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Predicting Corporate Bankruptcy: A Cross-Sectoral Empirical Study - The Case of Greece

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ARTICLE INFO	ABSTRACT
Received 14 September 2018 Accepted 10 October 2018	This article explores the prediction of bankruptcy of Greek companies, in particular of the manufacturing industry, wholesale, retail and service sectors.
JEL Classifications C 38, C 53, G33, M 41	The Probit model was developed so as to try to highlight the differences in the predictive capacity of the model across the sectors but also to investigate any differences in the behavior of the financial indicators used in the model. Moreover, for the selection of these indicators, the technique of factor analysis was applied.
	The results showed significant explanatory capacity of the model in the four key sectors of the Greek economy up to four years before failure and bankruptcy, as well as a clear differentiation in the sector classification of companies Research limitations/implications
	This work can be used by managers, banks as well as by practitioners to identify the causes of firm's failure.
Keywords:	Originality/value
Bankruptcy, Corporate Bankruptcy, Sectoral Forecasting Models, Financial Ratios.	The limited investigation, to date, of the effects of sectoral features and the absence of sectoral samples of bankrupt companies with a higher degree of homogeneity in predicting bankruptcy may often lead prediction models to unreliable results. This paper has two main contributions to the relevant literature. At first, it serves as a work of distinguishing the differences between bankruptcy predictive power of the same financial indicators of enterprises belonging to different sectors. Secondly, the use of factor analysis in the selecting procedure of the appropriate variables provides better and more robust results in the field of bankruptcy prediction.
	Eastern Macedonia and Thrace Institute of Technology

1. INTRODUCTION

The evolution of bankruptcies in recent decades is of particular interest due to their economic and social impact and the impact on the banking system. The industry in which an enterprise operates and develops plays an important role in the course of the business (Chava and Jarrow, 2004; Stokes and Blackburn, 2002). Each sector of economic activity has different financial characteristics and may face particular problems, which may be due either to in-house or extraneous factors.Differences in the features and problems of an industry may stem from over-borrowing, the level of competition, the import and export of goods, the impact of macroeconomic policy, legislative the framework, the different management and valuation of inventories, differences between family and non-family enterprises (Duller, 2010), the degree of sensitivity and deterioration of the raw materials, the completely different production process, etc.

When a sector of activity is experiencing severe financial problems, this will also inevitably affect sector businesses and it is possible that a number of companies may go into

failure and bankruptcy. A large number of Greek companies that went bankrupt during the period 2003-2016 was used in this study. These companies were active in the major sectors of economic activity in the Greek economy, namely in the manufacturing industry, wholesale, retail and service sectors. The Probit model was developed so as to try to highlight the differences in the predictive capacity of the model across the sectors but also to investigate any differences in the behavior of the financial indicators used in the model. Moreover, for the selection of these indicators, the technique of factor analysis was applied.

This paper has two main contributions to the distinguishing the differences between bankruptcy predictive power of the same financial indicators of enterprises belonging to different sectors. Secondly, the use of factor analysis in the selecting procedure of the appropriate variables provides better and more robust results in the field of bankruptcy prediction. Finally, this work can be used by managers, banks as well as by practitioners to identify the causes of firm failures. The rest of the work is structured as follows:Section 2 reviews the relevant literature. Section 3 describes the database. Section 4 presents the choice of variables using factor analysis and the methodology followed for the development of the Probit model. Section 5 presents the results and their interpretation, while the conclusions are presented at the end of the paper, in Section 6.

2. LITERATURE REVIEW

The development of failure prediction models has been and still remains a topic of particular interest to researchers in recent decades in many countries. Beaver (1966) with the univariate analysis, Altman (1968) with multivariate discriminant analysis, Meyer and Pifer (1970) with the linear probability model, Martin (1977) and Ohlson (1980) with the development of the logarithmic probability (Logit), and Hanweck (1977).model Grablowsky and Talley (1981), and Zmijewski (1984), with the development of the normal probability model (Probit), laid the groundwork for later research in the field of business failure prediction.

In addition, a number of important studies that have been published and were based on the previous techniques refer to the prediction of business failure, such as: Deakin (1972), Edmister (1972), Blum (1974), Diamond (1976), Taffler and Tisshaw (1977); Altman, Haldeman and Narayanan (1977), Dambolena and Khoury (1980), Taffler (1982), Gombola and Ketz (1983), Micha (1984), Zavgren (1985), Frydman, Altman and Kao (1985), Gombola et al (1987), Aziz, Emanuel and Lawson (1988), Peel and Peel (1988), Keasey and McGuinness (1990); Platt and Platt (1990), Luoman and Laitinen (1991), Theodossiou (1993), Johnsen and Melicher (1994), Altman, Hartzell and Peck (1995), McGurr and DeVaney (1998), Dimitras, Slowinski, Susmaga and Zopounidis (1999), Kahya and Theodossiou (1999), Charitou et al (2004), Agarwal and Taffler (2008); Wu et al. (2010).

Charalambakis and Garrett (2016) investigate whether accounting and marketdriven variables appropriately predict financial distress for developed market firms (USA), also predict financial distress in another developed market (UK) and in an emerging market (India). They show that for the UK, a model that combines book leverage and excess returns, market capitalization and return volatility amplify the prediction of financial distress for UK firms. In the case of Indian firms they find that market-based variables do not impact on the probability of financial distress when they are combined with accounting information.

The bulk of published research on business failure predictions refer to samples of bankrupt industrial firms, samples of industrial and commercial, as a whole, businesses, samples of companies in different sectors, and samples of banks.One of the most important elements (perhaps the most important) of a successful bankruptcy prediction is the creation of appropriate samples of bankrupt (failed) businesses, which should bring together the qualitative and quantitative characteristics of the financial information of the financial statements.

The limited investigation, to date, of the effects of sectoral features and the absence of sectoral samples of bankrupt companies with a higher degree of homogeneity in predicting bankruptcy may often lead prediction models to unreliable results. In order to highlight the importance of sectoral features, Altman et al. (1974), applied multivariate discriminant analysis (MDA) to a sample of 35 problematic and 99 healthy textile companies in France, with fairly good results. Also in 1993, recognizing the diversity of sectoral effects, he revised his model (Z-Score, 1968) into a four-variable model, subtracting the asset turnover ratio variable, "X5 Sales to Total Assets", in order to minimize the potential sectoral effects.

Skogsvik K. (1990) investigated the predictive capacity of the Probit model in industrial mining companies in Sweden. Michalopoulos et al. (1993) applied the Regressive Differentiation Algorithm to a sample of twenty-one Greek textile companies (9 bankrupt and 12 healthy). McGurr (1996) investigated the predictive power of the discriminant analysis model in United States retailers, while McGurr and DeVaney (1998) compared the technique of discriminant analysis (MDA) with the logarithmic probability model (Logit), using US retailers from 1989 to 1993. Parsa et al. (2011) state that the variables location, affiliation, and size are significant influences on restaurants' failure. Pinkwart et al. (2015) analyzed the determinants for the business failure of German New Technology-Based Firms (NTBF) in different financial stages. They showed that the different financial states should be analyzed separately when determining factors of business failure.

Gemara et al (2016) use survival analysis techniques in the Spanish hotel industry They argue that the survival of hotels depends on their size, location, management and launch in a time of prosperity. Soo, (2018) investigates the key determinants of US hospitality firms' financial distress between 1988 and 2010 using ensemble models. Financial ratios such as debtto-equity ratio and net profit margin, among others, were defined as significant financial distress predictors.

In studies undertaken since 1982, Standard and Poor's has highlighted significant differences between the same financial indicators of enterprises belonging to different sectors. Comparing the sectoral features of bankrupt businesses of the key sectors of an economy (manufacturing industry, wholesale, retail and services) which affect model behavior, is an important element of research.

Despite the development of the normal probability model (Probit) by Hanweck (1977) in order to investigate the bankruptcy of a group of banks, by Zmijewski (1984), who first applied the Probit model to the corporate bankruptcy prediction, by Skogsvik (1990), but also Grablowsky and Talley (1981), Gloubos and Grammatikos (1988), Theodossiou (1991), Papoulias and Theodossiou (1992), Ginoglou (1994), Spanos et al (1999), and Lin (2009), who compared the application of the Probit model with other models, its use is very limited, although its implementation results are encouraging. The earlier perception of implementation difficulties due to the complex calculations reported by some researchers such as Stock and Watson(2006), does not apply due to the development of software which allows any computational difficulties and problems encountered in the development of the Probit model to be overcome, Chris Brooks(2008).

3. DATA DESCRIPTION

The collection of the basic data of bankrupt Greek companies was carried out by the Hellenic Statistical Authority (ELSTAT) and includes bankrupt businesses across the whole country on which controls and verifications have been performed, while the search for the financial data of the financial statements was carried out by ICAP GROUP S.A.

The data and features of the final sample of the bankrupt companies are as follows:

• The number of companies in the sample amounted to 339 and refers to companies that went bankrupt in the period 2003-2016, whose published financial data refer to the period 2003-2014. The year in which a firm is declared bankrupt does not coincide with the year of publication of the latest financial statements due to the time required to complete the bankruptcy process.

• All the companies in the sample have the legal form of the public limited company.

• Bankruptcy is a result of the formal bankruptcy process.

• All the companies in the sample followed the same accounting principles, and their published financial statements were prepared based on the principles of the Greek General Accounting Plan.

• The companies are active in the four main sectors of economic activity of the Greek economy.

• In the absence of certain financial data, due to non-publication of financial statements, for some years before bankruptcy, the latest available data were used.

Year													
before	200	200	200	200	200	200	200	201	201	201	201	201	Tot
bankrupt	3	4	5	6	7	8	9	0	1	2	3	4	al
cy													
-1					51	64	73	61	44	32	9	5	339
-2			1	9	62	67	53	42	30	8	2		274
-3		1	8	58	70	53	39	30	9	3			271
-4	1	7	56	64	51	38	31	8	3				259
-5	7	52	59	51	33	32	7	4					245
-6	44	55	48	35	29	8	5						22 4
-7	50	49	33	27	8	5							172
-8	39	29	26	7	5								106
-9	26	26	6	5									63
-10	23	6	5										34
-11	5	5											10
-12	5												5
Total	200	230	242	256	309	267	208	145	86	43	11	5	2,00 2

Table 1. Availability of data of bankrupt companies per year before bankruptcy

Also, a random sample of 339 active, nonbankrupt companies was created, which were matched to the bankrupt ones, based on year, sector and sub-sector. As Zmijewski (1984) states, non-random selection of sample enterprises creates bias problems. Then, in order to analyze the behavior of the individual sectors of the Greek economy, the companies were classified into the following sectors of economic activity by creating corresponding samples (see Figure 1): Manufacturing industry (101 companies), Wholesale trade (111 companies), Retail trade(58 companies), Services sector (69 companies).



Figure 1. Bankruptcy by sector

4. METHODOLOGY Econometric analysis

4.1 Selection of financial indices (independent variables)

The criteria with which the financial indicators were initially selected are:

• Their capacity and their interpretative power, which has been acknowledged in earlier investigations in

other countries as well (Kung Chen and Thomas Shimerda, 1981).

• Their frequency and popularity, with which they appear in the international literature (Edward Altman, 1968).

• Covering all operational features of the company (Liquidity, Activity, Capital Efficiency, Capital Structure) (Dambolena and Khoury, 1980).

The following financial indicators cover a wide range of information and highlight the qualitative features of the individual samples.

X1 : Sales to Total Assets	X8
: Net Profit Margin	
X2 : EBITDA to Total Assets	X9
: Return on Capital Employed	
X3 : Net Working Capital to Total	Assets
X10 : Return on Equity	
X4 : Loan Capital to Total Funds	X11
: Interest Coverage by EBITDA	
X5 : Current Assets to Current Lia	abilities
X12 : Sales to Receivables (Customers)	
X6 : Gross Profit Margin	X13
: Total Reserves to Total Funds	

X7 : Equity to Loan Capital X14 : Operating Cash Flows to Total Assets.

The method of factor analysis ¹ was used in order to identify and select the most appropriate financial ratios to be used in the development of business failure prediction models. This is a statistical technique designed to reduce the dimensions of the problem being analyzed. This reduction is achieved by minimizing the initial number of financial indices (independent variables) to a level that allows for better management, provided that the final number of variables retains as much as possible of the information that was given on the problem by the initial number of variables.

Descriptive statistics on the bankrupt and healthy companies in the sample are listed in the tables below.

Variable description	Varia ble	Mea n	Std. Dev.	Min	Max
Sales to Total Assets	x 1	0.81 0	0.693	0.002	4.650
EBITDA to Total Assets	x2	- 0.01 6	0.154	-0.837	0.269
Net Working Capital to Total Assets	x3	- 0.04 5	0.528	-3.349	0.854
Loan Capital to Total Funds	x4	0.91 3	0.508	0.103	4.324
Current Assets to Current Liabilities	x5	1.46 4	2.655	0.044	26.31 5
Gross Profit Margin	x6	0.27 9	0.212	0.009	1.000
Equity to Loan Capital	x7	0.40 9	1.192	-0.769	8.697
Net Profit Margin	x8	- 0.56 3	2.962	- 28.163	0.425
Return on Capital Employed	x9	- 0.08 7	0.205	-1.307	0.193
Return on Equity	x10	- 0.05 6	2.207	- 11.978	12.42
Interest Coverage by EBITDA (EBITDA to interest expense ratios)	x11	- 3.99 8	48.116	- 346.03 2	181.3 59

Table 2. Descriptive statistics of bankrupt companies in the sample

¹ See, for example, Kim and Mueller, 1978 -- Kim, J. O., & Mueller, C. W. (1978). Introduction to factor analysis: What it is

and how to do it. (Sage University Paper Series on Quantitative Applications in the Social Sciences, series no. 07-013). Newbury Park, CA: Sage.

Sales to Receivables (Customers)	x12	$\begin{array}{c} 4.02\\7\end{array}$	11.322	0.002	93.14 7
Total Reserves to Total Funds	x13	- 0.24 1	0.773	-5.466	0.354
Operating Cash Flows to Total Assets	x14	0.05 8	0.184	-0.525	0.712

Table 3. Descriptive statistics of healthy companies in the sample

Variable description	Variable	Mean	Std. Dev.	Min	Max
Sales to Total Assets	x1	1.097	0.934	0.075	5.184
EBITDA to Total Assets	x2	0.082	0.114	-0.227	0.503
Net Working Capital to Total Assets	x3	0.206	0.281	-0.820	0.883
Loan Capital to Total Funds	x4	0.599	0.250	0.023	0.995
Current Assets to Current Liabilities	x5	2.338	4.085	0.214	33.183
Gross Profit Margin	x6	0.340	0.201	0.042	1.000
Equity to Loan Capital	x7	1.815	5.127	0.005	42.065
Net Profit Margin	x8	-0.006	0.272	-2.108	0.436
Return on Capital Employed	x9	0.027	0.127	-0.588	0.415
Return on Equity	x10	-0.002	0.851	-5.077	2.446
Interest Coverage by EBITDA (EBITDA to interest expense ratios)	x11	69.172	305.765	-557.419	2139.559
Sales to Receivables (Customers)	x12	8.408	18.929	0.186	123.286
Total Reserves to Total Funds	x13	0.059	0.096	0.000	0.457
Operating Cash Flows to Total Assets	x14	0.067	0.173	-0.387	0.731

4.2 Factor analysis

In technical terms, with factor analysis, we identify the least common factors, let us say q of them, which compose linearly all the initial variables:

 $y_{ij} = z_{i1}b_{1i} + z_{i2}b_{2i} + \dots + z_{iq}b_{qi} + e_{ij}$ Where y_{ij} the value of the *i*th observation of the *j*th variable,

 \mathbf{z}_{ik} is the *i*th observation of the *k*th common factor, \mathbf{b}_{kj} the linear loadings of the model, and

 e_{ij} : the error condition of the model or the percentage of the *i*th observation of the *j*th

variable that cannot be explained by the common factors.

The assessment process is essentially based on the assessment of the common factors and their coefficients, following the steps below:

• Checking for correlations of variables.

• Determining the number of factors and assessing the model.

• Rotation of the model in order to better interpret the factors.

• Statistical verification of the suitability of the model.

For the assessment of the model, the maximum likelihood estimation will be used.

4.2.1. Variable correlations

Table 4. Variable correlations

	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x1 4
x 1	1													
x2	- 0.12	1												

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x3	- 0.07	0.05	1											
x4	0.07	- 0.06	- 0.99	1										
x5	- 0.08	0.02	0.12	- 0.10	1									
x6	- 0.12	- 0.03	- 0.16	0.15	- 0.01	1								
x7	- 0.10	0.02	0.12	- 0.12	0.76	0.04	1							
x8	0.04	- 0.02	0.03	- 0.03	0.01	0.11	0.01	1						
x9	- 0.08	0.77	0.11	- 0.13	0.05	0.01	0.05	$\begin{array}{c} 0.0\\ 5\end{array}$	1					
x1 0	- 0.02	- 0.12	- 0.01	0.01	- 0.01	0.08	- 0.01	0.0 0	- 0.09	1				
x1 1	- 0.01	0.32	0.02	- 0.02	- 0.26	0.01	- 0.39	0.0 0	0.19	0.04	1			
x 1 2	0.28	0.02	0.01	0.00	- 0.02	- 0.03	- 0.02	0.0 1	0.02	- 0.04	- 0.02	1		
x1 3	-0.05	0.15	0.95	- 0.96	0.00	-0.15	-0.02	0.0 2	0.24	- 0.03	0.09	0.01	1	
x1 4	0.21	- 0.08	0.09	- 0.09	-0.04	-0.05	-0.04	0.0 1	-0.03	0.01	-0.02	-0.02	0.0 9	1

We observe:

a. A relatively large positive correlation between the variables, EBITDA to Total Assets (x2) and Return on Capital Employed(x9).

b. A <u>largenegative</u> correlation between the variables, *Net Working Capital to Total Assets* (x3) and *Loan Capital to Total Funds*(x4).

c. A <u>largepositive</u> correlation between the variables, *Net Working Capital to Total Assets* and *Total Reserves to Total Funds*(x13).

 $d. \quad A \ \underline{largenegative} \ correlation \ between \ the \ variables, \ \textit{Loan Capital to Total Funds} (x4) \ \textit{Kal Total Reserves to Total Funds} (x13).$

e. A relatively large positive correlation between the variables, Current Assets to Current Liabilities(x5) και Equity to Loan Capital(x7).

4.2.2.Model assessment

The results of the assessment are presented in the table below. Based on the eigenvalues, the model favors the selection of 4 factors because 4 eigenvalues have a value greater than one. Table 5. Factor variance - factor weights

Factor	Eigenvalues	Difference	Proportion	Cumulative
Factor1	2.95753	1.20902	0.3378	0.3378
Factor2	1.74850	0.59367	0.1997	0.5375
Factor3	1.15483	-0.45817	0.1319	0.6694
Factor4	1.61301	1.14793	0.1842	0.8536
Factor5	0.46508	0.30723	0.0531	0.9067
Factor6	0.15785	-0.12666	0.0180	0.9248
Factor7	0.28451	0.09416	0.0325	0.9573
Factor8	0.19035	0.00654	0.0217	0.9790
Factor9	0.18380		0.0210	1

Table 6. Factor variance - factor weights

Variab	Facto	Facto	Facto	Facto	Facto	Facto	Facto	Facto	Facto	Uniquen
le	r1	r2	r3	r4	r5	r6	r7	r8	r9	ess
x 1	-0.116	-0.210	0.968	0.069	0.003	0.000	0.000	0.000	0.000	-0.116
x2	0.198	0.042	-0.162	0.966	-0.001	0.000	0.000	0.000	0.000	0.198

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x3	0.944	0.094	0.074	-0.129	0.050	0.262	-0.002	0.007	0.005	0.944
x4	-0.953	-0.075	-0.071	0.123	-0.078	-0.213	-0.010	0.010	0.012	-0.953
x5	0.024	0.990	0.132	-0.003	-0.045	0.000	0.000	0.000	0.000	0.024
x6	-0.146	0.019	-0.140	-0.024	0.057	-0.066	0.351	-0.003	0.091	-0.146
x7	0.006	0.789	0.067	-0.001	0.611	0.000	0.000	0.000	0.000	0.006
x8	0.018	0.002	0.049	-0.013	0.004	0.011	0.313	0.140	0.03	0.018
x9	0.273	0.060	-0.089	0.723	0.016	-0.189	0.142	0.136	-0.056	0.273
x10	-0.029	-0.005	-0.019	-0.120	-0.005	0.016	0.155	-0.187	0.014	-0.029
x11	0.096	-0.270	-0.078	0.312	-0.278	0.052	0.120	-0.309	0.091	0.096
x12	-0.004	-0.054	0.273	0.065	0.002	0.011	-0.037	0.132	0.172	-0.004
x13	0.397	-0.033	0.060	-0.034	0.001	0.000	0.000	0.000	0.000	0.397
x14	0.069	-0.074	0.211	-0.057	0.009	0.029	0.060	-0.064	-0.365	0.069

The graphical representation of the eigenvalues is shown in the figure below.



Figure 2. Eigenvalue chart

4.2.3 Model Rotation

For the best possible interpretation of the factors, a rotation of the model was applied. In particular, the varimax method was used, according to which the number of variables, which is very heavy for each factor, is minimized. After the model rotation, the results are presented in the table below:

Factor	Variance	Difference	Proportion	Cumulative
Factor1	2.970	1.076	0.339	0.339
Factor2	1.893	0.154	0.216	0.555
Factor3	1.739	0.598	0.199	0.754
Factor4	1.141	0.868	0.130	0.884
Factor5	0.273	0.028	0.031	0.916
Factor6	0.245	0.001	0.028	0.944
Factor7	0.244	0.056	0.028	0.972
Factor8	0.188	0.127	0.022	0.993

Table 7. Factor variance - factor weights after rotation

Table 8.	Factor	variance -	factor	weights	after	rotation

Variab	Facto	Uniquen								
le	r1	r2	r3	r4	r5	r6	r7	r8	r9	ess
x 1	-0.042	-0.054	-0.063	0.996	-0.006	-0.002	0.002	0.013	0.000	-0.042
x2	0.043	0.005	0.992	-0.058	-0.060	0.062	-0.012	-0.024	-0.058	0.043
x3	0.988	0.078	0.003	-0.021	-0.010	0.008	0.006	-0.001	-0.098	0.988
x4	-0.989	-0.068	-0.014	0.021	0.001	-0.008	0.026	-0.020	0.047	-0.989

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x5	0.047	0.944	0.014	-0.030	-0.017	0.061	0.317	-0.008	0.001	0.047
x6	-0.157	0.020	-0.012	-0.128	0.355	0.083	-0.064	-0.021	0.037	-0.157
x7	0.045	0.928	0.016	-0.046	0.022	-0.097	-0.352	0.003	-0.005	0.045
x8	0.027	0.007	0.006	0.048	0.338	-0.047	0.032	0.005	-0.034	0.027
x9	0.126	0.035	0.791	-0.023	0.126	-0.089	0.030	0.033	0.133	0.126
x10	-0.009	-0.004	-0.125	-0.031	0.109	0.204	-0.040	0.057	0.021	-0.009
x11	0.039	-0.345	0.300	-0.007	0.015	0.403	0.101	-0.012	-0.008	0.039
x12	0.012	-0.013	0.032	0.286	0.017	-0.084	0.020	-0.195	-0.031	0.012
x13	0.378	-0.058	0.122	-0.008	-0.004	-0.017	0.024	-0.003	0.157	0.378
x14	0.095	-0.039	-0.061	0.202	-0.009	-0.017	-0.003	0.380	-0.001	0.095

4.2.4 Variable selection

The conclusions after the assessment are that four factors interpret (after rotation) more than 88% of the variance of the model. Reaching this conclusion is obvious, taking into account eigenvalues or fluctuations after rotation (see the above tables and the related chart). Additionally, the following table of selection criteria (AIC, BIC) reinforces this view.

Table 9. Factor selection criteria

factors	Loglik	df_m	df_r	AIC	BIC
1	-597.02	14	77	1222.04	1276.97
2	-307.65	27	64	669.31	775.26
3	-138.56	39	52	355.12	508.17
4	-92.03	50	41	284.06	480.28
5	-46.10	60	31	212.20	447.65
6	-19.00	69	22	176.01	446.78
7	-11.01	77	14	176.03	478.19
8	-3.34	84	7	174.68	504.32
9	-0.78	90	1	181.56	534.74

The selection of the most important variables for the analysis can primarily result from the above table, where the highest weighted variables are identified per most important factor. Apicture can also be given by the Kaiser-Meyer-Olkin (KMO) criterion in the following table. For KMO criteria above 0.5, the sample and variables are considered appropriate.

Table 10. Kaiser-Meyer-Olkin Criterion (KMO)

Kaiser-J	Kaiser-Meyer-Olkin(KMO) measure of sampling adequacy									
Variable	КМО	Variable	КМО							
x 1	0.626	x8	0.610							
x2	0.713	x9	0.735							
x3	0.739	x10	0.596							
x4	0.683	x11	0.684							
x5	0.618	x12	0.480							
x6	0.515	x13	0.839							
x7	0.512	x14	0.340							
		Overall	0.678							

Finally, taking into account the correlations between the initial variables and the results of the factor analysis, the variables to be used in the model are as follows:

Table 11.	Variables	to be	used in	the model
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Variable description	Variables
Sales to Total Assets	x 1
EBITDA to Total Assets	x2
Loan Capital to Total Funds	x4
Current Assets to Current Liabilities	x 5
Interest Coverage by EBITDA	x11

In other words, the variables with the greatest weight in each factor were chosen, taking also into account the correlations between them and avoiding the simultaneous use of highly correlated variables, in order to minimize any problems of multicollinearity.

4.2.5 Econometric analysis

The Logit and Probit models are widely used for the form of analysis in this study. As mentioned above, their difference is in the hypothesis made concerning the form of the distribution. The logistic distribution is similar to normal, with only differences in heavy tails². Therefore, for intermediate estimated values (**x'b**), for example in the range -1,2 and 1,2, the models give similar probabilities (Green, 2002). Different results in models can be observed when there are very few observations about the dependent variable or when there is a large fluctuation in the values of significant explanatory variables and, especially, when both apply(Green, 2002). Therefore, in the present study, since the sample is large in most estimates, no differences are expected between the models.

The model selected in order to investigate the prediction of failure and bankruptcy of Greek companies is the model of normal distribution (Probit).

Probit models use the standard normal cumulative distribution function to predict the probability that the dependent variable will take value 1:

$$Pr(y_i = 1|x_i) = \int_{-\infty}^{x'b} f(x)d(x) = \Phi(x'b)$$

with f(z) thestandard normal probability density function:

$$f(z) = (2\pi)^{-1/2} e^{-(z^2/2)}$$

Therefore, according to the above, the model to be used will be in the form:

$$Pr(y = 1) = \Phi(c + b_1x1 + b_2x2 + \cdots + b_kxk)$$

5. RESULTS

Detailed tables of results and company classification can be found in the appendix at the end of this paper. However, in this section the results are presented through comparative tables as follows.

5.1 Comparative tables

One year before bankruptcy

Variables	Manufa sect	$\begin{array}{c c} Manufacturing \\ sector \\ \hline \\ \hline \\ Coef. \\ p > Z \\ \hline \\ 0.604 \\ \hline \\ 0.016 \\ \hline \end{array}$		Wholesale sector		Retail sector		Services sector	
	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z	
χ1	-0.604	0.012	-0.076	0.288	-0.545	0.021	-0.40455	0.017	
χ2	-3.534	0.018	-3.135	0.002	-7.140	0.008	-1.05822	0.234	
χ4	3.327	0.000	2.616	0.000	3.850	0.000	2.160966	0.000	
χ5	0.036	0.190	0.049	0.064	-0.105	0.195	-0.15225	0.246	
χ11	-0.001	0.512	-0.001	0.276	-0.009	0.171	0.000179	0.705	
Cons	-1.827	0.000	-1.759	0.000	-2.149	0.007	-1.00154	0.087	

Table 12. Estimates of the coefficients of the Probit model

² According to Green (2003) it is more like to resembles a t-

distribution with 7 degrees of freedom.

Two years before bankruptcy

Variables	Manufa sect	Manufacturing sector Coef. p > Z -0.325 0.166 -1.967 0.280 2.798 0.000	Wholesale sector		Retail sector		Services sector	
	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z
χ1	-0.325	0.166	-0.0192	0.8110	0.0131	0.9390	-0.031022	0.862
χ2	-1.967	0.280	-4.3556	0.0010	-7.3504	0.0010	-1.122032	0.262
χ4	2.798	0.000	2.2109	0.0000	3.1678	0.0010	2.015190	0.003
χ5	0.072	0.446	0.0379	0.2060	-0.0356	0.8530	-0.282369	0.277
χ11	-0.010	0.316	-0.0003	0.8640	0.0006	0.3150	-0.001611	0.314
Cons	-1.560	0.005	-1.4310	0.0010	-2.1959	0.0120	-0.909404	0.172

Table 13. Estimates of the coefficients of the Probit model

Three years before bankruptcy

Variables	Manufact secto	turing or Wholesa		sector	Retail sector		Services sector	
	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z
χ1	0.171667	0.455	-0.0875857	0.310	0.1316329	0.378	0.0270708	0.861
χ^2	-6.46724	0.000	-2.7134110	0.011	-3.7817130	0.047	-2.752004	0.038
χ4	2.383378	0.000	2.9102760	0.000	2.0870100	0.037	2.704942	0.000
χ5	0.05265	0.235	0.0440249	0.139	0.0210751	0.956	-0.138254	0.205
χ11	-0.00043	0.572	-0.0003467	0.417	0.0013221	0.303	-0.000424	0.558
Cons	-1.46485	0.005	-1.8886700	0.000	-1.7722450	0.112	-1.480488	0.016

Four years before bankruptcy

 Table 15. Estimates of the coefficients of the Probit model

Variables	Manufacturing es sector		bles Manufacturing Wholesale sector		Retail sector		Services sector	
	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z	Coef.	p > Z
χ1	0.700137	0.018	-0.0738529	0.353	0.2168703	0.108	-0.022478	0.837
χ2	-4.84049	0.008	-0.7272684	0.584	-2.6516810	0.069	-0.967590	0.393
χ 4	2.261233	0.002	1.4431500	0.016	2.8783030	0.005	1.531131	0.044
χ 5	0.121206	0.406	0.0557438	0.270	0.1605971	0.396	0.0580878	0.768
χ11	-0.00609	0.261	-0.0158125	0.105	0.0000581	0.747	-0.000504	0.389
Cons	-1.84138	0.004	-0.8992389	0.082	-2.5981240	0.009	-0.997750	0.179

As shown in Tables 12, 13, 14 and 15, the financial variable of the debt burden, "X4 Loan Capital to Total Funds" is statistically significant for all sectors and years before bankruptcy.

The financial variables "X1 Sales to Total Assets" and "X2 EBITDA to Total Assets" are statistically significant in some cases, while the financial variables "X5 Current Assets to Current Liabilities" and "X11 Interest Coverage by EBITDA" are by no means statistically significant.

Table 10. Fotal Directive capacity of the ritobit model by secto	Table 16. Total	predictive ca	pacity of the	Probit model	bv sector
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	MANUFACTURI NG SECTOR	WHOLESAL E SECTOR	RETAI L SECTO R	SERVICE S SECTOR
1 YEAR BEFORE BANKRUPTCY	74,26%	73,87%	79,31%	72,46%
2 YEARS BEFORE BANKRUPTCY	76,58%	66,85%	78,72%	71,19%
3 YEARS BEFORE BANKRUPTCY	74,40%	68,97%	64,13%	71,30%
4 YEARS BEFORE BANKRUPTCY	65,24%	61,90%	68,18%	63,27%

As can be seen in Table 16, the total predictability of the Probit model by sector and year before bankruptcy ranges from 61.90% to 79.31%.

Table 17. Fredictive Capacity of the Frobit Model, of Dankrupt companies	Table 17. Predictive C	apacity of the	Probit Model, o	of bankrupt companies
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	MANUFACTURI NG SECTOR	WHOLESAL E SECTOR	RETAI L SECTO R	SERVICE S SECTOR
1 YEAR BEFORE BANKRUPTCY	75,25%	79,28%	75,86%	78,26%
2 YEARS BEFORE BANKRUPTCY	79,75%	74,16%	78,72%	77,97%
3 YEARS BEFORE BANKRUPTCY	77,38%	74,71%	58,70%	75,93%
4 YEARS BEFORE BANKRUPTCY	67,07%	75,00%	70,45%	71,43%

The above table shows that in the manufacturing and retail trade sectors, the difference in the 1^{st} and 2^{nd} year classification rates is increasing in the second year before bankruptcy. Normally, as the bankruptcy approaches, the classification rates of bankrupt companies are rising.

This leads us to the conclusion that an attempt was made by a number of companies to exercise creative accounting in order to improve their financial data and to embellish the data of the financial statements. The upward trend in inventories (Table 18), as the firms that are bankruptcy candidates approach the collapse, reinforces the conclusion of the falsification of the financial statements through intervention in the end-of-year inventory.

This intervention in the inventory entails the improvement of the results and the ratio of the general liquidity through the enhancement of the current assets and the general embellishment of the financial statements.

Table 18. Average	Inventories of	Companies in	Bankruptcy Regime

YEAR BEFORE BANKRUPTCY	AVERAGE INVENTORIES OF COMPANIES IN BANKRUPTCY REGIME(€)	CHANGE (%)
-1	2.107.681	9,28
-2	1.928783	2,57
-3	1.880.406	6,73

-4	1.761.768	1,27
-5	1.739.657	

The attempt to alter the results in the last year before bankruptcy in the industrial and retail sectors can even better be shown by the profitability in the last year before bankruptcy in the following table (19).

Table 19. Evolution of Results (P	Profit/Loss) from 5 years to 1 year before ban	kruptcy

YEAR BEFORE BANKRUPTCY	PROFIT BEFORE TAX (Average)	EBITDA (Average)
-1	23.177	348.497
-2	-217.715	127.454
-3	-40.711	297.899
-4	3.656	386.191
-5	51.035	266.683

In a total of 159 companies in the manufacturing industry and retail trade sectors, 34 companies or 21.38% presented profits. More specifically, in the manufacturing industry sector, in a total of 101 companies in the sample, 20 companies (19,80%) show profits in the last year before bankruptcy, while respectively in the retail trade, in a total of 58 companies in the sector, 14 companies reported profits (24.13%).

The above are also consistent with the international literature. As Argenti(1976), Sweeney (1994), Charitou et al(2007), and Lara et al (2009) report, when an enterprise is close to bankruptcy, the management increasingly intervenes by applying profit management practices in order to alter the results and embellish the financial statements.

5. CONCLUSIONS

There is significant explanatory capacity of the Probit model in the 4 key sectors of the Greek economy, which varies:

For the first year before bankruptcy between 72.46% and 79.31%.

For the second year before

bankruptcy between 66.85% and 78.72%.

For the third year before bankruptcy between 64,13% and 74,40%.

For the fourth year before bankruptcy between 61.90% and 68.18%.

• There is a clear differentiation in the classification of companies among the sectors of the Greek economy, which is explained by the specific features of each sector and the degree of homogeneity of the samples of the bankrupt and healthy (non-bankrupt) companies. This differentiation is also referred to in Standard and Poor's surveys, which have highlighted

significant differences between the same financial indicators of enterprises belonging to different sectors.

• The predictive capacity of the Probit model is superior in the retail sector, which in the 1st and 2nd year before bankruptcy reached 79.31% and 78.72%, respectively.

• Tendencies towards creative accounting by a number of companies are observed in their last year of operation, before bankruptcy, in the industrial and retail trade sectors, in order to embellish the financial statements. Exercising creative accounting in the above sectors is characterized by greater ease, and is achieved in the industrial sector by altering the inventory (stocks of many and different species), while in the retail sector it is achieved not only through the falsification of the inventory but also by creating fictitious sales.

• The financial variable of the debt burden, "X4 Loan Capital to Total Funds", presents the greatest stability and contributes substantially to the interpretative power of the Probit model. It is presented with a positive sign and is statistically significant in all sectors and in all years before bankruptcy, which means that an increase in the value of this variable increases the probability of bankruptcy.

• The financial variable "X2 EBITDA to Total Assets" is statistically significant in the majority of cases, while it is presented with a negative sign in all sectors and in all years before bankruptcy, which means that a decrease in its value increases the probability of bankruptcy.

• The financial variable "X1 Sales to Total Assets" is statistically significant in 4 cases, while in the majority of cases it is presented with a negative sign, which means that a decrease in the value of the variable increases the probability of bankruptcy.

• In none of the cases is the financial variable "X5 Current Assets to Current Liabilities" statistically significant. However, the current ratio is not in itself representative of liquidity. There are many cases of companies which, while being on the verge of bankruptcy, have index values higher than 2, as well as cases of companies in which a relatively low index (depending on the industry in which the business operates) can be considered satisfactory. Therefore, adverse effects on a case-by-case basis reduce the overall effect on the model.

• In none of the cases is the financial variable "X11 Interest Coverage by EBITDA" statistically significant and this is due to the mixed effects that take place and reduce the overall impact on the model. Companies with the ability to cover interest from the operating result are less likely to fail. However, an increase in this indicator may indicate an increase in investment activity, i.e. the implementation of investment projects partly based on bank lending; a process which entails an increase in interest rates and a decline in the index, without the firm being considered to have failed (rather the opposite).

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A1. Manufacturing sector (One year before bankruptcy)								
Coef.	Std. Err	Z	p >z	<u>[</u> 95% Conf.	Interval			
-0.604	0.241	-2.510	0.012	-1.076	-0.131			
-3.534	1.491	-2.370	0.018	-6.455	-0.612			
3.327	0.582	5.720	0.000	2.186	4.468			
0.036	0.028	1.310	0.190	-0.018	0.090			
-0.001	0.001	-0.660	0.512	-0.004	0.002			
-1.827	0.440	-4.150	0.000	-2.690	-0.965			
	Coef. -0.604 -3.534 3.327 0.036 -0.001 -1.827	Coef. Std. Err -0.604 0.241 -3.534 1.491 3.327 0.582 0.036 0.028 -0.001 0.001 -1.827 0.440	Coef. Std. Err z -0.604 0.241 -2.510 -3.534 1.491 -2.370 3.327 0.582 5.720 0.036 0.028 1.310 -0.001 0.001 -0.660 -1.827 0.440 -4.150	B C -9 I -9 Coef. Std. Err z p >z -0.604 0.241 -2.510 0.012 -3.534 1.491 -2.370 0.018 3.327 0.582 5.720 0.000 0.036 0.028 1.310 0.190 -0.001 0.001 -0.660 0.512 -1.827 0.440 -4.150 0.000	BCJJCoef.Std. Errz $p > z$ $[95\%$ Conf0.6040.241-2.5100.012-1.076-3.5341.491-2.3700.018-6.4553.3270.5825.7200.0002.1860.0360.0281.3100.190-0.018-0.0010.001-0.6600.512-0.004-1.8270.440-4.1500.000-2.690			

cons	-1.827	0.770	-4.150	0.000	-2.030	-0.905
1		Classified		D	-D	Total
2		+		76	27	103
3		-		25	74	99
4		Total		101	101	202
5	Sensitivity			Pr(+D)	75.25%	
6	Specificity			Pr(-~D)) 73.27%	
7	Positive predictive value			Pr(D +)) 73.79%	
8	Negative predic	ctive value		Pr(~D -)) 74.75%	
9	False + rate for	∙ true ~D		$Pr(+\sim D$) 26.73%	
10	False - rate for true D			Pr(- D)	24.75%	
11	False + rate for classified +			Pr(~D +) 26.21%	
12	False - rate for classified -			Pr(D -)	25.25%	
13	Correctly classified			,	74,26%	

As planned in this paper, the variable bankr=1 represents the bankrupt companies, while the variable bankr=0 represents the "healthy" (sound) ones.

With this data, the table of results is interpreted as follows:

- 1. symbol"**D**": bankrupt companies
- 2. symbol"~**D**": "helathy" companies

3. symbol"+":classification as bankrupt

4. symbol"–":classification of "healthy"

5. Sensitivity : the percentage of correct classification of bankrupt companies

6. Specificity : the percentage of correct classification of healthy companies

7. Positive predictive value : the percentage of the actually bankrupt companies in the total of those that were classified as bankrupt (in the example 76/103=73,79%)

8. Negative predictive value: the percentage of actually "healthy" companies in the total of those that were classified as "healthy" (in the example 74/99=74,75%)

9. *Typell* error

10. *Typel* error

11. the error of the percentage in "*Positive predictive value*"

12. the error of the percentage in "*Negativepredictive value*"

13. the total predictive capacity of the model.

A2. Manufacturing sector (Two years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[µ95% Conf.]	Interval
x 1	-0.325	0.235	-1.390	0.166	-0.786	0.135
x2	-1.967	1.819	-1.080	0.280	-5.533	1.599
x4	2.798	0.664	4.210	0.000	1.496	4.099
x5	0.072	0.094	0.760	0.446	-0.113	0.256
x11	-0.010	0.010	-1.000	0.316	-0.030	0.010
cons	-1.560	0.551	-2.830	0.005	-2.640	-0.480

1	Classified	D	-D	Total
2	+	63	21	84
3	_	16	58	74
4	Total	79	79	158
5	Sensitivity	Pr(+D)	79.75%	
6	Specificity	Pr(- ∼D)	73.42%	
7	Positive predictive value	Pr(D +)	75.00%	
8	Negative predictive value	Pr(~D -)	78.38%	
9	False + rate for true ~D	$Pr(+\sim D)$	26.58%	
10	False - rate for true D	Pr(- D)	20.25%	
11	False + rate for classified +	$Pr(\sim D +)$	25.00%	
12	False - rate for classified -	Pr(D -)	21.62%	
13	Correctly classified	76,5	68%	

A3. Manufacturing sector (Three years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[[95% Con	f. Interval]
x 1	0.172	0.230	0.750	0.455	-0.279	0.622
x2	-6.467	1.657	-3.900	0.000	-9.715	-3.220
x4	2.383	0.642	3.710	0.000	1.125	3.641
x5	0.053	0.044	1.190	0.235	-0.034	0.140
x11	0.000	0.001	-0.570	0.572	-0.002	0.001
cons	-1.465	0.519	-2.820	0.005	-2.482	-0.448

1	Classified	D	-D	Total
2	+	65	24	89
3	-	19	60	79
4	Total	84	84	168
5	Sensitivity	Pr(+D)	77.38%	
6	Specificity	Pr(- ∼D)	71.43%	
7	Positive predictive value	Pr(D +)	73.03%	
8	Negative predictive value	Pr(~D -)	75.95%	
9	False + rate for true ~D	$Pr(+\sim D)$	28.57%	
10	False - rate for true D	Pr(- D)	22.62%	
11	False + rateforclassified +	$Pr(\sim D +)$	26.97%	
12	False - rateforclassified -	Pr(D -)	24.05%	
13	Correctlyclassified	74,4	40%	

A4. Manufacturing sector (Four years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[µ95% Con	f. Interval]
x 1	0.700	0.297	2.360	0.018	0.118	1.282
x2	-4.840	1.838	-2.630	0.008	-8.444	-1.237
x4	2.261	0.729	3.100	0.002	0.832	3.690
x5	0.121	0.146	0.830	0.406	-0.165	0.407
x11	-0.006	0.005	-1.120	0.261	-0.017	0.005
cons	-1.841	0.645	-2.850	0.004	-3.106	-0.577

1	Classified	D	-D	Total
2	+	55	30	85
3	-	27	52	79
4	Total	82	82	164
5	Sensitivity	Pr(+D)	67.07%	
6	Specificity	Pr(- ∼D)	63.41%	
7	Positivepredictivevalue	Pr(D +)	64.71%	
8	Negativepredictivevalue	Pr(~D -)	65.82%	
9	False + rate for true \sim D	$\Pr(+\sim D)$	36.59%	
10	False - rate for true D	Pr(- D)	32.93%	
11	False + rateforclassified +	$Pr(\sim D +)$	35.29%	
12	False - rateforclassified -	Pr(D -)	34.18%	
13	Correctlyclassified	65,9	24%	

A5. Wholesale sector(One year before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[95% Conf.	Interval
x 1	-0.076	0.072	-1.060	0.288	-0.216	0.064
x2	-3.135	1.023	-3.060	0.002	-5.141	-1.129
x4	2.616	0.499	5.240	0.000	1.638	3.593
x5	0.049	0.027	1.850	0.064	-0.003	0.101
x11	-0.001	0.001	-1.090	0.276	-0.002	0.001
cons	-1.759	0.407	-4.330	0.000	-2.556	-0.962

1	Classified	D	-D	Total
2	+	88	35	123
3	_	23	76	99
4	Total	111	111	222
5	Sensitivity	Pr(+D)	79.28%	
6	Specificity	Pr(- ∼D)	68.47%	
7	Positive predictive value	Pr(D +)	71.54%	
8	Negative predictive value	Pr(~D -)	76.77%	
9	False + rate for true ~D	$Pr(+\sim D)$	31.53%	
10	False - rate for true D	Pr(- D)	20.72%	
11	False + rate for classified +	$Pr(\sim D +)$	28.46%	
12	False – rate for classified -	Pr(D -)	23.23%	
13	Correctly classified	73,8	37%	

A6. Wholesale sector (Two years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[55% Conf.]	Interval
x 1	-0.0192	0.0802	-0.2400	0.8110	-0.1763	0.1379
x2	-4.3556	1.3707	-3.1800	0.0010	-7.0421	-1.6691
x4	2.2109	0.5379	4.1100	0.0000	1.1565	3.2652
x5	0.0379	0.0300	1.2600	0.2060	-0.0209	0.0967
x11	-0.0003	0.0017	-0.1700	0.8640	-0.0036	0.0030
cons	-1.4310	0.4306	-3.3200	0.0010	-2.2749	-0.5871

1	Classified	D	-D	Total
2	+	66	36	102
3	-	23	53	76
4	Total	89	89	178
5	Sensitivity	Pr(+D)	74.16%	
6	Specificity	Pr(-~D)	59.55%	
7	Positive predictive value	Pr(D +)	64.71%	
8	Negative predictive value	Pr(~D -)	69.74%	
9	False + rate for true ~D	Pr(+~D)	40.45%	
10	False - rate for true D	Pr(- D)	25.84%	
11	False + rate for classified +	$Pr(\sim D +)$	35.29%	
12	False – rate for classified -	Pr(D -)	30.26%	
13	Correctly classified	66,8	35%	

A7. Wholesale sector (Three years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[≤95% Con	f. Interval]
x 1	-0.088	0.086	-1.020	0.310	-0.257	0.081
x2	-2.713	1.068	-2.540	0.011	-4.807	-0.619
x4	2.910	0.615	4.740	0.000	1.706	4.115
x5	0.044	0.030	1.480	0.139	-0.014	0.102
x11	0.000	0.000	-0.810	0.417	-0.001	0.000
cons	-1.889	0.483	-3.910	0.000	-2.835	-0.943

1	Classified	D	-D	Total
2	+	65	32	97
3	_	22	55	77
4	Total	87	87	174
5	Sensitivity	Pr(+D)	74.71%	
6	Specificity	$Pr(-\sim D)$	63.22%	
7	Positive predictive value	Pr(D +)	67.01%	
8	Negative predictive value	Pr(~D -)	71.43%	
9	False + rate for true \sim D	Pr(+~D)	36.78%	
10	False - rate for true D	Pr(- D)	25.29%	
11	False + rate for classified +	$Pr(\sim D +)$	32.99%	
12	False – rate for classified -	Pr(D -)	28.57%	
13	Correctly classified	68,9	97%	

A8. Wholesale sector (Four years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[95% Conf	. Interval]
x 1	-0.074	0.080	-0.930	0.353	-0.230	0.082
x2	-0.727	1.330	-0.550	0.584	-3.333	1.879
x4	1.443	0.601	2.400	0.016	0.265	2.621
x5	0.056	0.051	1.100	0.270	-0.043	0.155
x11	-0.016	0.010	-1.620	0.105	-0.035	0.003
cons	-0.899	0.516	-1.740	0.082	-1.911	0.113

	1	Classified	D	-D	Total
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2	+	63	43	106
3	_	21	41	62
4	Total	84	84	168
5	Sensitivity	Pr(+D)	75.00%	
6	Specificity	Pr(-~D)	48.81%	
7	Positive predictive value	Pr(D +)	59.43%	
8	Negative predictive value	Pr(~D -)	66.13%	
9	False + rate for true ~D	$Pr(+\sim D)$	75.00%	
10	False - rate for true D	Pr(- D)	48.81%	
11	False + rate for classified +	$Pr(\sim D +)$	59.43%	
12	False – rate for classified -	Pr(D -)	66.13%	
13	Correctly classified	61,9	90%	

A9. Retail sector (One year before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[⊂95% Conf.	Interval]
x 1	-0.545	0.236	-2.310	0.021	-1.007	-0.083
x2	-7.140	2.713	-2.630	0.008	-12.457	-1.823
x4	3.850	1.049	3.670	0.000	1.793	5.907
x5	-0.105	0.081	-1.290	0.195	-0.265	0.054
x11	-0.009	0.006	-1.370	0.171	-0.021	0.004
cons	-2.149	0.796	-2.700	0.007	-3.709	-0.589

1	Classified	D	-D	Total
2	+	44	10	54
3	_	14	48	62
4	Total	58	58	116
5	Sensitivity	Pr(+D)	75.86%	
6	Specificity	Pr(- ∼D)	82.76%	
7	Positive predictive value	Pr(D +)	81.48%	
8	Negative predictive value	Pr(~D -)	77.42%	
9	False + rate for true ~D	$Pr(+\sim D)$	17.24%	
10	False - rate for true D	Pr(- D)	24.14%	
11	False + rate for classified +	$Pr(\sim D +)$	18.52%	
12	False – rate for classified -	Pr(D -)	22.58%	
13	Correctly classified	79,31%		

A10. Retail sector (Two years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[µ95% Conf.	Interval
x 1	0.013	0.171	0.080	0.939	-0.321	0.347
x2	-7.350	2.184	-3.370	0.001	-11.631	-3.070
x4	3.168	0.958	3.310	0.001	1.289	5.046
x5	-0.036	0.192	-0.190	0.853	-0.412	0.340
x11	0.001	0.001	1.010	0.315	-0.001	0.002
cons	-2.196	0.875	-2.510	0.012	-3.911	-0.481

1	Classified	D	-D	Total
2	+	37	10	47

3	-	10	37	47
4	Total	47	47	94
5	Sensitivity	Pr(+D)	78.72%	
6	Specificity	Pr(- ∼D)	78.72%	
7	Positivepredictivevalue	Pr(D +)	78.72%	
8	Negativepredictivevalue	Pr(~D -)	78.72%	
9	False + rate for true ~D	$Pr(+\sim D)$	21.28%	
10	False - rate for true D	Pr(- D)	21.28%	
11	False + rateforclassified +	$Pr(\sim D +)$	21.28%	
12	False - rateforclassified -	Pr(D -)	21.28%	
13	Correctlyclassified	78,7	72%	

A11. R	Retail sector	(Three years	before	bankruptcy))
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bankr	Coef.	Std. Err	Z	p >z	[µ95% Con	f. Interval]
x 1	0.132	0.149	0.880	0.378	-0.161	0.424
x2	-3.782	1.903	-1.990	0.047	-7.512	-0.052
x4	2.087	0.999	2.090	0.037	0.128	4.046
x5	0.021	0.385	0.050	0.956	-0.734	0.776
x11	0.001	0.001	1.030	0.303	-0.001	0.004
cons	-1.772	1.114	-1.590	0.112	-3.955	0.410

1	Classified	D	-D	Total
2	+	27	14	41
3	_	19	32	51
4	Total	46	46	92
5	Sensitivity	Pr(+D)	58.70%	
6	Specificity	Pr(- ∼D)	69.57%	
7	Positivepredictivevalue	Pr(D +)	65.85%	
8	Negativepredictivevalue	Pr(~D -)	62.75%	
9	False + rate for true \sim D	$Pr(+\sim D)$	30.43%	
10	False - rate for true D	Pr(- D)	41.30%	
11	False + rateforclassified +	$Pr(\sim D +)$	34.15%	
12	False - rateforclassified -	Pr(D -)	37.25%	
13	Correctlyclassified	64,1	13%	

A12. Retail sector (Four years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[[95% Con	f. Interval]
x 1	0.217	0.135	1.610	0.108	-0.047	0.481
x2	-2.652	1.459	-1.820	0.069	-5.511	0.208
x4	2.878	1.021	2.820	0.005	0.877	4.880
x5	0.161	0.189	0.850	0.396	-0.210	0.531
x11	0.000	0.000	0.320	0.747	0.000	0.000
cons	-2.598	0.998	-2.600	0.009	-4.554	-0.642

1	Classified	D	-D	Total
2	+	31	15	46
3	-	13	29	42
4	Total	44	44	88

5	Sensitivity	Pr(+D)	70.45%
6	Specificity	Pr(-~D)	65.91%
7	Positivepredictivevalue	Pr(D +)	67.39%
8	Negativepredictivevalue	Pr(~D -)	69.05%
9	False + rate for true ~D	$Pr(+\sim D)$	34.09%
10	False - rate for true D	Pr(- D)	29.55%
11	False + rateforclassified +	$Pr(\sim D +)$	32.61%
12	False - rateforclassified -	Pr(D -)	30.95%
13	Correctlyclassified	68,1	8%

A13. Services sector(One year before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[µ95% Conf.]	Interval
x 1	-0.405	0.170	-2.380	0.017	-0.737	-0.072
x2	-1.058	0.888	-1.190	0.234	-2.799	0.683
x4	2.161	0.613	3.530	0.000	0.960	3.362
x5	-0.152	0.131	-1.160	0.246	-0.410	0.105
x11	0.000	0.000	0.380	0.705	-0.001	0.001
cons	-1.002	0.586	-1.710	0.087	-2.149	0.146

1	Classified	D	-D	Total
2	+	54	23	77
3	_	15	46	61
4	Total	69	69	138
5	Sensitivity	Pr(+D)	78.26%	
6	Specificity	Pr(-~D)	66.67%	
7	Positive predictive value	Pr(D +)	70.13%	
8	Negative predictive value	Pr(~D -)	75.41%	
9	False + rate for true ~D	$Pr(+\sim D)$	33.33%	
10	False - rate for true D	Pr(-D) 21.74%		
11	False + rate for classified +	$Pr(\sim D +)$	29.87%	
12	False - rate for classified -	Pr(D -) 24.59%		
13	Correctly classified	72,46%		

A14. Services sector (Two years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[55% Conf.]	Interval
x 1	-0.031	0.179	-0.170	0.862	-0.382	0.320
x2	-1.122	1.001	-1.120	0.262	-3.085	0.841
x4	2.015	0.682	2.960	0.003	0.679	3.352
x5	-0.282	0.260	-1.090	0.277	-0.791	0.227
x11	-0.002	0.002	-1.010	0.314	-0.005	0.002
cons	-0.909	0.666	-1.370	0.172	-2.214	0.395

1	Classified	D	-D	Total
2	+	46	21	67
3	-	13	38	51
4	Total	59	59	118
5	Sensitivity	Pr(+D)	77.97%	
6	Specificity	Pr(-~D)	64.41%	

7	Positive predictive value	Pr(D +)	68.66%
8	Negative predictive value	Pr(~D -)	74.51%
9	False + rate for true \sim D	Pr(+~D)	35.59%
10	False - rate for true D	Pr(- D)	22.03%
11	False + rate for classified +	$Pr(\sim D +)$	31.34%
12	False - rate for classified -	Pr(D -)	25.49%
13	Correctly classified	71,1	.9%

A15. Services sector (Three years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	[[95% Con	f. Interval]
x 1	0.027	0.155	0.170	0.861	-0.277	0.331
x2	-2.752	1.325	-2.080	0.038	-5.349	-0.155
x4	2.705	0.677	4.000	0.000	1.378	4.032
x5	-0.138	0.109	-1.270	0.205	-0.352	0.075
x11	0.000	0.001	-0.590	0.558	-0.002	0.001
cons	-1.480	0.612	-2.420	0.016	-2.679	-0.282

1	Classified	D	-D	Total
2	+	41	18	59
3	_	13	36	49
4	Total	54	54	108
5	Sensitivity	Pr(+D)	75.93%	
6	Specificity	Pr(-~D)	66.67%	
7	Positive predictive value	Pr(D +)	69.49%	
8	Negative predictive value	Pr(~D -)	73.47%	
9	False + rate for true ~D	$Pr(+\sim D)$	33.33%	
10	False - rate for true D	Pr(- D)	24.07%	
11	False + rate for classified +	$Pr(\sim D +)$	30.51%	
12	False - rate for classified -	Pr(D -)	26.53%	
13	Correctly classified	71,3	30%	

A16. Services sector (Four years before bankruptcy)

bankr	Coef.	Std. Err	Z	p >z	∑95% Conf.	Interval
x 1	-0.022	0.109	-0.210	0.837	-0.237	0.192
x2	-0.968	1.133	-0.850	0.393	-3.188	1.253
x4	1.531	0.760	2.020	0.044	0.042	3.020
x5	0.058	0.197	0.290	0.768	-0.328	0.445
x11	-0.001	0.001	-0.860	0.389	-0.002	0.001
cons	-0.998	0.742	-1.340	0.179	-2.452	0.457

1	Classified	D	-D	Total
2	+	35	22	57
3	-	14	27	41
4	Total	49	49	98
5	Sensitivity	Pr(+D)	71.43%	
6	Specificity	Pr(-~D)	55.10%	
7	Positive predictive value	Pr(D +)	61.40%	

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8	Negative predictive value	$Pr(\sim D -)$	65.85%
9	False + rate for true ~D	$Pr(+\sim D)$	44.90%
10	False - rate for true D	Pr(- D)	28.57%
11	False + rate for classified +	Pr(~D +)	38.60%
12	False - rate for classified -	Pr(D -)	34.15%
13	Correctly classified	63,27%	