Previous studies suggest possible sub-groups of variables, and we have tried to combine this empirical evidence with recent developments in the theory of financial distress costs. We had expectations that our model would include ratios that opposed profitability to debt.

The adequate *proxies* of these two dimensions that we wanted to analyse were also suggested for earlier studies. It was possible to build functions with good results, confirming the capacity of the ratio Financial Charges/Gross Operating Return Coefficient used in the *score* function of the Bank of France (Bardos, 1984). This kind of ratio continues to be used as a proxy for financial distress in recent studies like the one by Andrade and Kaplan (1998), so we would expect a negative relationship between the ratio of weight of the financial charges and the probability of insolvency.

On the other hand, Altman's model of 1968 is frequently accepted as the comparison pattern and benchmark for this type of study. The profitability ratios proved to be the most discriminating variables since the *Z Score* (Altman, 1968). One of the most interesting results confirmed in Altman, Haldman and Narayanan (1977) was the relevance of the ratio of Retained Earnings/Total Assets. If this kind of measure of accumulated profitability proves to be more discriminating than the traditional profitability ratios such as, Earnings before Interest and Taxes/Total Assets calculated for each business year, significant consequences could arise regarding the way in which the relationship between the capacity to generate results and corporate solvency is seen.

Furthermore, some other observations in the literature (Myers, 1984) indicate that a firm's profitability history has a strong effect on its financial flexibility and consequently on its insolvency risk. More recently, accumulated profitability continues to be recognised in Opler and Titman (1996) as one of the most important determinants of the capital structure. Dhumale (1998) uses this kind of ratio to confirm whether the retained earnings are indeed more significant in the context of bankruptcy to firms with a smaller set of investment opportunities, measured by Tobin's *q*.

It can be argued that the Retained Earnings ratio can be subject to manipulation and it can be argued that the dividend policy can deteriorate the relation between this ratio and the accumulated profitability, but it usually portrays added difficulties for a young firm to escape financial distress. There is, undoubtedly, a minimum profitability level beyond which bankruptcy is inevitable, and the works of Laitinen (1992) demonstrate that this minimum level changes according to the age and the accumulated profitability of a firm.

4. Results and sensibility analysis

A primary set of results, from the univariate analysis of the variables mentioned earlier, led the research towards two economic and financial dimensions which should be the object of any study on solvency: profitability and indebtedness. The selection of the variables was thus centred on previously established categories, which we believe to be closely related to these two dimensions: Profitability, Accumulated Profitability, Indebtedness, Weight of the Financial Charges.

Using the ratios from Altman's model, we can detect, as did Moyer (1977), that when the iterative methods[8] are applied in the selection of the variables, only some of them are selected for the models. The Accumulated Earnings/Total Assets ratio proves to be the most discriminating. Stress should also be laid on the fact that the indicators of the weight of financial charges, which opposed the financial charges to the results of corporate operation, are revealed to be systematically more discriminating than those measuring the indebtedness level.

After testing the several possible combinations of profitability and debt ratios, the ones that allow better classifications were included in model *B*.

4.1. *The base model* B

A model was thus obtained, which was called $B = -0.63494\ DIB_3 + 0.76451\ AE/TA_3$ A high level of efficiency was reached in the classification (89,58%), either in absolute terms, or when compared with the other empirical works mentioned troughout this study. Stress should be laid on the capacity of the model denominated as *B* to classify the firms in their original groups one year prior to the crisis with an error of approximately 10%.

The results of the models makes it possible to prepare classification matrices with the number of cases correctly and incorrectly assigned to each of the groups. One of the ways used to assess the relevance of the models consisted in calculating their total efficiency (percentage of correct classification), i.e., to determine, taking into account all observations, the number of cases where there is an identity between the source group (in the rows of the tables in Table II) and the assignment group (in the columns of the tables in Table II) determined by the function, versus the total number of firms.

The results of the LR confirmed the LDA model, reaching one less misclassified company in the group of insolvent firms. In addition to having good classification accuracy (91,67%) and other required statistical properties, this model contains variables with a behaviour consistent with our theoretical expectations.

The fact that our discriminant functions integrate only a limited number of ratios is the result of an extensive exploratory stage orientated by theoretical considerations, which allowed the grouping of ratios into categories and consequently the elimination of redundant information.

The selected ratios were the Accumulated Profitability/Total Assets (*AE/TA*) coefficient and the Distribution of Income by banks (*DIB* = Interest Charges/Total Income). These results confirm our belief that the two chief symptoms of insolvency inside the categories of Accumulated Profitability and the Weight of the Financial Charges.

The relevance of the Accumulated Profitability calls attention to the understanding of the strong conditioning factors to which the small companies are submitted, as they cannot count on a profitability "cushion", resulting from investments made in the past, to face future difficulties. On other hand, the relevance of the ratio, opposing financial charges to an income measure of the period, underlines the importance of an equilibrium between Operating Returns and Financial Charges drained by Banks.

These ratios are distinct from the remaining ones, considered as supplementary and not included in the final model, even if they had already been detected at a univariate level like the traditional profitability, liquidity, level or composition of debt ratios.

It can be considered that different users of the models will imply that adjustments need to be made to certain parameters of the models, such as the separation point between the groups, resulting from taking into account different *a priori* probabilities of belonging to each one of the groups as well as from differentiated costs of misclassifications. For example, the potential costs of an error for a credit institution are much higher when a firm in distress is classified as normal (Type I error) than otherwise (Type II error) (Altman, 1983). However, the incorporation of these costs does not present difficulties to any of the types of the multivariate analysis used. In this study, it is implicitly assumed that the differential of the misclassification cost is offset by the different a priori probabilities of each one of the situations, whereby the separation point, between the two groups, will remain 0 in LDA and 0.5 in LR (see Eisenbeis, 1977; Joy and Tollefson, 1975).

TABLE II
Classification results of discriminant model *B*

$B = -0.63494\ DIB_3 + 0.76451\ AE/TA_3$

21	3
2	22

Total efficiency: 89.58

Logistic regression results

22	2
2	22

Total efficiency: 91.67

4.2. *The Lachenbruch method: A resampling technique*

Joy and Tollefson (1975), in their criticism of Altman's studies and, later, Moyer (1977), drew attention to the need to compare the efficiency of LDA results with other possible alternatives of population division. Otherwise, the sample results would supply a false notion of usefulness of the method. In general, the models adjust better to the sample from which they are built than they would adjust to other samples drawn from the same population. Thus, the percentage of cases correctly classified by a discriminating function can be an inflated estimate of the real performance of the model.

One of the methods of obtaining non-biased rates of misclassification is Lachenbruch's method (Lachenbruch, 1967; Lachenbruch's and Mickey, 1968). This is an efficient way of testing the predicting ability of a discriminant function, because the samples of insolvent firms are not large enough to be divided at random into two parts. It is a "Jacknife" resampling technique, which consists of leaving out one case at a time and recalculating the function with the other (n – 1) cases and, thus, classifying the case left out.

The results in Table III obtained by Lachenbruch's methodology are similar to those found in the original sample, which seems to be an evidence of their methodological robustness and prediction capacity. The prediction error holds in a low level of efficiency of 10%.

4.3. *A test sample of the footwear manufacture sector*

Moreover, the error rates for test samples will be a good estimate of the sensitivity of the model. If the sample is large enough to be divided at random into two parts, one of them may be used to estimate the discriminating function and the other to test it. The error rates for the test samples will better reflect efficiency of the model. However, this methodology requires a large quantity of information and, when there is a limited number of observations as in this case, no efficient use is made of all the information available.

With the aim of verifying to what extent our proposed function adequately classified cases which had not been considered in its construction, we applied the parameters of Score B to a global sample of the Footwear Sector. This holdout sample gathered all available observations without any pairing intention, irrespective of their financial situation.

As we can see in Table IV, model B continued to detect the crisis situation with great accuracy in the year immediately prior to the crisis. These results suggest that Score B is quite sensitive to the detection of insolvency situations. The percentage of misclassifications of normal firms increased, but the same had already happened in the test sample of the seminal work of Altman (1968) where 79% of the Non-Bankrupt firms were classified as bankrupt.

Altman (1968) tried to outline a third "uncertainty region", defined between the values where the indicator in question may predict a situation contrary to reality. The methodology used to draw the boundaries of this region, in spite of being subjective and sample specific, opens possible explanations for the classification of firms in this situation like the one where firms are temporarily economically, but not financially distressed. The way to isolate economical and financial distress needs further research (Andrade and Kaplan, 1998) and will not be investigated in this paper.

In short, we can say that in our parsimonious model, the B Score maintains a reasonable capacity to generalise, at least in comparison to the historical performance of widespread models like the Z Score.

4.4. *Model performance in earlier periods before the crisis*

The results obtained from the models built with 1990 and 1991 data seem to indicate that the financial distress situations persist for a rather long period of at least three years in approximately 80% of the cases. In Table V we can see the total effi-

TABLE III
Classification results of Lachenbruch tests of model B

Lachenbruch tests	
21	3
2	22
Total efficiency: 89.58	

TABLE IV
Classification results of model $B = -0.63494\ DIB_3 + 0.76451\ AE/TA_3$ applied to a test sample from the footwear sector

Discriminant analysis		Logistic regression	
8	1	8	1
55	190	60	185
Total efficiency: 77.95		Total efficiency: 75.98	

TABLE V
Percentage of correct classifications for earlier years

Models	Total efficiency	
	Discriminant analysis	Logistic regression
2 years before the crisis	81.25	79.17
3 years before crisis	85.42	79.17

TABLE VI
Summary of the estimated coefficients

Variables	Discriminant analysis	Logistic regression
Year 1990		
DIB_1	–0.91963	–0.3264
AE/TA_1	0.91712	0.1802
Constant		1.0900
Year 1991		
DIB_2	–0.71262	–0.1647
AE/TA_2	0.69089	0.2020
Constant		1.2823
Year 1992		
DIB_3	–0.63494	–0.1974
AE/TA_3	0.76451	0.2382
Constant		0.9540

ciency of the models built with the same ratios as model *B*, for the other years of available data.

Thus, it seems that insolvency seldom results from a brutal crisis, being rather the result of a slow process of deterioration. However, the final models considered were always those built with data from year immediately prior to the crisis, since these allowed higher efficiency in the classification. It can also be observed that Logistic Regression obtained classification results rather similar to those of LDA and systematically selected the same ratios as those presented in Table VI.

The results of the Discriminant Analysis for the third year before the crisis indicate a maintenance of the discriminant power of the discriminant models developed with data other than those from the immediately exercise before the crisis.

It should be taken into account that the prediction capacity of a model is limited by the stability of the coefficients over time. The variables included in estimated models are significant at a 0.05 significance level, every year. Table VI shows that the models for each year integrate the same variables, with the same sign and very similar coefficients. As regards the relative importance of each variable within the models, and observing the standardised coefficients and the correlation[9] of each variable with the function, it may be concluded that the weights of the different variables are quite similar.

4.5. *The inclusion of other ratios in the model*

A more detailed analysis of the results redirected our attention to a set of variables that tends to appear in models with a large discriminating capacity. An example of a variable frequently present in financial insolvency prediction models is the Returns on Total Assets (ROA). The differences between the groups at univariate level could have led us to expect a successful inclusion of this type of ratio in the model. However, the inclusion of this variable did not produce significant improvements in classification power and seemed to introduce a high degree of instability in model coefficients as we can verify in Table VII.

The only increase occurs in a logistic regression model built with data from one year before the crisis. For the models developed with data from other periods, the ROA coefficients are not significant at 0.05 level. Moreover, the coefficients of the variables became unstable as we can see by comparing Table VIII with Table VI.

It seems that this ratio of short-term profitability is only one supplementary symptom of financial vulnerability and does not add any critical information of insolvency prediction to our base model.

The total effectiveness of the models when we tried to include other ratios like the debt or liquidity ratios, which had also revealed good discriminatory power at univariate level and in the traditional *Z Score*[10] model (Altman, 1968, 1983) was even worse, particularly in earlier years.[11] The inclusion of these ratios did not produce better adjustments and made the coefficients sample specific.

TABLE VII
Percentage of correct classification of the models resulting from the inclusion of the Return on Total assets (ROA) in our base model *B*

Models	Total efficiency	
	Discriminant analysis	Logistic regression
1 year before the crisis	89,58	93,75
2 years before the crisis	81.25	79.17
3 years before crisis	79.17	79.17

TABLE VIII
Summary of the Estimated Coefficients of the models resulting from the inclusion of the Return on Total assets (ROA) to our base model *B*

Variables	Discriminant analysis	Logistic regression
Year 1990		
DIB_1	–0.91485	–0.3361
AE/TA_1	0.92976	0.1870
ROA_1	0.04918	–0.0878
Constant		3.2666
Year 1991		
DIB_2	–0.71355	–0.1646
AE/TA_2	0.71665	0.1018
ROA_2	0.07090	0.0027
Constant		–1.2499
Year 1992		
DIB_3	–0.68478	–0.2537
AE/TA_3	0.62798	0.3612
ROA_3	0.22791	0.5038
Constant		–4.6726

In our opinion, the inclusion of these ratios can only be justified, following Keasey and Watson (1991), when attempting to define possible different typologies of insolvency processes, which will determine the relevance of certain financial ratios in the model, following the frequency of different insolvency processes in the sample.

5. Conclusions

The results of the parsimonious models built from a reduced number of accounting variables publicly available show the advantage of focusing the research of insolvency indicators on a reduced number of financial ratios, which can be interpreted in the light of financial theory. When trying to build an insolvency prediction model, we need to keep in mind that the financial analysis of small companies is frequently constrained to the accounting information available.

These conclusions are supported by results of our empirical study and offer an alternative strategy for developing insolvency prediction models. An exploratory stage that groups the ratios into categories controls for the multicollinearity of accounting data and the use of LR in parallel to LDA can be an effective method to assess the stability of the established relations models.

Our Score *B* is a discriminant function with only two variables, supported by the financial theory, which gives stability to the model that reaches a level of classification accuracy of above 90%. Several robustness tests were presented. Particularly, we verified that, when through the same methodology we estimate models with data from other years before the crisis, the same variables remain significant, with quite stable coefficients and without losing much classification power. Even when we use these models to classify a test sample we still obtain good results particularly for insolvent firms.

We can say that this work confirms our expectations of the relevance of a certain type of ratios. The models estimated by LDA and LR converge in the cases misclassified and thus we can conclude that the results do not depend on the estimation procedure. Moreover, both types of models select the same variables, which is a strong indication of the relevance of those variables in insolvency prediction.

We should remember that the model coefficients allow a prediction, as they are calculated before the emergence of the insolvency. This means that success in the discrimination does not ensure success in the prediction in spite of strong evidence that it is possible to predict insolvency in small firms of this industry.

Appendix 1. Description of the ratios analysed and their classification by categories

1) RATE OF GROWTH OF PRODUCTION (RGP)
Change in Production/Production in year n – 1
Category: Activity

2) CHANGE OF SALES GROWING RATE (CSGR)
Change in Net turnover/Net turnover of in n – 1
Category: Activity

3) ADDED VALUE GROWING RATE (AVGR)
Change in GVA/GVA in year n – 1
Category: Activity

4) RETURN ON EQUITY (ROE)
Gross Operating Return/Total Equity
Category: Profitability

5) GROSS RETURN FROM OPERATIONS (GRO)
Gross Operating Return/Operating capital
Category: Profitability

6) NET RETURN FROM OPERATIONS (NRO)
Net Operating Return/Operating capital
Category: Profitability

7) RETURN ON TOTAL ASSETS (ROA)
Gross Operating Return/Gross total assets
Category: Profitability

8) GROSS OPERATING MARGIN (GOM)
Gross Operating Return/Sales and services
Category: Profitability

9) COVERAGE OF FIXED ASSETS (COFA)
Gross fixed assets/Stable resources
Category: Stability of resources

10) COVERAGE OF CAPITAL INVESTMENT (COCI)
Invested capital/Stable resources
Category: Accumulated Profitability

11) FINANCIAL AUTONOMY (FA)
Total Equity (after tax and distribution of profits)/Total net assets
Category: Accumulated Profitability

12) LEVERAGE RATIO (LR)
Borrowed Capital/Own resources
Category: Indebtedness

13) RATE OF GROSS VALUE ADDED (RGVA)
GVA/Production, sales of merchandise and subsidies
Category: Degree of transformation

14) EQUIPMENT PRODUCTIVITY (EPR)
GVA/Tangible fixed assets
Category: Productivity

15) INVESTMENT RATE (IR)
Total investment/Total Income
Category: Investment

16) RATE OF COVERAGE THROUGH SELF-FINANCING (COSF)
Self-financing/Total investment
Category: Coverage through self-financing

17) TOTAL ASSETS TURNOVER (TAT)
Sales and Services/Total gross assets
Category: Sales turnover

18) OPERATING WORKING CAPITAL REQUIREMENTS TURNOVER (OWCRT)
Sales and Services rendered/Operating working capital requirements
Category: Sales turnover

19) INVENTORY TURNOVER (INVT)
Sales/Average of annual of stocks
Category: Sales turnover

20) TOTAL ASSETS/OWN RESOURCES COEFFICIENT (TA/OR)
Total gross assets/Own resources
Category: Profitability

21) OPERATING WORKING CAPITAL REQUIREMENTS/TOTAL ASSETS COEFFICIENT (OWCR/TA)
Operating working capital requirements/Total gross assets
Category: Financial operating weight

22) STOCKS/OPERATING WORKING CAPITAL REQUIREMENTS COEFFICIENT (S/OWCR)
Average of annual of stocks/Operating working capital requirements
Category: Financial operating weight

23) DISTRIBUTION OF INCOME BY PERSONNEL (DIP)
Personnel Costs/Total Income
Category: Degree of transformation

24) DISTRIBUTION OF INCOME BY BANKS (DIB)
Interest Charges/Total income
Category: Weight of financial charges

25) DISTRIBUTION OF INCOME BY SELF-FINANCING (DISF)
Self-financing/Total income
Category: Creation of self-financing

26) LABOUR PRODUCTIVITY (LRP)
GVA/Employment volume
Category: Productivity

27) CAPITAL-EMPLOYMENT COEFFICIENT (CEC)
Tangible fixed assets/Employment volume
Category: Productivity

28) CUSTOMER CREDIT PERIOD (CCP)
Commercial credit/Sales
Category: Operating financing

29) SUPPLIER CREDIT PERIOD (SCP)
Commercial debits/Purchases and External Supplies and Services
Category: Operating financing

30) ACCUMULATED EARNINGS/TOTAL ASSETS (AE/TA)
Accumulated Earnings = (Total Equity – Contributions of Capital by Shareholders)/Total Assets
Category: Accumulated Profitability

31) BANKING INDEBTEDNESS/BORROWED CAPITAL (BI/BC)
Banking Indebtedness = Short-term debts towards credit institutions + Long-term debts towards credit institutions
Category: Banking indebtedness

32) SHORT-TERM BANKING INDEBTEDNESS/ WORKING CAPITAL REQUIREMENTS (STBI/WCR)
Short-term debts towards credit institutions/Operating working capital requirements
Category: Banking indebtedness

33) SHORT-TERM BANKING INDEBTEDNESS/ BORROWED CAPITAL (STBI/BC)
Short-term debts towards credit institutions/Borrowed Capital
Category: Banking indebtedness

34) SHORT-TERM BANKING INDEBTEDNESS/ PRODUCTION (STBI/PR)
Short-term debts towards credit institutions/Production
Category: Operating financing

35) FINANCIAL CHARGES/GOR (FC/GOR)
Interest charges/Gross Operating Return
Category: Weight of financial charges

36) APPARENT INTEREST RATE (IR/BC)
Interest charges/Borrowed Capital
Category: Indebtedness

37) CURRENT RATIO (CR)
Floating Assets/Current Liabilities
Category: Liquidity

38) ACID TEST RATIO (ATR)
Current Assets/Current Liabilities
Category: Liquidity

39) WORKING CAPITAL REQUIREMENTS/PRODUCTION COEFFICIENT (WCR/PR)
Operating working capital requirements/Production, sales of merchandise and subsidies
Category: Financial operating weight

40) SELF-FINANCING CAPACITY/BORROWED CAPITAL (CFC/BC)
Self-financing capacity/Borrowed Capital
Category: Coverage through self-financing

41) INVESTMENT IN TANGIBLE ASSETS/GVA (ITFA/GVA)
Total investment in tangible assets/GVA
Category: Investment

42) GOR/INTEREST PAID (GOR/J)
Gross Operating Return/Interest paid.
Category: Weight of financial charges

Production = Sales of goods and services + Change in stock levels + Own Work capitalised
Financing = Loans through convertible bonds (medium- and long term and short-term) + Loans through non-convertible bonds (medium- and long term and short-term) + Loans through participating bonds (medium- and long term and short-term) + Medium-term debts towards credit institutions + Other loans received (medium- and long term and short-term)
Borrowed Capital = Accounts held by partners and shareholders + Financing + Short-term debts towards credit institutions
Stable recourses = Accounts held by partners and shareholders + Financing + Own resources
Own resources = Own funds (Equity) + Depreciation + Provisions
Investment = Purchase of financial assets + Purchase of (tangible and intangible) fixed assets + Self-provision of work to the firm itself regarding financial investments, tangible fixed assets and intangible fixed assets
Total investment = Financial investment + Investment in tangible assets + Investment in intangible assets + Change in operating working capital Requirements (+)/Resources (–)
Invested capital = Gross intangible assets + Operating working capital requirements
Operating capital = Capital invested in the operation = Tangible fixed assets + Operating working Requirements (+)/Resources (–)
Floating Assets = Stocks + Total short-term debts from third parties + Negotiable securities + Banking deposits and Cash
Current Assets = Short-term debts from third parties + Negotiable securities + Banking deposits and Cash
Total income = GVA + Other operating profits and gains – Other operating costs and gains + Financial profits and gains + certain extraordinary profits and gains
Self-financing = Net Profit for the year – Distribution of profits for the year + Depreciation + Provisions
Self-financing capacity = Net Profit for the year + Depreciation + Provisions
Operating Working Capital Requirements (+)/Resources (–) = Stocks + Commercial credit + Other operating credit – Other commercial debits – other operating debits.

Appendix 2: Summary table of univariate tests and graphical analysis

Variables	*(three years before the crisis)*				*(two years before the crisis)*				*(one year before the crisis)*			
	G	*t*	*w*	*Sw*	*G*	*t*	*w*	*sw*	*G*	*t*	*w*	*sw*
RGP												
				X								
CSGR							X					
				X								
AVGR				X							X	
ROE												
								X				
GRO										X	X	X
												X
NRO								X		X	X	
				X								X
ROA				X				X		X	X	X
								X				X
GOM				X				X		X	X	X
								X				X
COFA			X			X	X			X	X	X
COCI				X		X	X			X	X	
				X				X				X
FA		X	X	X		X	X	X		X	X	X
				X				X				X
LR		X	X			X	X	X		X		
RGVA				X		X	X	X				
				X				X				X
EPR				X								
IR		X	X							X	X	
								X				X
COSF		X	X							X	X	
TAT							X			X	X	
				X				X				X
OWCRT						X	X			X	X	
INVT			X				X			X	X	
TA/OR			X			X	X			X		
												X
OWCR/TA								X				
				X				X				X
S/OWCR											X	
DIP										X		
				X				X				X
DIB		X	X			X	X			X	X	
								X		X		
DISF		X	X	X		X	X			X	X	
				X				X				
LRP										X	X	X
				X				X				
CEC												
				X				X				
CCP		X	X	X		X	X			X	X	
				X				X				
SCP		X	X			X	X			X	X	
				X				X				
AE/TA		X	X			X	X			X	X	
				X				X				X
BI/BC						X	X					
STBI/WCR		X				X	X					
STBI/BC												
STBI/PR		X	X			X	X			X		
FC/GOR		X	X			X	X	X		X	X	
				X				X				
FC/BC							X				X	
								X				
CR		X	X	X		X	X			X	X	X
ATR						X				X	X	
								X				
WCR/PR				X				X				
				X				X				
CFC/BC		X	X			X	X			X	X	
ITA/GVA										X	X	
GOR/J		X	X			X	X			X	X	X
										X		

Data: Sample of the Footwear Sector of the Central Balance Sheet Data Office of Banco de Portugal (CBBP).

Notes:
(a) For each ratio the first line contains the results for the Insolvent firms, and the second the results for the group of Normal firms. The lines in dark and italic signal the ratios that have been considered as the most discriminant.
(b) *G*: results of the graphical analysis (dark shadowed when the differences of performance are visible between firms in distress and normal firms).
(c) *t*: test *t*, equivalent to test *F*, to the equality of the equality of means.
(d) *w*: test of Wilcoxon, non-parametric test to the equality of means.
(e) *sw*: test of Shapiro-Wiks, to the Normality of the variables.

Notes

1 Source: MOPE – Informação para a Gestão de Empresas, Lda.
2 Classification according to Decree-Law no. 177/86, published in the Portuguese Official Gazette, of 2 July, and to Decree-Law no. 132/93, of 23 April.
3 Zmijewski (1984) noted that by using this type of samples (which identifies two population groups and subsequently selects separate cases of each group, based on a given

criterion), and if the assumptions of the linear discriminant analysis are complied with, only the function constant will be affected.

[4] See list and calculation formula in Annex 1. Additional information can be found in Banco de Portugal (1993).

[5] The following sources were privileged: Altman (1968, 1977, 1984) and Bardos (1984, 1991) although other contributions were also taken into account.

[6] These normality tests are discussed in the next section and the results can be consulted in Appendix 2.

[7] Altman, Haldman and Narayanan (1977) estimate models for different years before the crisis, but abandoned this strategy concluding that it might give rise to some confusion as to which model should be applied to the new data.

[8] The Mahalanobis Distance (D^2) is a generalised measure of the distance between two groups and was the criterion used to obtain our final results. Mahalanobis distances are calculated for the two groups and the variable with the highest D^2 is selected for inclusion in the model.

[9] Pearson's correlation in *Score I*: *AE/TA*$_3$ 0.77261; **DIB**$_3$ –0.64468

[10] Where:

R1 = Working capital/Total Assets
R2 = Retained Earnings/Total Assets
R3 = Earnings Before Interest and Taxes/Total Assets
R4 = Market Value of Equity/Book Value of Total Debt
R5 = Sales/Total Assets

[11] The authors can supply these results upon request.

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