INSOLVENCY PREDICTION IN THE PORTUGUESE TEXTILE INDUSTRY

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ABSTRACT

This study explores the main characteristics of the business bankruptcy phenomenon. Some financial ratios are analysed in the context of bankruptcy prediction in Portuguese textile industry, using statistical instruments of multivariate analysis, particularly the discriminant analysis and the conditional analysis of probability (*logit*). Although these models have been frequently used, it must be underlined that the great popularity assigned to financial ratios as indicators of the firms' financial health, is still evident in some of the most recent research. The results seem to show that financial distress could be anticipated with an accuracy that ranges from 75% to 97%, three years and one year before bankruptcy respectively. Thus, we believe that if managers, auditors and regulators, paid the necessary attention to the instability exhibited by such indicators, it might be possible to prevent some of the problems revealed in this sector,

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which experienced a wave of bankruptcy with enormous economic and social impact, especially in the north of the country.

Key Words: Insolvency Prediction; Financial Ratios; Bankruptcy.
JEL Codes: C53, G33, M41.

I. INTRODUCTION

The pioneering work on bankruptcy prediction, which is still a reference for today's research, relied mainly on accounting information, concretely financial ratios (e.g. Altman, 1964; Beaver, 1966; Blum, 1974). Thereafter, many other researchers have conducted studies using these ratios (e.g. Ohlson, 1980; Taffler, 1983; Back *et al*, 1995a & 1995b; Back ***et al***, 1997; Spanos ***et al***, 1999). For instance, Blum (1974) and Storey ***et al*** (1987) regard financial variables as the symptoms (not causes) of the firms' health reduced to scalars. More recently, Voulgaris ***et al*** (2000) continue to share this view by regarding financial ratios as unbiased quantitative representations of the firms' internal and external context.

A common denominator between all of the research into firms' survival and performance consists of a lack of grounded explanation for the set of financial ratios included in the models. The arguments have almost invariably been the popularity of certain financial ratios in the relevant literature and their performance according to statistical search techniques. Even in the pioneering work of Altman (1964, p.594) it is mentioned: ***"The ratios are chosen on the basis of their popularity in the literature, potential relevancy to the study, and a few "new" ratios initiated in this paper."*** Likewise, Beaver (1966) considered a list of 30 ratios that were either popular or that were in previous research that had been found to be a good predictor.

It is interesting to notice that despite the increased methodological sophistication taking place recently, targeted at improving accuracy in bankruptcy prediction, the criteria for financial ratios' selection remain the same as in previous decades. For example, Golinski (1998, p.4) provides a very poor justification for the inclusion of a slightly modified version of Altman's ratios into his neural network: ***"Given the vast amount of research that Altman and others have done in***

determining these ratios, it is safe to assume that they cover in a broad, but concise stroke, the financial characteristics of the individual firms to be examined".

As previously indicated, statistical techniques play a large part in determining the final set of financial ratios used in bankruptcy and performance research. Indeed, it is common to narrow down the initial list of ratios drawn from the literature by means of a range of statistical techniques so that an optimal set is identified to fit the particular model and data. For instance, Altman (1964) started by analysing 22 ratios, and the list was then narrowed down to five ratios, which were those that predicted the best as assessed by statistical techniques. Beaver (1966) selected the "best" six ratios out of the initial list of 30 by means of a dichotomous classification test.

As Storey ***et al*** (1987) argue, when statistical techniques are employed to find which ratios best discriminate between bankrupt and non-bankrupt firms in the specific sample, external validity (understood as generalisation potential) may be low. Nevertheless, profitability, liquidity and solvency ratios, although measured differently, are almost invariably given importance to predict bankruptcy [with a few exceptions though, like Shirata, (1998)].

Thus, despite certain limitations mentioned on bankruptcy prediction, the issue reveals great importance to stakeholders (firms, creditors, investors and legislators) in the attempt, on ex-ante basis, of solving the causes of failure, before reaching extreme situations.

In this study, we attempt to show that there is relevant evidence to corroborate that the financial information offers valuable information on the deterioration process of financial ratios, revealing potential business crisis. We turned to the textile sector of clothing because it has become, in the last years, one of the most fragile sectors in what concerns the economical and social environment.

II. DATA AND METHODOLOGY

This empirical study relies on a sample of firms belonging to the textile industry and Portuguese clothing (Code of Economical Activity 17) during the period of 1996-2002. The sample is characterized by the presence of non-bankrupt firms and of firms experiencing financial difficulties. We define insolvents the firms which made a request for bankruptcy or had its insolvency declared between 2000 and 2001.

Thus, a sample of 26 insolvent firms and another of 26 firms without signs of business crisis during 1997-2000 was obtained. The indicators used were collected from MOPE database, complemented with information supplied by the Portuguese Statistic National Institute.

The global sample was subsequently divided in two sub-samples. The first, composed by 34 firms, from which half were considered "healthy" and the other half exhibit a financial insolvency situation, with the purpose of derivation of the discriminant and ***logit*** models. The second sub-sample was built with financial information of 18 firms (with reference to December 2000), from which 9 were insolvent and the remaining considered "healthy", which served to attest the results and the models' capacity of the ex-ante prediction.

During the mentioned period, and for each of the firms belonging to the main sample, 15 financial ratios[3] we selected according to its use in the literature.

The bankruptcy prediction relies on a model that considers, as dependent variable, a dichotomy variable that represents the firm's financial situation: "healthy" or in bankruptcy. Thus, the empirical tests are no more than a model of binary choices, on which the dependent variable assumes the value *1* (y = 1) when the company is "healthy", or *0* (y = 0) when the company is in a bankruptcy situation.

III. EMPIRICAL ANALYSIS

A. Discriminant Analysis

Through the discriminant analysis we identify the variables that have a stronger relation with insolvency, that is, those that distinguish between "healthy" and "non-healthy" firms, resulting in the following canonical discriminant function for 1999:

$$ED = -2.795 + 0.538\, X_1 + 9.105\, X_2 + 4.479\, X_3 \qquad (1)$$

Were, X_1 = Working capital/ Total Liabilities; X_2 = Earnings before interest and taxes/sales; X_3 = Earnings before taxes/Earnings before

[3] The selected ratios are commonly established in the literature and can be provided upon request.

interest and taxes. The ED overall index (discriminant score) is quite negative, indicating a higher risk of a firm's distress. The canonical correlation is 93%, being highly predictive. This parameter is a comparable measure to the determination coefficient, and evaluates the quality of the model through the Pearson correlation coefficient between the discriminant score and the variable Y.

Also, the ***Wilks Lambda*** statistic (0.136) is statistically significant, which confirms that the discriminant function is highly significant (p_value tend to zero). However, the Box Test (113. 55) presents a p_value of zero, meaning that we reject the null hypothesis of equality of covariance-variance matrixes for the two groups analysed. One of the main indicators of the models' efficiency is the capacity to identify the firms in the appropriate groups. The classification errors can be of two types: the type I errors occur when the model classifies a bankrupt firm, or about to bankrupt, as "healthy". When the model classifies a "healthy" firm as bankrupted, we come across in presence of a type II error. As Altman ***et al.*** (1977) refers, the type I error can be considered as more serious, because considering a bankrupt company as "healthy" might implicate huge costs at several levels.

Table 1
Classification matrix of the firms one year before bankruptcy

Discriminant Analysis $ED = -2.795 + 0.538X_1 + 9.105X_2 + 4{,}479X_3$		**Y**	**Predictive Group**		**Total**
			Bankrupt	**Non-Bankrupt**	
Group	**Value**	**Bankrupt**	17	0	17
		Non-Bankrupt	1	16	17
	%	**Bankrupt**	100	0	100
		Non-Bankrupt	5.9	94.1	100
Global model's adjustment					**97.1%**

As reference to 1999 (n-1), the discriminant function (Table 2) displays a rate of correct classification of 97.1%, indicating that a year before bankruptcy, the type I error was null. Thus, we may not reject the hypothesis that the actual groups of bankrupted would be equal to the ex-post group. The results also indicate that only 5.9% of firms from the main sample were classified outside the correct group (type II error). Applying the same procedure two and three years before bankruptcy, the separation error increase, as shown in the following results:

Table 2
Classification matrix of the firms in (n-2) and (n-3)

<table>
<tr><td colspan="2" rowspan="3">Discriminant Analysis
ED = -2.795 + 0.538X1 + 9.105X2 + 4,479X3</td><td colspan="4">Classification (n-2)</td><td colspan="4">Classification (n-3)</td></tr>
<tr><td rowspan="2">Y</td><td colspan="2">Predictive Group</td><td rowspan="2">Total</td><td rowspan="2">Y</td><td colspan="2">Predictive Group</td><td rowspan="2">Total</td></tr>
<tr><td>Bankrupt</td><td>Non-bankrupt</td><td>Bankrupt</td><td>Non-bankrupt</td></tr>
<tr><td rowspan="4">Group</td><td rowspan="2">Value</td><td>Bankrupt</td><td>15</td><td>2</td><td>17</td><td>Bankrupt</td><td>12</td><td>5</td><td>17</td></tr>
<tr><td>Non-bankrupt</td><td>3</td><td>14</td><td>17</td><td>Non-bankrupt</td><td>3</td><td>14</td><td>17</td></tr>
<tr><td rowspan="2">%</td><td>Bankrupt</td><td>88.2</td><td>11.8</td><td>100</td><td>Bankrupt</td><td>70.6</td><td>29.4</td><td>100</td></tr>
<tr><td>Non-bankrupt</td><td>17.6</td><td>82.4</td><td>100</td><td>Non-bankrupt</td><td>17.6</td><td>82.4</td><td>100</td></tr>
<tr><td colspan="5">Global model's adjustment</td><td>85%</td><td colspan="3">Global model's adjustment</td><td>76%</td></tr>
</table>

As we can see, the discriminant model presents an accuracy rate (global adjustment) of 85% two years prior to insolvency, and the type I error has increased up to 11.8%. Despite that, in relative terms, only two firms were inappropriate classified. Regarding the type II error, the 17.6% value indicates that three "healthy" firms were wrongly classified as bankrupt.

Regarding the results, the variable which presents higher individual significance is X_1 (solvency ratio). However, as shown in Table 3, the discriminant function is essentially explained by variable X_3, meaning that the classification between "healthy" and bankrupt firms is mainly due to the profitability ratio. The "discriminant" ratios (profitability and solvency ratios) are in accordance with the mentioned literature. The positive signs exhibited by variables are the expected, showing that the higher the bankruptcy potential of the firm, the lower will be the ED score.

Table 3
Coefficients of the discriminant function

Variables	Structural Coefficients	Normalized Coefficients	Non-Normalized Coefficients	Ranking
X_1	0.208	0.610	0.538	3
X_2	0.359	1.094	9.105	2
X_3	0.319	1.462	4.479	1

Table 4 below, reveals some proximity between the selected values in the sample and the sector, mainly on the discriminant variables X_1

and X_2. The industry mean values for the solvency ratio (X_1), approaches to the average value of the "healthy" firms in the sample.

Table 4
Mean sample and sector values (discriminant variables, 1999)

Discriminant Variables	Sample firms		Total of Textile Industry
	Non-bankrupt	Bankrupt	
X_1	1.22	0.06	1.23
X_2	0.21	0.02	0.03
X_3	0.60	0.03	0.28

Given that the solvency ratio reflects the capacity of the firms to re-adjust on the payment dates, as the debt increases, the lower this ratio will be and, consequently, the higher the risk of bankruptcy. As we can see in the groups of bankrupt and non-bankrupt firms, this ratio ranges from 0.06 to 1.22, respectively. In fact, approaching the bankruptcy date implies a high amount of debt, and the total firm's liabilities tend to exceed its own capital.

Also, this ratio, together with the assets turnover (sales/total assets), reflects the economical profitability of sales and is one of the main financial indicators of firms. Being a ratio directly related to the firms' value, it is expected to discriminate between groups of distress and "healthy" firms. A year before bankruptcy, the distressed firms show a lower production and consequent decreasing in sales. Thus, the higher this ratio's value, the higher the ED index and, consequently, the lower the risk of business bankruptcy in ceteris paribus conditions.

On the other hand, the X_3 ratio seems to be the coefficient with the higher discriminant power a year prior to bankruptcy, meaning that in the presence of imminent insolvency, the most prevalent factor in the distinction between a "healthy" and a distressed firm is the amount of debt and, consequently, the amount of financial responsibilities.

B. Logistic Regression

From the financial ratio matrixes used earlier, we derived the coefficients of the logistic function. For the *logit* model we used the

stepwise forward Wald procedure, which resulted in the following logistic function:

$$P = \frac{1}{1-e^{-z}} \Leftrightarrow P = \frac{1}{1-e^{-(-3.987+22.624X2+6.649X3)}} \qquad (2)$$

Where, X_2 and X_3 are as previously defined, and P is the probability of bankruptcy. The firm is classified as distressed if P < 0.5 or as "healthy" if P > 0.5.As shown in Table 5, the *logit* model presents an accuracy rate of 97.1%, which is similar to the one exhibited by the discriminant analysis. Also, the misclassified firm is the same in both models.

Table 5

Classification matrix of firms one year before bankruptcy

Logistic Regression: $P = \frac{1}{1-e^{-(-3.987+22.624X2+6.649X3)}}$		**Y**	**Predictive Group**		**Total**
			Bankrupt	**Non-Bankrupt**	
Group	**Value**	Bankrupt	17	0	17
		Non-Bankrupt	1	16	17
	%	Bankrupt	100	0	100
		Non-Bankrupt	5.9	94.1	100
Global model's adjustment					**97.1%**

As already stated for the discriminant analyses, the *logit* model reveals a decreasing prediction's capacity, as far as we deviate from the referenced date (Table 6). In fact, the global adjustment of 85.3% for (n-2) and 76.5% for (n-3), as well as the type I (11.8%) and type II (17.6%) errors, are very similar to their previous values.

Table 6

Classification matrix of the firms in (n-2) and (n-3)

Logistic Regression $P = \frac{1}{1-e^{-(-3.987+22.624X2+6.649X3)}}$		**Classification (n-2)**				**Classification (n-3)**			
		Y	**Predictive Group**		**Total**	**Y**	**Predictive Group**		**Total**
			Bankrupt	**Non-bankrupt**			**Bankrupt**	**Non-bankrupt**	
Group	**Value**	Bankrupt	15	2	17	Bankrupt	11	6	17
		Non-bankrupt	3	14	17	Non-bankrupt	2	15	17
	%	Bankrupt	88.2	11.8	100	Bankrupt	64.7	35.3	100
		Non-bankrupt	17.6	82.4	100	Non-bankrupt	11.8	88.2	100
Global model's adjustment					**85.3%**	**Global model's adjustment**			**76.5%**

Regarding the classification errors, equation 2 gives an error of approximately 35%, classifying six distressed firms as "healthy" (type I error) and 12% of the "healthy" firms were classified as bankrupted (type II error).

It should be reinforced that the use of the two statistic techniques (***logit*** and discriminant) for comparison purposes, seems to have been attained. In fact, the ratios selected by the ***logit*** model, as those which best predict bankruptcies (X2 and X3) are within the set presented by the discriminant analysis (X_1, X_2 and X_3). Moreover, as we can see in Table 7, the model's accuracy is (again) similar, despite the lower number of explicative variables.

Table 7
Results of the *logit* and discriminant models

Models / Years	Discriminant Analysis			Logistic Regression		
	Precision	Type I error	Type II error	Precision	Type I error	Type II error
1997 (n-3)	76.0%	29.4%	17.4%	76.5%	35.3%	11.8%
1998 (n-2)	85.0%	11.8%	17.6%	85.3%	11.8%	17.6%
1999 (n-1)	97.1%	0%	5.9%	97.1%	0%	5.9%

Although several authors prefer the use of the logistic regression (e.g.: Eisenbeis, 1977; Maddala, 1991), arguing that they present fewer violations to the underlying statistical assumptions, this synopsis table allows us to conclude that both models attained identical results, except for 1997, where the classification errors diverge between the two methods.

C. External Validation of the Models

With the purpose of testing the ex-ante prediction capacity of the models, we set a sample (external validation sample) of 18 firms for the subsequent period, with reference to December 2000, from which 9 were insolvent and the remaining considered "healthy". The three original ratios (X_1, X_2 and X_3) were also selected, but now constructed on the financial information supplied by the new sample. The results are illustrated in the table below:

Table 8
Classification matrix (external sample validation)

Models / Years	**Discriminant Analysis** ED = -2.795 + 0.538X_1 + 9.105X_2 + 4.479X_3			**Logistic Regression** $P = \frac{1}{1-e^{-(-3.987+22.624X2+6.649X3)}}$		
	Precision	Type I error	Type II error	Precision	Type I error	Type II error
1997 (n-3)	67%	33%	33%	67%	33%	33%
1998 (n-2)	89%	0%	22%	89%	0%	22%
1999 (n-1)	65%	20%	50%	65%	20%	50%
2000 (n)	78%	11%	33%	78%	11%	33%

It seems equally true, in this validation sample, that a balance between the prediction accuracy of these models exist. Although the lower precision levels and the higher number of classification errors, the validity of the previous results remains valid, given the small dimension of this second sample.

Moreover, the results are in accordance with the cited literature. In fact, for instance, Altman (1993) tested an identical procedure and concluded that the classification errors increased on average 15% to 20% in the subsequent sample period.

In such a context, our results seem to confirm the previous studies, which mention that bankruptcy derives mainly from a slow and continuous process of financial distress, and seldom from a visible firm crisis.

IV. CONCLUDING REMARKS

This study explores the main characteristics of the business bankruptcy phenomenon, using statistical instruments of multivariate analysis, such as the discriminant analysis and the conditional analysis of probability (***logit***). We have attempted to show that the firm's financial data gives valuable information on the deterioration process of financial ratios, revealing potential business crisis. The analysis relied on financial ratios in the context of the Portuguese textile industry, because it has become, in the last few years, one of the most fragile economic sectors in Portugal.

The results seem to show that financial distress could be anticipated with an accuracy of 97%, 85% and 76.5%, one, two and three years before bankruptcy, respectively. The discriminant analysis and the logistic regression applied on a sample of 52 firms for the period of 1996-2002, allowed us to conclude that bankruptcy can be predicted and, consequently, it might be possible to prevent some of the factors associated with the firm's distress.

Even when tested in an external validation sample, for the period of 1997-2000, the models correctly classify, on average, 75% of the firms in the sample. Thus, by exhibiting a high degree of accuracy, these models prove to be an extremely important diagnosis tool, as shown in several studies, on what concerns the distinction between solvent and insolvent firms.

Also, while the discriminant model allows us to distinguish between "healthy" firms and those in financial distress, the ***logit*** model provides the firm's bankruptcy probability, within the same ex-ante basis. In fact, both exhibit identical results, denoting that they might be applied together.

Thus, despite some limitations previously mentioned, the bankruptcy prediction issue reveals great importance to managers, in the attempt to solve the causes of failure, before reaching the extreme situation. We believe that if managers, auditors and regulators, pay the necessary attention to the instability exhibited by such estimates, it might be possible to prevent some of the problems revealed in this sector, and avoid the negative economic and social impact of bankruptcy.

Finally, and for further research purposes, it must be noted that the analyses may not be restricted only to the firm's performance, and should consider other factors, such as the economic conjuncture analysis, the quality of management and the organizational characteristics of the firms.

REFERENCES

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal Finance*, Vol. 13, pp. 589–609.

Altman E. I., Haldeman R. and Narayanan P. (1977). Zeta analysis: a new model to identify bankruptcy of corporation. *Journal of Banking and Finance*, Vol. 1, pp. 29-54.

Altman, E. I. (1993). *Corporate Financial Distress and Bankruptcy: a complete guide to predicting & avoiding distress and profiting from bankruptcy*. 2nd ed., New York: John Wiley & Sons.

Back, B., Laitinen, T., Hekanaho, J. and Sere, K. (1997). The Effect of Sample Size on Different Failure Prediction Methods. *TUCS Technical Report No 155.*

Back, B., Oosterom, G., Sere, K., and Wezel, M. van (1995b). A Comparative Study of Neural Networks in Bankruptcy Prediction. *Web Working Paper.*

Back, B., Sere, K. and Wezel, M. van (1995a). Choosing the Best Set of Bankruptcy Predictors. *In Proceedings of the Nordic Workshop on Genetic Algorithms*, Waasa University (Finland), pp 295-299.

Beaver, W. (1966). Financial Ratios as predictors of failures. *Empirical Research in Accounting*, selected studies, in supplement to the *Journal of Accounting Research,* pp. 71-111.

Blum, M. (1974). Failing Company Discriminant Analysis. *Journal of Accounting Research*, Spring, pp. 1-25.

Eisenbeis, R.A. (1977). Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics. *Journal of Finance*, Vol. 32, No. 3, pp. 875-900.

Golinski, G. (1998). Bankruptcy Prediction using Neural Networks. *MBA Paper*.

Maddala, G. (1991). A perspective on the use of limited-dependent and qualitative variables models in accounting research. *Accounting Review*, Vol. 66 (4), pp.78-807.

Ohlson, J.A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, Vol. 18, No. 1, pp. 109-131.

Shirata, C.Y. (1998). Financial Ratios as Predictors of Bankruptcy in Japan: An Empirical Research. *Web Working Paper.*

Spanos, M., Dounias, G., Matsatsinis, N. and Zopounidis, C. D. (1999). A Fuzzy Knowledge-Based Decision Aiding Method for the Assessment of Financial Risks: the Case of Corporate Bankruptcy Prediction. *Web Working Paper (Technical University of Crete).*

Storey, D., Keasey, K., Watson, R. and Wynarczk, P. (1987). The Performance of Small Firms, London: Croom Helm.

Taffler, R. J. (1983). The Assessment of Company Solvency and Performance Using a Statistical Model. *Accounting and Business Research*, Vol.13, No. 52, pp. 295-308.

Voulgaris, F., Doumpos, M. and Zopounidis, C. (2000). On the Evaluation of Greek Industrial SMEs': Performance via Multicriteria Analysis of Financial Ratios. *Small Business Economics*, Vol. 15, pp. 127-136.