Predicting financial distress in Greek business: A viability factors perspective

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Abstract
The motivation of this study is to approach the issue of financial distress signalling within an alternative conceptual framework. We develop an accounting-based model for the prediction of financial distress with Greek business data from a viability factors perspective. One of the main objectives of this study is to provide evidence about the prediction of financial distress in a way to guide managerial action towards the adoption of strategic policies that enhance the financial viability of companies. The present study incorporates multiple discriminant analysis and logit analysis for the construction of a model for the prediction of financial distress. The paper provides evidence in support of the existing traditional prediction models vis-à-vis liquidity and corporate structure and acknowledges the contribution of human capital to company's profitability and sales growth as critical success factors for the viability of Greek business. The empirical results of the study indicate that the logit model outperforms the MDA model in terms of correct classification and Type I error. The contribution of this paper is the proposition of new value-relevant variables concerning the activity, the profitability and the dividend policy of Greek business that enhance the accuracy of the existing financial distress prediction models.

Keywords: Financial distress, prediction models, viability, bankruptcy

JEL classifications: G32, G33, M21, M41

Introduction

Financial distress signalling has been a sword-play field among academics and professionals for the last four decades and the current financial turmoil has intensified it since the prediction of financial distress affects a variety of stakeholders such as employees, managers, shareholders, financial institutions, auditors, clients, suppliers and the society in general. The effort to discriminate the financially viable from the financially distressed companies was initiated by Beaver (1966) and Altman (1968). However, the orientation of the research in the ensuing years has been confined to

1 the recognition of the variables with incremental information content in predicting financial distress and
2 the comparison of the results of the existing models in favour of one model or methodology against the other.

Admittedly, this perspective reflected financial institutions' agony to evaluate their credit risk exposure and mitigate their losses derived from misclassification errors.

The main objective of the paper is to contribute to the current debate about the prediction of financial distress in a way to guide managerial action towards the adoption of strategic policies that enhance the financial viability of companies. Furthermore, a viability factors perspective is adopted for the development of an accounting-based model for the prediction of financial distress based Greek business data. This study aims to verify the validity of the existing familiar variables (financial ratios) of the current literature and identify new value-relevant variables that attribute incremental predictive power to financial distress models in a Greek business context.

The remainder of this paper is organised as follows: In the second part, we present an extensive literature review concerning the prediction of financial distress. In the third part, we describe our research methodology about the data collection, the statistical methods and the variable selection. The results of our study and discussion of these results are embedded in the fourth part of this paper. Practical implications of this study are reported in the fifth part. Our conclusions are summarised in the last part of this paper.

Literature review

During the last four decades academics and researchers have been exhausted in the prediction of financial distress. Hopefully, the current literature exhibits a variety of prediction models employing numerous variables. In a nutshell, there are two major categories of financial distress prediction models i) statistical models including univariate and multivariate models (discriminant, logit and probit analysis) and ii) artificial expert systems (artificial neural networks, support vector machines, genetic programming). The most popular statistical techniques used for the prediction of corporate financial distress are univariate analysis, multivariate analysis and probability models (LPM, discriminant, logit, probit). The majority of the research has been implemented with the use of financial ratios.

Beaver (1966) developed a model for the prediction of corporate financial distress, with the use of univariate analysis based on a sample of 79 pairs of healthy and bankrupt firms at least 5 years before bankruptcy. Specifically the methodology was pair sample design in which each failed firm was paired with a healthy one. Beaver came to the conclusion that certain financial ratios, most notably cash flow/total liabilities, gave statistically significant signals well before actual business failure. Later, Edmister (1972) concluded that none of these ratios is by itself an accurate predictor in compare with a small set of independent ratios.

Altman (1968) employed multiple discriminant analysis (MDA) and included five financial ratios for the construction of his prediction model. The discriminant function gave a value limit (z-score) for each company and classified it as bankrupt or not. Altman suggested as cut-off point the z-score of 2.675. Hence, corporations that exceeded that score were classified as non-bankrupt and corporations that failed to achieve that score were classified as bankrupt. The results of correct classification were significantly better than Beaver's. Altman found that these five ratios outperformed Beaver's cash flow to total debt ratio. Later, Altman et al (1977) extended Z-score model into ZETA model by using seven ratios. The results of ZETA (96%) exhibited better classification rate than Z-score (94%) model one year before bankruptcy.

According to Eisenbeis (1977) the method of MDA simply classifies the business and doesn't provide an estimate of the risk of bankruptcy. Additionally, Ohlson (1980) raised some objections regarding the reliability of the discriminant analysis concerned with the statistical restrictions of the method such as the normality of the sample. The Linear Probability Model was used as an alternative to the discriminant analysis. Meyer and Pifer (1970) were the first who used this model for the prediction of bank bankruptcy. Collins (1980) also used the LPM to compare the methodology for determining the independent variables followed by Meyer and Pifer with the simple methodology used by Altman (1968). Furthermore, Horrigan (1966), Pinches et al. (1973), Pogue and Soldofsky (1969) and Edmister (1971) adopted the same methodology.

Logit analysis was first employed by Martin (1977) in a survey regarding the financial difficulties of banks. This method became known by Ohlson (1980) who constructed a model of nine independent variables for the prediction of corporate failure. His sample included industrial listed firms. He ended up with 105 failed firms and 2000 non failed firms. Three models were estimated: the first to predict failure within 1 year, the second to predict failure within 2 years and the third to predict failure in 1 or 2 years. He then used a logistic function to predict the probability of failure for the firms using each model.

However, traditional statistical models are usually based on the assumptions of linearity and normality that are rarely witnessed in the real world. In an attempt to improve the accuracy of the proposed models, researchers turned to artificial neural networks (ANN) which are non-parametric classifiers that learn and generalise by experience of complex and non-linear data and make decisions based on information processing units (artificial neurons). A multi-layer perceptron network contains an input layer (predictor variables), one or more hidden layers and an output layer (classification groups). The multi-layer network is usually trained by a learning algorithm. The majority of the existing literature provides evidence that the accuracy of ANN approaches is superior to that of the traditional statistical models (MDA and logit – probit analysis) in different sectors, economies and eras (Altman et al., 1994; Lin and McClean, 2001; Alfaro et al., 2008; Yim and Mitchell, 2007; Tsukuda and Baba, 1994; Ozkan-Gunay and Ozkan, 2007; Etemadi et al., 2008; Lin, 2009; Huang et al., 2008; Wu et al., 2010). An interesting approach was made by Altman et al (1994) who tried to combine the method of ANN with LDA. In some classification tests, the results were significantly better than MDA.

Research methodology

Data collection

The financial statements for this research were obtained from ICAP GROUP database. In particular, the financial data of 60 companies from Northern Greece were collected for the period 2003-2009. 31 of them have gone bankrupt or suspended their operations during this period and the other 29 were non-failed companies. The names of the financially distressed companies were collected from the district courts of Thessaloniki, Serres, Kavala and Drama. The financially viable companies were selected from the Hellenic Chamber of Commerce & Industry of the above cities.

Due to lack of data, the calculation of some ratios was not possible for all companies. For this reason they were removed from the sample. The final sample is consisted of 27 financially distressed and 27 financially viable companies. Table 1 presents the sets of companies according to the sector of their activity. It should be noted that the classification by industry was made under the codification of ICAP GROUP database.

Table 1: Distribution of Companies by Industry Sector

INDUSTRY	Total
Apparel-Accessories-Lingerie	28
GAS & Chemicals	2
Food & Beverages	3
Textiles	12
Paper & Products	1
Plastics	4
Building & Construction	2
Footwear	2
Total	54

The research sample includes only companies with limited liability (Ltd) and societe anonyme (s.a.). The main reason for this was to overcome the scarcity of publicly available information since these companies are obliged to disclose financial statements such as the balance sheet and the income statement in accordance with the Greek Financial Reporting Standards. As it is shown in Table 1, sample selection processes entail only industrial companies. Trade and financial services companies were deliberately excluded from the sample.

Statistical methods

MDA is the most popular method among academics to solve classification problems where the dependent variable is categorical. In financial distress signalling, the dependent variable has two mutually exclusive categories (financially distressed versus financially viable companies) and hence there is only one discriminant function (the number of discriminant functions equals to the number of categories of the dependent variable minus one). The discriminant function has the following form:

$$Ci = a + \sum_{j=1}^{n} b_{ji} FR_{ji}$$

where Ci represents the multiple discriminant score for the category i, a represents a constant term, FR represents j discriminant variables (financial ratios) and b represents j discriminant coefficients. A cornerstone of MDA is that the two sets of the dependent variable are predetermined and the objective is to identify the financial ratios which ideally classify companies between financially distressed and financially viable.

On the other hand, logit analysis is the logistic transformation of the ordinary regression model used for the prediction of the probability π of financial distress. The logit model has the following form:

$$\text{logit}(\pi) = \log[\pi / (1-\pi)] = c + \sum_{k=1}^{n} b_k FR_k = Z$$

where $\pi/(1-\pi)$ is the odds ratio, c represents the intercept, FR represents k financial ratios and b represents k regression coefficients. The formula expressing the logistic regression model directly in terms of π is

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

where the probability π of financial distress varies between zero and one when the value of Z varies from $-\infty$ to $+\infty$ for all FR_k values (Agresti and Finlay, 1997).

Variable selection

The process for the selection of the independent variables that better classify the financially distressed companies from the financially viable entails three stages. During the first stage the selection and computation of 41 financial ratios is performed. In Table 2 we can see the definition of 8 liquidity ratios, 12 activity ratios, 12 profitability ratios, 7 capital structure ratios and 2 investment ratios that originally used for the model construction.

In particular, for the financially distressed companies the computation of the financial ratios is based on the last available financial statements prior to distress while for financially viable companies, the mean value of financial ratios is derived from the financial statements of the period 2003-2008. This methodological choice is expected to mitigate the influence of exceptional items on the financial statements of the companies. In the second stage, one tail T-test is implemented for all the preceding financial ratios and at the last stage we conducted univariate discriminant analysis (UDA) in order to identify the variables from each group that exhibit enhanced predictive power.

Table 2: Definition of financial ratios

RATIOS		DEFINITION
Liquidity	FR_1	Current assets to current liabilities
	FR_2	Current assets minus inventory to current liabilities
	FR_3	Current assets minus inventory to daily operating expenses
	FR_4	Natural logarithm of FR_3
	FR_5	Distributable earnings minus reserves and directors' reimbursement plus depreciation
	FR_6	Natural logarithm of FR_5
	FR_7	FR5 to current liabilities
	FR_8	FR5 to total liabilities
Activity	FR_9	Inventory to Cost of goods sold multiplied by 360 days
	FR_{10}	Natural logarithm of FR_9
	FR_{11}	Receivables to annual sales multiplied by 360 days
	FR_{12}	Natural logarithm of FR_{11}
	FR_{13}	Trade Creditors to Cost of goods sold minus depreciation multiplied by 360 days
	FR_{14}	Natural logarithm of FR_{13}
	FR_{15}	FR_9 plus FR_{11} minus FR_{13}
	FR_{16}	Natural logarithm of FR_{15}
	FR_{17}	Annual sales to equity
	FR_{18}	Annual sales to fixed assets
	FR_{19}	Annual sales to total assets
	FR_{20}	Annual sales t minus annual sales t-1 to annual sales t-1
Profitability	FR_{21}	Gross profit to annual sales
	FR_{22}	Earnings before taxes to annual sales
	FR_{23}	Earnings before taxes plus interest paid to capital employed
	FR_{24}	Earnings before taxes to equity
	FR_{25}	Earnings before taxes to total assets
	FR_{26}	FR_{24} to FR_{23}
	FR_{27}	Earnings before taxes to interest paid
	FR_{28}	Earnings before taxes to number of employees
	FR_{29}	Natural logarithm of FR_{28}
	FR_{30}	CoGS t minus CoGS t-1 to CoGS t-1
	FR_{31}	Gross profit t minus gross profit t-1 to gross profit t-1
	FR_{32}	Earnings before taxes t minus earnings before taxes t-1 to earnings before taxes t-1
Capital Structure	FR_{33}	Total liabilities to total assets
	FR_{34}	Total liabilities to equity
	FR_{35}	Non-current liabilities to equity
	FR_{36}	Equity to total liabilities
	FR_{37}	Fixed assets to total assets
	FR_{38}	Equity plus non-current liabilities to fixed assets
	FR_{39}	Reserves to share capital
Investment	FR_{40}	Dividends to earnings before taxes
	FR_{41}	Dividends to equity

Results and discussion

The descriptive statistics, the T-test and UDA results of the liquidity ratios for the financially distressed and financially viable companies are embedded in Table 3. As we can see, the alternative hypothesis that the financially viable companies exhibit higher values in the liquidity ratios than the financially distressed companies is accepted for FR_1, FR_2, FR_5, FR_7 and FR_8. Moreover, the T-test and UDA results are coherent since the preceding statistically significant financial ratios achieve the highest UDA hit ratios ranging from 66,7% to 61,1%.

Table 3: T-test and UDA results of liquidity ratios

Ratio	Financially viable		Financially distressed		t-value	P-value	UDA
	Mean	Standard Deviation	Mean	Standard Deviation			
FR_1	1,778	1,023	1,164	0,351	2,95	0,003***	66,7%
FR_2	1,373	1,028	0,832	0,316	2,61	0,007***	63,0%
FR_3	279	215	370	599	-0,	0,232	55,6%
FR_4	2,366	0,2532	2,3748	0,3548	-0,10	0,459	53,7%
FR_5	1053223	2318320	-106220	1785202	2,06	0,022**	61,1%
FR_6	3,89	3,87	3,16	3,81	0,69	0,245	51,9%
FR_7	0,312	0,809	-0,0156	0,2477	2,01	0,027**	64,8%
FR_8	0,2156	0,4509	-0,0171	0,2466	2,35	0,012**	64,8%

Note: *P<0,1, **P<0,05 and *** P<0,01

Identically, the descriptive statistics, the T-test and UDA results of the activity ratios for the financially distressed and financially viable companies are depicted in Table 4. Only three (FR_{14}, FR_{17} and FR_{20}) out of twelve activity ratios exhibit statistically significant difference in their mean values between the two groups of companies. These results are also consistent with UDA results because these three activity ratios have the highest UDA hit ratios ranging from 64,8% to 61,1%.

Table 4: T-test and UDA results of activity ratios

Ratio	Financially viable		Financially distressed		t-value	P-value	UDA
	Mean	Standard Deviation	Mean	Standard Deviation			
FR_9	117,7	90,8	1118	5139	-1,01	0,161	51,9%
FR_{10}	1,92	0,4094	2,026	0,673	-0,70	0,244	57,4%
FR_{11}	217	169,7	1571	7168	-0,98	0,168	51,9%
FR_{12}	2,244	0,28	2,288	0,538	-0,38	0,353	53,7%
FR_{13}	137,9	97	842	3432	-1,07	0,148	51,9%
FR_{14}	2,063	0,2603	2,2381	0,5155	-1,58	0,062**	61,1%
FR_{15}	196,9	170,3	1847	8878	-0,97	0,172	51,9%
FR_{16}	2,020	0,887	1,82	1,295	0,67	0,254	61,1%
FR_{17}	3,884	3,821	9,22	12,38	-2,14	0,020**	64,8%
FR_{18}	12,66	23,52	32,2	113,9	-0,87	0,195	55,6%
FR_{19}	0,9591	0,4113	1,097	0,764	-0,82	0,208	50,0%
FR_{20}	0,0672	0,1367	-0,1108	0,3652	2,37	0,012**	64,8%

Note: *P<0,1, **P<0,05 and *** P<0,01

Accordingly, Table 5 presents the descriptive statistics, the T-test and UDA results of the profitability ratios for the financially distressed and financially viable companies. Surprisingly, only two (FR_{29} and FR_{30}) out of twelve profitability ratios exhibit statistically significant difference in their mean values between the preceding groups of companies. In addition, evident discordance is witnessed between the T-test and UDA results. Although FR_{29} and FR_{30} are among the profitability ratios with higher UDA hit ratios, there are also ratios with enhanced discriminant power and contradictory T-test results. In fact, FR_{31} and FR_{32} have no significant difference in their mean value between financially distressed and viable companies despite their UDA results where they achieved the highest hit ratio (72,2%).

Table 5: T-test and UDA results of profitability ratios

Ratio	Financially viable		Financially distressed		t-value	P-value	UDA
	Mean	Standard Deviation	Mean	Standard Deviation			
FR_{21}	0,2578	0,1027	0,216	0,1342	1,28	0,102	61,1%
FR_{22}	0,0422	0,0713	-2,09	10,96	1,01	0,160	51,9%
FR_{23}	0,06079	0,04305	0,0468	0,0818	0,78	0,219	61,1%
FR_{24}	0,0936	0,2019	0,324	2,041	-0,58	0,282	51,9%
FR_{25}	0,03727	0,04925	0,0187	0,0827	1,01	0,160	64,8%
FR_{26}	2,616	3,696	6,1	20,51	-0,87	0,197	59,3%
FR_{27}	114	538	4,51	19,67	1,06	0,150	50,9%
FR_{28}	5823	6155	3556	8659	1,11	0,137	66,7%
FR_{29}	3,553	0,45	2,74	1,17	3,36	0,001***	66,7%
FR_{30}	0,064	0,1475	-0,1073	0,3854	2,16	0,019**	64,8%
FR_{31}	0,0559	0,536	-0,0816	0,641	0,85	0,198	72,2%
FR_{32}	0,0495	3,031	-0,362	1,429	0,64	0,263	72,2%

Note: *P<0,1, **P<0,05 and *** P<0,01

The same phenomenon also appears in Table 6 which contains the descriptive statistics, the T-test and UDA results of the capital structure ratios for the financially distressed and financially viable companies. There are two (FR33 and FR36) out of seven capital structure ratios with statistically significant difference in their mean values between the two groups and simultaneously with the highest UDA hit ratios (68,5% and 66,7%). But there are also ratios with significant (insignificant) T-test results that exhibit low (high) UDA hit ratios (FR_{34}) and vice versa (FR_{38}).

Table 6: T-test and UDA results of capital structure ratios

Ratio	Financially viable		Financially distressed		t-value	P-value	UDA
	Mean	Standard Deviation	Mean	Standard Deviation			
FR_{33}	0,595	0,2243	0,7615	0,1357	-3,30	0,001***	68,5%
FR_{34}	2,991	2,964	6,74	9,92	-1,88	0,035**	55,6%
FR_{35}	0,435	0,66	0,289	0,675	0,81	0,212	61,1%
FR_{36}	1,13	1,308	0,35	0,2998	3,02	0,003***	66,7%
FR_{37}	0,2505	0,1893	0,2097	0,1651	0,84	0,201	53,7%
FR_{38}	3,913	4,135	3,73	7,78	0,11	0,457	63,0%
FR_{39}	0,56	0,853	0,73	0,882	-0,72	0,237	55,6%

Note: *P<0,1, **P<0,05 and *** P<0,01

Finally, Table 7 reports the descriptive statistics, the T-test and UDA results of the investment ratios for the financially distressed and financially viable companies. Unfortunately, there are no discrepancies between T-test and UDA results in a sense that none of the proposed investment ratios is statistically significant while their predictive performance can be moderately characterised as poor. Nevertheless, it is worth mentioning that the financially distressed companies exhibit much higher pay out ratios than the financially viable ones.

Table 7: T-test and UDA results of investment ratios

Ratio	Financially viable		Financially distressed		t-value	P-value	UDA
	Mean	Standard Deviation	Mean	Standard Deviation			
FR_{40}	0,2529	0,2259	0,349	0,993	-0,49	0,315	46,3%
FR_{41}	0,0401	0,0657	0,329	1,415	-1,06	0,150	53,7%

Note: *P<0,1, **P<0,05 and *** P<0,01

Vis-à-vis model construction, only one financial ratio from each category is selected in order to avoid multicollinearity. The linear classification functions derived from MDA for the financially distressed and viable companies can be summarised to the following:

C_{viable}= $-12,094-7,757FR_8-2,077FR_{20}+6,234FR_{29}+2,234FR_{36}-1,601FR_{41}$

$C_{distressed}$= $-7,957-5,994FR_8-4,120FR_{20}+5,073FR_{29}+1,128FR_{36}-0,974FR_{41}$

The preceding classifications functions predict 81,5% of the financially viable companies and 74,1% of the financially distressed companies one year prior to financial distress leading to a total 77,8% hit ratio. Accordingly, the probability to identify a financially distressed company as a viable one (Type I error) is 25,9% while the probability to identify a financially viable company as a distressed one (Type II error) is 18,5%. The MDA model can be perceived as robust since there is sufficient evidence (X^2) to accept the alternative hypothesis that the mean values of the preceding classification functions are not equal between financially distressed and viable companies.

Table 8: Estimates of the MDA and Logit model

Variables	MDA Model		Logit model
	Financially viable	Financially distressed	
Intercept	-12,094	-7,957	9,544
FR_8	-7,757	-5,994	2,519
FR_{20}	-2,077	-4,120	-2,400
FR_{29}	6,234	5,073	-2,800
FR_{36}	2,234	1,128	-1,697
FR_{41}	-1,601	-0,974	6,172
H&L Test (Sig.)			0,466
X^2 (Sig.)	0,001		
Accuracy			
Within groups	0,815	0,741	
Overall	0,778		0,796
Type I error		0,259	0,185
Type II error	0,185		0,222

In comparison with the MDA model, the logit model outperforms with a hit ratio 79,6% of valid classifications. Moreover, the Type I error reduces to 18,5% and the Type II error increases to 22,2% which is preferable because the latter assess opportunity cost while the former is far more important since it evaluates expected losses. We can assume that the logit model adequately describes the data set due to the Hosmer-Lemeshow X^2 statistic (0,466). A summary of the preceding analysis is highlighted in Table 8.

Practical implications

The results of this paper can be viewed from two different perspectives. The most popular one dictates to recognise the financial ratios employed by the MDA and Logit models as variables with incremental information content in predicting financial distress. Additionally, a comparison of the results of the preceding models is a common practice in favour of one model or methodology against the other. However, financial distress modelling is usually based on data sets with at least 50% prior probabilities and researchers tend to focus on the prediction of financial distress than the prediction of financial viability because Type I errors are admittedly far more damaging and costly than Type II errors. This perspective usually reflects financial institutions' agony to evaluate their credit risk exposure based on internal default experience or/and mapping to external data or/and statistical default models (BCBS, 2004, par.461).

Nevertheless, financial modelling could be used as a pilot and thus, guide managerial action in a way to identify the most significant factors for the financial viability of the companies. This viability factors perspective provides an alternative explanation for the underperformance of evidently accurate financial distress models in different settings (Wu et al., 2010; Lin, 2009; Baixauli and Modica-Milo, 2010). A financial ratio that seems to be important for the financial viability of a Greek business may not be appropriate for a respective Norwegian business. In that sense, current assets to current liabilities may be a significant viability factor for the Ohlson and Zmijewski models but a posteriori it seems to have no incremental information content in Greek business although the T-test and UDA results anticipated the opposite. A possible explanation for this discrepancy is the excessive inventory conversion period and the excessive receivables collection period of our data set in compare with the Ohlson's and Zmijewski's data sets. On the contrary, cash flow to total liabilities appears to be a more reliable ratio to ascertain the liquidity of a Greek business.

According to Argenti (1976) fatal corporate strategy decisions and "defective response to change" are usually responsible for the collapse of mature companies. Our results provide evidence in support of this argument since financially distressed companies fail to adapt to more competitive environment. In particular, sales growth is an activity ratio of massive significance for the viability of Greek business. Although our data set comprises primarily small and medium sized companies which are appreciated for their alleged flexibility, Greek business that exhibit negative sales growth are more likely to suffer from financial distress. Surprisingly, Greek businesses which witness a sales reduction fail to adapt to the new financial conditions and restructure their internal processes. Therefore, the ability of Greek business to adapt to a changing and more competitive business environment is one of the most significant viability factors.

This paper also provides evidence that the contribution of human capital to the profitability of a company is one of the prime causes of its success and sustainable viability. The natural logarithm of earnings before taxes per employee exhibits additional information content and is more important for Greek businesses than other traditionally familiar profitability ratios like earnings to total assets (e.g. Altman, Ohlson, Zmijewski). On the other hand, equity to total liabilities is a very familiar capital structure ratio which appears (or its reciprocal) in many of the existing financial distress models. Leverage is like a medicine which can be either therapeutic if it is provided appropriately or lethal in cases of excessive use. And this phenomenon appears in Greek business as well since the financially viable companies seem to make moderate use of leverage while financially distressed companies abuse it.

Although conservative dividend policy is a distinctive feature of low-risk and financial viable companies due to prudential managerial practice, financially distressed companies are expected to exhibit even more mitigated pay-out ratios since the majority of them suffers from constant losses and hence they are unable to pay any dividends at all. However, this is not the case in Greek business where the financially distressed companies have much higher pay-out ratio one year prior to distress than the financially viable companies. One possible interpretation of this phenomenon involves the use of creative accounting practices. Further research is necessary in order to accept or reject the preceding hypothesis.

Conclusions

Despite the scarcity of publicly available information, in this study we approach the issue of financial distress signalling within an alternative conceptual framework. We develop an accounting-based model for the prediction of financial distress with Greek business data from a viability factors perspective. The motivation of this perspective is to guide managerial action in a way to identify the most significant factors for the financial viability of companies. In order to identify the key variables for the financial viability of Greek businesses, we employ T-tests and univariate discriminant analysis. The empirical results of our study indicate that the logit model is more accurate than the MDA model in terms of correct classification and Type I error. Vis-a-vis liquidity and capital structure, our study provides evidence in support of the existing traditional prediction models.

Nevertheless, we identify new value-relevant financial ratios concerning the activity, the profitability and the dividend policy of Greek business. In conclusion, Greek businesses which witness negative sales growth are more likely to suffer from financial distress despite their proclaimed flexibility. Furthermore, the contribution of human capital to the profitability of a company is evidently one of the critical success factors of its viability and finally financially distressed Greek companies are acknowledged for their aggressive dividend policy. Further research is required to provide an interpretation of this latter phenomenon. In addition, the results of this paper provide a guide of managerial action towards the adoption of strategic policies that enhance the financial viability of companies.

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