PREDICTING BANKRUPTCY OF INDUSTRIAL FIRMS IN GREECE

By
THEOHARRY GRAMMATIKOS *
Graduate School of Business Administration
New York University

GEORGE GLOUBOS
National Bank of Greece

1. INTRODUCTION

Over the past decade or so a number of studies have appeared on corporate bankruptcy. The first attempts, in the U.S., to use publicly available data with various statistical techniques in order to predict business failure were made by Beaver (1967) and Altman (1968). Since then a growing number of related studies have tested bankruptcy prediction models in several industrial countries such as Germany, England, Ireland, the Netherlands, France, Japan, Australia, Canada and Brazil. This widespread interest in predicting financial distress is understandable. Identifying impending financial crisis is very important to analysts, stockholders and creditors of business firms as well as to the firms managers. The bankruptcy models can be used as early signals warning management that, unless corrective action is undertaken, the firm may be faced with financial crisis.

For the above reasons a study on business failures of Greek firms is very interesting and may prove useful for practical applications. The benefits may be particularly important for the Greek Banking System. At present the credit

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analysis, as performed, is based mostly on simple financial analysis of accounting data and on the major owners' credit worthiness. The models that we will estimate can provide an objective measurement of the financial health of firms and thus, assist credit analysts in their work. The major objective of this study, therefore, is to test and evaluate the relative performance of bankruptcy prediction models using data on Greek industrial firms.

The rest of the paper is organized as follows : In Section 2 similar studies for the USA and various other countries are examined. In Section 3 the data and methodology are explained and the major findings are discussed. The classification performance of the estimated models is presented in Section 4. Finally, in the last section the major conclusions of this study are outlined.

2. BANKRUPTCY PREDICTION MODELS : A SURVEY

In this section we present a brief survey of bankruptcy prediction models that have appeared in the international business literature. Although the list is not complete, it covers some important studies which clearly demonstrate the major features and performance ability of these models.

Beaver (1967) was the first to identify the characteristics of failing firms in comparison to a matched paired sample of healthy firms. Using univariate discrimination tests he found that certain financial ratios can be very useful predictors of failure even five years before it happens. This study can be thought of as the pioneering work which initiated a series of other works in the same area. Following this first study two major (statistical techniques, Multiple Discriminant Analysis (MDA) and Regression Analysis (RA), were applied by many authors to predict impending bankruptcies. E. Altman (1968, 1978) was the first to apply the MDA method to the failure prediction problem and his model (known as Z analysis) was 90% accurate in classifying firms correctly one statement prior to failure. MDA was also applied by Deakin (1972) who found that his models were at least 95% accurate for the first three years prior to bankruptcy. [1] Regression Analysis was applied by Edmister (1971) who obtained high classification results. However, one major shortcoming was the fact that

1. However, it should be pointed out that he estimated a separate model for each year. Although this approach gives higher classification rates it creates problems of interpretation. For example, which model should be used for forecast purposes? What should the conclusion be if two or more models give conflicting results?

he did not use the variables in their raw form but, instead, he transformed each variable into zero-one variables based on arbitrary cutoff points. The two techniques (MDA and RA) were compared in a study by Collins (1980) who concluded that both methods provided good predictive results. When they were used on the same data set MDA performed as well as or better than RA.

In other countries the major statistical method used was MDA. In Japan a number of studies (for example, Nikkei-Business, Takahashi and Ko) obtained high classification performances (85% or above). Some other studies that applied MDA were those contacted by Von Stein (1981) in Germany, Weibel (1973) in Switzerland, Taffler and Tissaw (1977) and Marais (1979) in England, Bilderbeek (1977) in Netherlands and Altman and Lavallee (1981) in Canada. In all of these studies the estimated models had high success rates ranging from 70% to 90%. Similar studies by Altman (1973) in France and Castagna and Matolscy (1981) in Australia obtained mediocre results. Regression Analysis was not commonly applied in studies outside the U.S.

Given the overall high success rates of the estimated models in both the U.S. and other countries it would be interesting to perform a comparative study with similar models for Greek firms. If the Greek bankruptcy models turn out to be as predictive as their international counterparts they would prove valuable aids for credit decision making by the Greek banking firms. In addition, since both MDA and RA can be applied to forecast failures it would be of interest to compare the predictive ability of these two statistical models.

3. DATA, METHODOLOGY AND MAJOR FINDINGS

As discussed above, two major statistical models have been applied in other similar studies ; Multiple Discriminant Analysis (MDA) and Regression Analysis. In this section both methods are applied in trying to predict bankruptcies and an evaluation of their relative statistical performance is performed.

3.1. The Data

The sample of this study consists of 29 industrial firms that went bankrupt or applied for bankruptcy proceedings during the period 1977-1981. Each failed firm was matched with a healthy one in the same industry, with similar asset size and for the same calendar years. Thus we collected financial statement data of 29 pairs of firms from one financial statement prior to bankruptcy. To assess the predictive accuracy of the models data for the second and third years prior to bankruptcy were also collected. However, because of data limitations it was not trace all the original firms. Thus, the sample sizes were 25 and 20 pairs for two and three years before failure respectively. The data were derived from various issues of the «Government Gazette», where all firms are required to publish their financial statements.

Before calculating accounting ratios some adjustments of the published statements had to be made in order to make them uniform and directly comparable across firms. A typical example of the type of adjustments that we performed is the treatment of the annual losses. When firms showed the annual losses as a separate asset account with a debit balance we reduced both the assets and the equity accounts by this annual loss.[2] Another problem, which unfortunately could not be solved, was lack of representative income statements. The only information that could be obtained for all firms was gross income and net income. Data on interest charges and sales were not uniformly available.

The 58 companies that were analyzed along with their industry classifications can be found in Appendixes I and II while Appendix **III** gives the accounting ratios (variables) that were calculated for each firm. As can be seen, some of the ratios are not commonly found in other similar studies. The major reason for using them was the desire to extract as much information as possible from the available data since many useful ratios (for example, times interest earned, asset turnover etc.) could not be estimated.

3.2. Methodology

Discriminant analysis is a statistical technique that can be employed to clasify objects (firms) into one or more mutually exclusive categories (for example bankrupt and non-bankrupt firms). This classification is based on various individual characteristics of the objects (i.e. a firm's financial ratios). Historical data concerning potentially relevant (i.e. discriminating) characteristics are collected

2. It should be noted that adjusting accounting data is a common procedure when dealing with different national accounting systems.

for a paired sample of objects (firms) and the discriminant analysis model determines the linear combination of these characteristics that best discriminates between the two categories.

The discriminant function takes the form :

$$Z=V_1X_1+V_2X_2+V_sX_3+\ldots+V_nX_n$$

where :

$V_1, V_2, V_3, \ldots, V_n$ = discriminant coefficients

$X_{l5}\ X_2, X_3, \ldots, X_n$ = independent variables

MDA defines the discriminant coefficients (V's) and the discriminant score (or Z-value) along with a critical Z* value (which is also estimated by the model) is used to classify the objects (firms).

Regression Analysis has been used in bankruptcy prediction studies in the form of the Linear Probability Model (LPM). The model is a regression of a dummy dependent variable on a set of explanatory variables. The dependent variable is dichotomous, taking the value of 1 for companies that are healthy and 0 for bankrupt firms. The model is of the following form :

$$Y = b_0 + b_1X_1, + b_2X_2 + \ldots +b_nXn +u$$

where :

X= a set of explanatory variables (in our case financial ratios)

Y= 1 for bankrupt firms

Y = 0 for healthy firms

The name «linear probability model» stems from the fact that Y can be interpreted as the conditional probability that the firm will not go bankrupt given the set of explanatory variables, that is, Pr (Y= 1/X). Thus, E(Y/X) gives the probability of a firm staying healthy whose financial ratios are given by the set of X's.[3] This model can be easily estimated with the usual Ordinary Least Squares

3. For a discussion on this issue see D. Gujarati, ch. 14, pages 312- 319.

3.3. Major Empirical Findings

To select the best discriminating variables a stepwise selection criterion is applied for both MDA and LPM. For MDA the Wilk's criterion is applied, which is the overall multivariate F-ratio for the test of differences among the group centroids. The variable which maximizes the F-ratio also minimizes Wilk's lambda, a measure of group discrimination. For the LPM a forward inclusion method is applied. Independent variables are entered only if they meet certain statistical criteria. The order of inclusion is determined by the respective contribution of each variable to explained variance.

The models are estimated with the help of the SPSS Statistical Package. The final estimated functions using data from one statement prior to bankruptcy are the following :

$$\text{MDA}: Z = -.863 - 2.461X_1 + 5.330X_2 - .022X_3 + 3.676X_4 + 3.543X_5 + 4.223X_6$$

$$\text{LPM}: Y = .313 + .546X_2 + 805X_5 + .979X_6$$

Where : X_1 = Current Assets/Total Assets

X_2 = Net Working Capital/Total Assets

X_3 = Inventories/Net WorkingCapital

X_4 = Notes Payable/Total Assets

X_6 = Earnings After Taxes/Current Liabilities

X_6 = Gross Income/Total Assets

Z = overall Z - score

Y = overall Y-score

From the construction of the above models it is clear that the higher (lower) si the Z or Y score the healthier (weaker) is the company. The theoretical cutoff points are 0.0 for Z and 0.5 for Y. Thus, companies having negative Z scores or Y scores smaller than 0.5 have a high probability for bankruptcy. A brief discussion of the included variables is now in order.

1. X_1. Current Assets/Total Assets (CA/TA). This is a measure of the liquid assets of the firm relative to its total capitalization. Normally a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

2. X_2. Net Working Capital/Total Assets (NWC/TA). The net working capital is defined as the difference between current assets and current liabilities. Thus, X_3 is simply a measure of the firm's net liquidity relative to its total assets. Ordinarily we would expect that this variable should fall as the firm approaches bankruptcy. It should also be pointed out that this ratio is the best predictor of ultimate failure in this study.

3. X_3. Inventory/Net Working Capital (INV/NWC). This variable measures the proportion of inventory to networking capital. Although not commonly used, this ratio can capture the investment in inventories relative to the firm's net liquidity. Since the sales figures were not available, X_3 measures the importance of inventories (which are the least liquid assets and liabilities. An increasing X_3, all other things held constant, would indicate excessive inventories which would deteriorate the firm's financial condition.

4. X_4 Notes Payable/Total Assets (NP/TA). This variable was the best among the financial leverage ratios examined and the second best predictor of ultimate failure for the MDA model. It measures the firm's notes payable relative to total assets. One would expect that an increasing X_4 would indicate signs of financial distress.

5. X_5. Earnings After Taxes/Current Liabilities (EAT/C L). This ratio is a measure of the firm's profitability relative to its currrent obligations. A decreasing ratio would indicate that it is more difficult for the firm to satisfy its current liabilities with internally generated funds and thus, its financial condition is probably worsening.

6. X_6. Gross Income/Total Assets (GI/TA). This is another profitability measure which appeared important in this study. X_e illustrates the gross income generating ability of the firm's assets. Consistently low profitability ratios (X_5 and/or X_6) should indicate an increasing probability of bankruptcy.

The estimated signs for the above variables conform to our hypothesis with the exception of X_1 and X_4 for the MDA model. It appears that a higher leverage and a lower current to total assets ratio increases the pobability for survival which, of course, is counter - intuitive. The answer to this «paradox» has to do with the essence of the MDA model. One cannot assess the relative importance of one variable in the MDA framework «ceteris paribus». Each variable exerts an influence on Z in association with all the rest of the variables and therefore, an attempt to justify the estimated signs (or magnitudes) with the help of partial effects may be misleading. The LPM in our case does not suffer from interpretation problems because all variables have the expected sign. Notice also that all three important variables in the LPM are also important in the MDA model. This offers an encouraging indication that X_2 (NWC/TA), X_5 (EAT/CL) and X_6 (GI/TA) are consistently important discriminating variables.

To test the individual discriminating ability of the variables, an F-test is performed. This test relates the difference between the average values of the ratios in each group to the spread of values of the ratios within each group and the results are presented in Table 3-1.

Table 3 – 1 : Variable Means and Tests of Significance

Variable	Bankrupt Group Mean	Non bankrupt Group Mean	F–Ratio[a]
X_1	.594	.682	3.69
X_2	–.219	.188	35.52[b]
X_3	4.391	.467	1.08
X_4	.601	.337	19.07[b]
X_5	–.105	.183	41.68[b]
X_6	.090	.245	26.68[b]

a. F = between – groups mean square/within – groups mean square
b. Significant at the .001 level

All three variables that are common in MDA and LPM are very significantly different between the two groups. In addition, X_2 is also significant, whereas X_1 and X_3 appear to be statistically insignificant at the .05 level.[4] To assess the relative discriminating contribution of each variable in a multivariate setting one can examine the standardized coefficients of the MDA and LPM models. The standardized coefficients represent the relative contributions of their corresponding variables to the estimated functions abstracting from differences in scale. Table

4. A word of caution is in order here. Since the F-test used above is a univariate test the fact that X_3 is insignificant in a univariate sense does not mean that it must be insignificant in a multivariate sense.

3-2 gives the standardized Values and the relative rankings of the variables in terms of importance for the two models.

Table 3 – 2 : Relative Contribution of the Variables

	MDA		LPM	
Variable	Stand. Values	Ranking	Stand. Values	Ranking
X_1	−.431	5		
X_2	1.384	1	.356	1
X_3	−.316	6		
X_4	.849	2		
X_5	.601	3	.355	2
X_6	.482	4	.267	3

The highest contributing variable for both models is X_2 (NWC/TA). The surprising observation, though, is about X_4 (NP/TA) which is the second highest contributing variable in the MDA but does not appear af all in the LPM model. A leverage ratio like X_4 should, on an intuitive basis, be an important discriminating variable but the LPM model does not fully confirm this. The apparent difference between the,two models as far as this leverage ratio is concerned is not difficult to be explained. The fact that X_4 enters the MDA model with the counter-intuitive positive sign, as discussed above, means that its importance-stems from its composite relation to the other variables. Since regression analysis does not incorporate other than one to one relationships between independent and dependent variables X_4 naturally is not included. There are no surprises for the other variables. Indeed, X_s (EAT/CL) and X_6 (GI/TA) are both very important discriminating variables and have the same relative importance. The overall conclusion, therefore, is that with the exception of X_4 (which becomes important only in a multivariate setting), the most important variables for both models are : X_2 (Net Working Capital/Total Assets), X_5 (Earnings After Taxes/ Current Liabilities) and X_e (Gross Income/Total Assets).

Moving to the statistical properties of the two models now, Table 3-3 gives the estimated coefficients and various measures useful for statistical inference. As can be seen in Table 3-3 all individual variables are statistically significant at the .001 level. A measure of the MDA function's ability to discriminate among groups is given by the canonical collection. We can interpret the canonical

Table 3 – 3 : Model Statistics

	MDA		LPM	
Variable	Coefficient	F–value	Coefficient	T–value
X_1	–2.461	2.049[a]		
X_2	5.330	11.751[a]	.45	3.602[a]
X_3	–.022	3.292[a]		
X_4	3.676	4.958[a]		
X_5	3.543	12.149[a]	.805	3.375[a]
X_6	4.223	7.976[a]	.979	2.688[a]
Constant	–.863		.313	4.304[a]

Canonical correlation :	.8119	Multiple R:	.7778
Group centroids		Group predicted means	
Group 1 : 1.3667		Group 1 :	.8025
Group 2 : –1.3667		Group 2 :	.1975

a. Significant at the .001 level.

correlation squared as the proportion of variance in the discriminant function explained by the groups. Thus, the bankrupt and nonbankrupt groups explain 65.92% of the variance of Z. A related measure for the LPM model is the multiple R. We can interprète the multiple R squared as the proportion of variance of Y which is explained by the function. Thus, the estimated LPM model explains 60.50% of the variation in Y. One final statistical observation can be made on the standardized means of Z and Y. In the MDA model the means of the Z- scores are +1.3667 and-1.3667 for the nonbankrupt and bankrupt firms respectively. To examine the overall discriminating power of the model we perform an F-test where. The F-value is the ratio of the sums-of-squares between groups to the within-groups sums-of-squares. The F-value was estimated at 3.88 and the hypothesis that the observations (Z-values) come from the same group is rejected at the .0001 level.

For the LPM the means of the Y values are .8025 and .1975 for the nonbankrupt and bankrupt firms respectively. A similar F-test is performed and again the hypothesis that the observations (Y-values) come from the same group is rejected. Thus, both models appear to have high discriminating power.

4. CLASSIFICATION PERFORMANCE

Although the statistical analysis performed in the previous section is important because it establishes the validity of the two models in statistical terms, from a practical perspective it is also interesting to examine their classification performance. After all, bankruptcy models are useful only as long as they can be used for forecasting the firm's financial status.

The presentation format for the classification results is given in Table 4-1. C_1 measures the number of bankrupt firms that are classified correctly as bankrupt. D_1 is the number of bankrupt firms that are classified incorrenctly as nonbankrupt (in our case $C_1 + D_1 = 29$). Also, notice that D_1 represents a type I error (rejecting the hypothesis that a firm is bankrupt when it is true). D_2 measures the number of nonbankrupt firms that are misclassified as bankrupt and C_2 is the number of nonbankrupt firms that are classified correctly. Notice that D_2 represents a type II error (accepting the hypothesis that a firm is bankrupt when it is wrong). Finally, the total number of correct classifications is C_1+C_2 and the total number of incorrect classifications is D_1+D_2.

Table 4-2 presents the classification results for the original sample using data from the first financial statement before bankruptcy. We should expect to find a high degree of successful classification when using the original sample because both models (MDA and LPM) were estimated from this data set. For one year prior to bankruptcy where is no appreciable difference between the two

Table 4-1 : Presentation Format

	Predicted	
Actual	Bankrupt	Nonbankrupt
Bankrupt	C_1	D_1
Nonbankrupt	D_2	C_2

models since both are very accurate in classifying 91.4% of the total sample correctly. The results are encouraging but we should keep in mind the upward selection bias. To gain a more objective view of the classification performance of two models more classifications and validation tests are required.

Next we examine the performance of the models using data from two years before bankruptcy. A reduction in the models' accuracy should be expected because bankruptcy is not eminent. A few comments are necessary here : first, because of data limitations the sample consists of 25 of the original firms ; se-

Table 4 – 2 : Classification Results : Original Sample

	Number Correct	Percent Correct	Percent Error	N	Actual	Predicted Bankrupt	Predicted Nonbankrupt
MDA :							
					Bankrupt	27	2
					Nonbankrupt	3	26
Type I	27	93	7	29			
Type II	26	90	10	29			
Total	53	91.4	8.6	58			
LPM :							
					Bankrupt	26	3
					Nonbankrupt	2	27
Type I	26	90	10	29			
Type II	27	93	7	29			
Total	53	91.4	8.6	58			

cond, the classification was performed using the previously estimated models (see Table 3 - 3). In some other works [see Deakin (1972)] a separate model is built for each year prior to failure. Although the per year classification in this case is very high it is not clear how these different models are to be applied. To clarify, it is not evident what the conclusion should be if one model (for example using data from one year prior to bankruptcy) gives a very low Z or Y score and another model (for example using data from three years prior to bankruptcy) gives high Z or Y scores. For this reason only the models estimated with data from one year prior to bankruptcy are used. As can be seen in Table 4-3, the classification success for both models falls to 78% and 76% for the MDA and LPM respectively. Although a reduction was expected, the correct assignments are still very high indicating that bankruptcy can reasonably be predicted two years prior to the event. Furthermore, the LPM still compares favorably with the MDA model. One final observation is that both models show a higher frequency of type I than type II errors which means that there is a higher probability to misclassify a bankrupt than a nonbankrupt firm. This reduces somehow the practical use of the models because, after all, we want to predict bankruptcy rather than rionbankruptoy. However, even with this observptior* the models are still rather successful since MDA classifies 60% and the LFM 68% of the ban-

Table 4 – 3 : Two Statements Prior to Bankruptcy

	Number Correct	Percent Correct	Percent Error	N	Actual	Predicted Bankrupt	Predicted Nonbankrupt
MDA :							
					Bankrupt	15	10
					Nonbankrupt	1	24
Type I	15	60	40	25			
Type II	24	96	4	25			
Total	39	78	22	50			
LPM :							
					Bankrupt	17	8
					Nonbankrupt	4	21
Type I	17	68	32	25			
Type II	21	84	16	25			
Total	38	76	24	50			

krupt firms correctly. In this sense the LPM appears to outperform the MDA model.

A similar analysis on the estimated models is performed using data from three years prior to bankruptcy. The sample consists of 20 pairs of the original firms and the results are shown in Table 4-4. The overall accuracy of the models falls to 70% for the MDA and increases to 78% for the LPM. Although both models have high accuracy even 3 years prior to bankruptcy the LPM clearly outperforms the MDA. The superiority of the LPM is more evident when one examines the correct classifications of bankrupt firms (Type I) which are 55% and 70% for the MDA and LPM respectively. These observations lead us to conclude that LPM is clearly more robust than the MDA model. It outperforms MDA both in the overall success rate and in successfully classifying bankrupt firms and thus, has higher practical value.

Overall, these results are very similar to those obtained in other related studies indicating that bancruptcy prediction models are successful tools for assessing the firm's financial health. On the other hand, our conclusion that LPM is robust than MDA contradicts Collins (1980) who found that MDA works just

Table 4 – 4 : Three Statements Prior to Bankruptcy

	Number Correct	Percent Correct	Percent Error	N	Actual	Predicted Bankrupt	Predicted Nonbankrupt
MDA :							
					Bankrupt	11	9
					Nonbankrupt	3	17
Type I	11	55	45	20			
Type II	17	85	15	20			
Total	28	70	30	40			
LPM :							
					Bankrupt	14	6
					Nonbankrup	3	17
Type I	14	70	30	20			
Type II	17	85	15	20			
Total	31	78	22	40			

as well or better than LPM. Perhaps the difference arises because of the different sample and the different application of these models in that study.

To gain a clearer perspective of the evolving financial changes that may lead to failure a trend analysis of the significant ratios is also performed.

As can be seen in Table 4 - 5 the Current Assets/Total Assets ratio (X_1) appears to increase slightly for the healthy companies and to fall slightly for the distres-

Table 4 – 5 : Evolution o Ratios Before Bankruptcy

	Bankrupt Firms Year Before Bankruptcy III	II	I	Nonbankrupt Firms Year Before Bankruptcy III	II	I
X_1 (CA /TA)	.624	.594	.594	.636	.661	.682
X_2 (NWC/TA)	.025	.069	–.219	.189	.158	.188
X_3 (INV/NWC)	2.651	4.391	3.973	10.978	–6.485	.467
X_4 (NP/TA)	.422	.492	.601	.306	.356	.336
X_5 (EAT/CL)	–.009	–.027	–.105	.155	.128	.183
X_6 (GI/TA)	.119	.100	.090	.219	.229	.245

sed companies. The Net Working Capital/Total Assets ratio (X_2) offers a striking comparison confirming our previous conclusions. This ratio starts to fall for the distressed firms at least years before the crisis and becomes even negative towards the end whereas for nonbankrupt firms it remains relatively stable. The Inventory/Net Working Capital ratio (X_3) is not so consistent and is more difficult to explain. It appears that bankrupt firms have a relatively stable ratio whereas healthy firms have a decreasing ratio. There are no surprises in the rest of the variables. The Notes Payable/Total Assets (X_4) measure increases consistently for the distressed companies and stays relatively stable for the healthy firms. Both profitability ratios (X_5 and X_6) show signs of deterioration for the weak firms throughout the three year period before bankruptcy. Nonbankrupt firms, on the other hand, show a slight improvement. Overall, the above ratios show signs of distress at least three years before bankruptcy.

The classification results that we discussed above may be biased upward because of search bias. While a set of variables may be effective in the initial sample, there is no guarantee that it will be effective for the population in general. To examine the robustness of the estimated models we perform a validation test which was first suggested by Frank, Massy and Morisson (1965). We estimate the parameters of the models using only a subset of the original sample and then we classify the remainder of the sample based on the estimated parameters. We finally apply a t-test to assess the significance of the results. Two replications of this method are tested ; first, the estimation subset consists of every other pair of firms, with those pairs that are left out used for the classification test ; second, the estimation subset consists of the first 15 pairs while the last 14 pairs are used for the classification test. Since the findings of the two replications are very similar in Table 4 - 6 we only report the classification results from the first validation test. In both replications the models perform surprisingly well. The MDA classifies 83% of the cases correctly in both replications whereas the LPM classifies 93% and 100% of the cases in the two replications respectively.

It is also evident that MDA suffers from a type I error bias which is consistent with our previous observations. We can substantiate statistically our conclusions with a simple t-test where the t-value is estimated as follows.

$$t = \frac{[\text{Proportion Correct} - 0.5]}{[0.5\ (1-0.5)/n]^{1/2}}$$

Table 4 – 6 : Classification Results : Validation Test

	Number Correct	Percent Correct	Percent Error	N	Actual	Predicted Bankrupt	Predicted Nonbankrupt
MDA :							
					Bankrupt	10	5
					Nonbankrupt	0	15
Type I	10	67	33	15			
Type II	15	100	0	15			
Total	25	83	17	30			
	Value of t = 3.62[a]						
LPM :							
					Bankrupt	14	1
					Nonbankrupt	1	14
Type I	14	93	7	15			
Type II	14	93	7	15			
Total	28	93	7	30			

a. Significant at the 0.01 level

In both cases the hypothesis that there is no difference between the groups is rejected. Thus, the models possess discriminating power on observations other than those to establish the parameters and any search bias does not appear to be significant.

For practical applications the two models can be refined with the establishment of «zones of ignorance». A «zone of ignorance» is a range of Z-scores or Y-scores where misclassification is observed. The practical use of these zones is simple. Firms falling to the right of the zone are classified as nonbankrupt while those falling to the left of the zone are classified as having a high probability for bankruptcy. Finally, for those companies falling within the «zone of ignorance», or «gray» area, Judgement is reserved because the models may not be very succesful. [5]

5. An examination of the individual Z-scores and Y-scores reveals that the gray area for the MDA is from -.4754 to .2747 and for the LPM from .4175 to .6104. There are five firms that we should reserve judgsment about. If we extend the same ««gray areas» for two and three years before bankruptcy the correct classifications increase slightly to 83 % and 80 % for the **MDA** and 88 % and 86 % for the LPM respectively.

5. SUMMARY AND CONCLUSIONS

Bankruptcy prediction models have proven to be valuable tools for assessing the financial health of firms for outsiders (creditors, stockholders and financial analysts) and managers alike. Outsiders are primarily interested in assessing the value of their current and future investment and therefore, have a strong interest in evaluating the firm's ability for survival. Insiders on the other hand are concerned with the effect of their current and future decisions on the financial strength tof the firm.

Although the usefulness of these models has been clearly established in the United States and in many other countries, there is an apparent lack of studies on Greek firms. The first objective of this study has been to bridge this gap and offer some evidence on the success of these models for predicting bankruptcies of Greek firms. It was shown that both methods examined, Multiple Discriminant Analysis and the Linear Probability Model, are very successful in predicting financial crisis even three years prior to the eventual failure. For the MDA the overall successful classification rates are 91./%, 78% and 70% for the first, second and third years before bankruptcy. The corresponding classification rates for the LPM are 91.4%, 76% and 78%. The second objective of this study has been to critically evaluate and compare these models both on statistical and practical grounds. Such critical evaluation has interest both for the Greek and International bibliography. MDA is a more advanced and complicated method than the LPM. However, it suffers from problems of interpretation which make its practical application prone to ambiguity. Therefore, it is important to examine whether the benefits of the MDA outweigh those obtained from the LPM. A marginal cost marginal benefit analysis is clearly a necessary step before one puts one or the other model in use. The conclusion in this study is that, at least for our sample, the simpler LPM works at least as well as the more complicated MDA. It is more robust and appears to do a better job in forecasting failure two or three years before it happens. In addition, since it gives a higher success rate for bancrupt firms than MDA it is probably more effective for practical applications.

To our knowledge this is the first scholarly study on Greek bankruptcy. We hope that it has contributed to a better understanding of business failures which is a subject of great importance for Greek policy makers and the business community in general.

I. BANKRUPT FIRMS

Number	Bankrupt Co.	Industry	Z–score	Y–score
201	Thessalian Pulp et Paper Ind., S.A.	Paper & Paper Articles	–1.3388	.2019
202	Avrassoglou, D, A. G.	Transportation Equipment	–1.0922	.2422
203	Standard Hellas, S.A.	Textiles	–.9635	.3040
204	Scrap, S.A.	Hardware	.0052*	.4101
205	Vetoplast, S.A.	Plastics & Rubber	–2.4411	.0326
206	Scoulides, S.A.	Textiles	–.2008	.3280
207	Enis Hellas, S.A.	Plastics & Rubber	–2.4411	.0326
208	Triantex, E., S.A. Triantopoulos	Textiles	–.0339	.3483
209	Stamatelos G &C. Stam., S.A.	Wood & Cork	–2.2865	–.1150
210	Stamatopoulos S.A. Screws et Bolts	Hardware	–1.8612	.0724
211	Papahelopoulos Bros., S.A.	Textiles	–1.9932	.1660
212	EGL, Paper Mills, Ladopoulos, S.A.	Paper & Paper Articles	–4.4094	–.6746
213	Tzanatos G., S.A.	Hardware	–1.2617	.2455
214	Petrides, M., S.A.	Clothing & Footwear	–1.8291	.3184
215	Flexaco Hellas, S.A.	Furniture	–2.1137	.4689
216	Xenokratis, C., S.A.	Textiles	–.9836	.3602

Number	Bankrupt Co.	Industry	Z–score	Y–score
217	Thomoglou Cosmas, S.A.	Textiles	–1.2800	.3147
218	Klemart, S.A.	Clothing & Footwear	–1.7127	.0997
219	Coracryl, S.A.	Textiles	–1.5986	.0671
220	Maounis, Dem., Decor., S.A.	Furniture	–1.2488	.1941
221	Xylexotic, S.A.	Wood & Cork	.2742*	.6104*
222	Thessaloniki Spinning Mills.	Textiles	–2.6375	–.1587
223	Medhel Hellas, S.A.	Chemicals	.0092*	.4191
224	Sinan, Cotton Spinning Mills Co., S.A.	Textiles	–1.9896	–.0239
225	Spintex, S.A.	Textiles	–.1150	.5523*
226	Syrmatodomiki S.A.	Hardware	–1.3164	.1696
227	Technoplastic, S.A.	Plastic & Rubber	–.2288	.4588
228	Stil, S.A.	Textiles	–1.7373	.1652
229	Caramolegos, J.D. Maroulidis, S.A.	Electrical Equipment	–1.2761	.1456

* These firms were misclassified

II. HEALTHY FIRMS

Number	Nonbankrupt Co.	Industry	Z–score	Y–score
101	Vis Containers Mfg. Co.,	Paper & Paper Articles	2.0022	.9851
102	Saracakis Bros., et Indv. Co. S.A.	Transportation Equipment	2.2335	.9513
103	Tricolan Franco-Hellenique, S.A.	Textiles	.4942	.6399
104	Ereco, Industrial Erections & Constructions, S.A.	Hardware	.8342	.6787
105	Helliniki Plastic Mfrs., S.A.	Plastics & Rubber	1.5269	.7548
106	Hellenic Pella Mills, S.A.	Textiles	.3866	.5128
107	International Clothing Ind., S.A.	Clothing & Footwear	1.3273	.7673
108	Naussa Spinning Mills, S.A.	Textiles	1.0479	.5497
109	ABEX Timber Manufacturing Co., S.A.	Wood &Cork	3.1504	1.2429
110	Mavisso, S.A.	Hardware	1.0064	.6307
111	Leftheris, El. Gregoriades, S.A.	Textiles	1.7389	.7905
112	Hartellas, S.A.	Paper & Paper Articles	1.5742	.6920
113	Altec Vayonis, S.A.	Hardware	–.1487*	.7181
114	Allegro, A. Negrin et Co., S.A.	Clothing & Footware	.1999	.6889

Number	Nonbankrupt Co.	Industry	Z–score	Y–sco–e
115	Xintavelonis Bros. «TIGER», S.A.	Furniture	4.0228	1.4531
116	Hellenic Fabrics. S.A.	Textiles	.2819	.6225
117	Iliofin, S.A.	Textiles	.9615	.6398
118	Maroussis, C., S.A.	Clothing et Footware	–.4754*	.4175*
119	Molokotos, A. & Son, S.A.	Textiles	1.5924	.8871
120	Skouropoulos, S.A.	Furniture	1.5924	.8871
121	Demetropoulos, B.C., S.A.	Wood & Cork	1.9609	.9865
122	Attica Spinning Mills, S.A.	Textiles	1.4772	.8835
123	Minerva Pharma-ceutical, S.A.	Chemicals	2.2154	.9968
124	Tsotras, S., J. Sclavis, S.A.	Textiles	.3257	.4916*
125	Ioniki Ifantourgia, S.A.	Textiles	2.0117	.9319
126	Syrmatourgiki, S.A.	Hardware	2.8741	1.2040
127	Viocon, S.A.	Plastics & Rubber	.9716	.7688
128	Abatzis, Chr. et Co., S.A.	Textiles	1.4636	1.0153
129	Karson, S.A.	Electrical Equipment	.8181	.4534*

* These firms were misclassified

III. VARIABLES USED IN THE STUDY

1. Current Assets/Current Liabilities
2. (Current Assets - Inventory)/Current Liabilities
3. Current Assets/Total Assets
4. Networking Capital/Total Assets
5. Inventory/Networking Capital
6. Total Liabilities/Total Assets
7. Total Liabilities/Total Equity
8. Current Liabilities/Total Liabilities
9. Notes Payable/Total Assets
10. Notes Payable/Total Equity
11. Notes Payable/Total Liabilities
12. Earnings After Taxes/Total Assets
13. Earnings After Taxes/Total Equity
14. Earnings After Taxes/Current Liabilities
15. Gross Income/Total Assets
16. Gross Income/Total Equity
17. Gross Income/Current Liabilities

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