An Alternative Model for Bankruptcy Prediction Under Stressed Conditions: The Case of Listed Companies in Greece and Cyprus

EVANGELOS SFAKIANAKIS[1]

Abstract

Firm bankruptcies have been tantalising investors, risk managers, markets, entrepreneurs/ investees, regulators, or even the State/ government as they may cause disruptions in the modus operandi of the interested stakeholders. The period during and after the financial and the subsequent sovereign crisis proved to be important from that perspective, especially for countries that faced an extended adverse economic environment, such as Greece and Cyprus. This study attempts to predict bankruptcies of listed manufacturing firms domiciled in Greece and Cyprus by introducing a bankruptcy prediction model that employs discriminant analysis (DA) over a balanced matched sample of 42 firms for the period 2008-2015. Evidence is provided that a series of financial ratios (quick ratio, cash flow interest coverage, and economic value added (EVA) divided by total assets) significantly affect the predictability of bankruptcies in both countries. As a matter of fact, the tested determinants exhibited strong classification accuracy, well in advance (three years), reflecting the global financial health of the firm under examination. This can be a valuable tool in the hands of the involved stakeholders, such as investors, risk officers, and the competent authorities.

Keywords: bankruptcy, discriminant analysis, distressed economies, economic value added, financial ratios, manufacturing firms

Introduction

The Great Financial Crisis (GFC) of 2008 caused unanticipated global turmoil and a series of economic shocks. International markets were subjected to a new economic framework with long-term implications for the financial sector. Countries that were already distressed, facing debt amounts that had been accumulating over the years, like countries of the European South – among which the most proclaimed example/ case is Greece – entered a prolonged and painful financial crisis that definitely left its

[1] Adjunct Professor of Finance, National and Kapodistrian University of Athens.

mark in their recent history. A rescue mechanism was put to work, offering a lending mechanism that would render the borrowing cost of these countries - and especially Greece - viable (also referred to as 'bail-out'). At the same time though, the public and private finances of the country had to be restructured so that the debt was serviceable; this resulted into a series of fiscal/ austerity measures which affected materially the (incomes of) households and enterprises of the country. The reduction of revenues led several firms to the verge of bankruptcy with a material number of them actually filing for bankruptcy.

Just across Greece, Cyprus was dealing too with a similar economic situation. However, after experiencing severe negative spillovers from the Greek debt crisis, which began in 2010, Cyprus was compelled to execute a new banking practice known as bail-in. This led uninsured depositors (defined in the European Union as people with deposits larger than €100,000) in the Bank of Cyprus to lose a substantial portion of their deposits.

Both countries had similar economic problems to deal with, during the same period, making them, at many levels, closely connected. This provided the opportunity to establish a new bankruptcy prediction model for distressed economies that discriminates bankrupt from non-bankrupt firms in Greece and Cyprus, using a combined sample.

Academics and practitioners – primarily from the disciplines of finance and accounting - have put over the years remarkable efforts in predicting bankruptcies. Such predictions are of increased importance to all stakeholders during periods of financial crises. Starting with investors (both shareholders and creditors) it is evident that they are interested in the evolution of the creditworthiness and default rates of the firms that are candidates for investment before placing their capital in them. Consequently, a wide range of bankruptcy prediction models have been generated. Researchers have employed a series of methods, the most well-known of which are discriminant analysis (DA), probit analysis, neural networks, etc. The contribution of Altman with his Z-score model (1968), based on discriminant analysis, has been influential.

This study aims at developing a model the employs an appropriate set of predictor variables, using discriminant analysis, that *ex ante* predicts bankruptcy on a combined sample of both Greek and Cypriot listed manufacturing firms.

Literature Review

Univariate discriminant analysis (UDA) seems to have been the founding stone of models that attempt to predict bankruptcy, followed by multivariate discriminant analysis (MDA). The first studies employing each of these analyses were (i) for UDA, this of Beaver (1966) who identified an array of financial ratios which exhibited a good predictive capacity; and (ii) for MDA, this of Altman,[2] who introduced the infamous Z-Score model. Ever since, this approach has been applied to several country-specific datasets (as depicted in Table I that follows).

Table I: Country specific firm bankruptcy predictive models

Country of domiciliation	Author and year
US	Altman (1968) Altman & *Ors* (1977) Altman (2000) Bhandari & Iyer (2013)
Italy	Pozzoli and Paolone (2016)
Vietnam	Tung and Phung (2019) Thinh & *Ors* (2020)
Greece	Sfakianakis (2018, 2021)
Visegrad group (Slovakia, Czech Republic, Poland, Hungary)	Kliestik & *Ors* (2018) Kovacova & *Ors* (2019)
Cyprus	Ioannou & *Ors*(2020)

Beyond country specific studies, we discern a series of literature strands (i) focusing on one or more sectors/industries; (ii) employing one or more methods; and (iii) testing for different financial ratios. As far as the first strand is concerned, Altman[3] produced possibly the first comprehensive research at global level, by advancing his initial model –applied to private and public, manufacturing and non-manufacturing firms–[4] to an array of private firms from all industries except from the financial sector, domiciled in 31 European countries, China, Colombia, and the United States.

[2] Edward I. Altman, 'Financial ratios, Discriminate Analysis and the Prediction of Corporate Bankruptcy' (1968) 23(4) *Journal of Finance* 589-609.

[3] Edward I. Altman & Ors, 'Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model' (2017) 28(2) *Journal of International Financial Management & Accounting* 131–171.

[4] Edward I. Altman, *Corporate Financial Distress: A Complete Guide to Predicting, Avoiding and Dealing with Bankruptcy* (2nd edn, New York: Wiley, 1983).

Other researchers concentrated on a specific industry, such as banking;[5] small and medium enterprises (SMEs);[6] manufacturing;[7] and retail.[8]

When it comes to the methods employed, we note the application of logit[9] and probit[10]analysis in addition to DA. Combinations of analyses are also noted, such as discriminant, logit, and probit analysis[11] or discriminant and logit analysis.[12]

When it comes to the variables tested, we observe that the majority of the relevant studies involve one or more of the ordinary financial ratios, such as liquidity, solvency, profitability, leverage, and activity. The use of the economic value added (EVA) as predictor variable is first noted in Sfakianakis.[13] The comparative advantage of EVA[14] versus other performance metrics is that it unveils the genuine profitability of

5 Timothy J. Curry, Peter J. Elmer, Gary S. Fissel, 'Equity Market Data, Bank Failures and Market Efficiency' (2007) 1259(6) *Journal of Economics and Business* 667 – 676; Laura Chiaramonte, Federika Poli, Mingming Zhou, 'How Accurately Can Z-Score Predict Bank Failure?' (2016) 25(5) *Financial Markets Instructions & Instruments* 333–360.

6 Francesco Ciampi, 'The Need for Specific Modelling of Small Enterprise Default Prediction: Empirical Evidence from Italian Small Manufacturing Firms' (2017) 12(12) *International Journal of Business and Management* 251-262; Muhammad M. Ma'aji, Nur A.H. Abdullah, Karren L.H. Khaw, 'Predicting Financial Distress among SMEs in Malaysia' (2018) 14(7) *European Scientific Journal* 91–102.

7 Rim El Khoury, Roy Al Beaino, 'Classifying Manufacturing Firms in Lebanon: An Application of Altman´s Model' (2014) 109(1) *Procedia: Social and behavioural sciences* 11-18; Evangelos Sfakianakis, 'Can Z-Score Model Predict Listed Companies' Failures in Greece? Evidence from an Empirical Investigation in the Food and Drinks Industry' (2018) 17(12) *Empirical Economics Letters* 1403-1410.

8 Amalendu Bhunia, F. Chand, Ruchira Sarkar (2011), 'A Study of Financial Distress based on MDA' (2011) 3(2) *Journal of Management Research* 1–11; Ashok Panigrahi, 'Validity of Altman's "Z" Score Model in Predicting Financial Distress of Pharmaceutical Companies' (2019) 4(1) *NMIMS Journal of Economics and Public Policy* 65-73.

9 James A. Ohlson, 'Financial Ratios and the Probabilistic Prediction of Bankruptcy' (1980) 18(1) *Journal of Accounting Research* 109-131; Loredana Cultrera, Xavier Bredart, 'Bankrupty Prediction: The Case of Belgian SMEs' (2016) 15(1) *Review of Accounting and Finance* 101-119; Nur A.H Abdullah & Ors, 'Predicting Financially Distressed Small-And Medium-Sized Enterprises in Malaysia' (2019) 20(3) *Global Business Review* 627–639.

10 Alexandros Benos, George Papanastasopoulos (2007), 'Extending the Merton Model: A Hybrid Approach to Assessing Credit Quality' (2007) 48(1-2) *Mathematical and Computer Modelling* 47-68.

11 Clive Lennox, 'Identifying Failing Companies: A Re-Evaluation of the Logit, Probit and D.A Approaches' (1999) 51(4) *Journal of Economics of Business* 347-364

12 A. Bunyaminu, Mohammed Issah, 'Predicting Corporate Failure of UK's Listed Companies: Comparing Multiple Discriminant Analysis and Logistic Regression' (2012) 94 *International Research Journal of Finance and Economics* 6-22; Matus Mihalovic 'Performance Comparison of Multiple Discriminant Analysis and Logit Models in Bankruptcy Prediction' (2016) 9(4) *Economics & Sociology* 101-118.

13 Evangelos Sfakianakis, 'Bankruptcy Prediction Model for Listed Companies in Greece' (2021) 18(2) *Investment Management and Financial Innovations* 166-180.

14 Stern Stewart and Co. (now known as Stern Value Management) developed the EVA concept in 1991 to evaluate the performance of business organisations expressed as value generation for shareholders.

firms as it appropriately captures the return they offer to shareholders for using their capital. The ordinary financial ratios may render a company 'profitable' without recognising the payoff towards the shareholders. By taking into consideration the cost of equity, EVA reflects the profit or loss during each reporting period.[15] Consequently, EVA is a metric that captures the actual profitability of a firm and mirrors management performance.

On top of this rationale, the inclusion of EVA in a bankruptcy model is justified by the available literature. EVA (i) can signal upcoming bankruptcy when the value of a firm becomes negative from positive ;[16] (ii) is not created by firms in the verge of distress;[17] (iii) indicates decreased bankruptcy probability when it increases;[18] (iv) is the most often used metric in evaluating the financial health of a firm;[19] and (v) increases the explanatory power of bankruptcy prediction models.[20] The use of EVA in bankruptcy prediction models is fully aligned with its attributes identified in the available literature.

Methodology, Data, and Variables

The present research creates a bankruptcy prediction model that addresses distressed economies, using discriminant analysis (DA). The model will adjust itself on the basis of the period that precedes bankruptcy (t-1, t-2, and t-3); it employs at all times a common collection of variables and achieves significant discrimination among both Greek and Cypriot listed, bankrupt and non-bankrupt, manufacturing firms.

Methodology

The methodology deployed in this manuscript relies on univariate and multivariate discriminant analysis. Both UDA and MDA were employed in order to identify the variables that optimally allow the discrimination between bankrupt and non-bank-

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15 Laura Vasilescu, Ana Popa, 'Economic Value Added: Pros and Cons' (2011) 1(13) *Finante – Provocarile Viitorului (Finance – Challenges of the Future)* 60-65.

16 Salmi Timo, Ilka Virtanen, 'Economic Value Added: A Simulation Analysis of the Trendy, Owner-Oriented Management Tool' (2001) 90 *Acta Wasaensia* 1-33.

17 R.B Pasaribu, 'Financial Distress Prediction in Indonesia Stock Exchange: Case Study of Trade Industry Public Company' (2008) 11(2) *Journal of Economics Business and Accounting* 153-172.

18 Saeid Anvarkhatibi, Ramin Mohammadi, Jamal Mohammadi, 'Investigation of the Effect of the Value Added, Earning Quality and Leverage Ratio on Bankruptcy in Organizations Accepted in Tehran's Stock Market' (2013) 2(2) *European Online Journal of Natural and Social Sciences* 223-229.

19 Marta B. Beros, Nicholas Recker, Melita Kozina, 'Economic and Social Development (Book of Proceedings)' *27th International Scientific Conference on Economic and Social* 1-905.

20 Sfakianakis (no 12).

rupt companies. The DA approaches by construction permit the categorisation of observations into non-intersecting sets based on the ranking produced by the appropriate quantitative predictor variables. The quality of this categorisation is strongly connected with the information contained in the predictor variables. The mathematical equivalent is essentially an optimisation problem, as the objective is to derive a set of coefficients ($a_i{}'s$) that multiply the financial ratios ($x_i{}'s$) in a linear equation of the form $z = a_0 + a_1x_1 + a_2x_2 + \cdots$ -nant criterion under consideration, where $\lambda = \frac{\text{(between group variance on z-scores)}}{\text{(within group variance on z-scores)}}$.

To elaborate on the use of UDA and MDA we note that UDA on one hand: (i) is used to realise that most of the selected financial ratios exhibited strong classification power even at a univariate level; and (ii) facilitated the separation of financial ratios to realise that liquidity, solvency, and performance ratios are the stronger in terms of classification capability. MDA, on the other hand, is perceived as more advantageous (by several researchers such as Altman, Taffler, and others) for producing bankruptcy prediction models, as it compiles a broad range of characteristics common to the relevant firms and the interaction among them.

By comparing UDA with MDA, one can see that the competitive advantage of MDA lies within (i) the simultaneous consideration of the metrics used for group assignments – whereas UDA considers one at a time; and (ii) the utilisation of indicators that may be deemed weak by UDA. As a result, the use of UDA is restricted to the provision of supplementary information compared to MDA that is used as a decision-making approach.

Following the aforementioned discussion, in this study MDA was performed for a period of one to three years before bankruptcy to identify the three predictor variables, the combination of which can accomplish a significant discrimination (bankrupt versus non-bankrupt), as far as three years prior to bankruptcy.

Data

The dataset comprises Greek and Cypriot listed/ public manufacturing firms for the period 2008–2015 which covers the years during and after the financial and — the subsequent— debt crisis. Data is drawn from the Datastream International and Bloomberg databases and is used for the estimation of the explanatory variables (Table II). The dataset is composed of 21 non-bankrupt firms (14 Greek and 7 Cypriot) and 21 firms (from 7 sectors) that did go bankrupt during the period under investigation (with no exceptions). The status of each firm (active, bankrupt) was validated through the Greek and Cypriot registries. The active and bankrupt firms were matched into groups based on their industry and asset size, yielding a sample of 21 pairs of firms (42 in total). The last disclosed financial statement is one that corresponds to the year prior to bankruptcy (t–1). The analysis was not limited though to only one year before the bankruptcy took place; it was extended as far as three years before its occurrence (t-1, t-2 and t-3), as the ability to distinguish between healthy and bankrupt companies early enough is indicative of the validity of the model and the discriminating capacity of its variables.

Variables

As mentioned earlier, this paper aims at identifying a collection of variables – including novel ones – that exhibit significant classification power in order to address the bankruptcy prediction problem with a fresh approach. Our guide in the quest of the appropriate variables is the recent literature, as well as the methods used by practitioners. This yields an inventory of candidate variables/ financial ratios - that are to be further assessed (Table II) - split into six ratio categories. The literature review section revealed that the first five out of the six ratio categories have been studied. It is only Sfakianakis[21]who has tested performance-indicating ratios (such as EVA), to realise that they have embedded an important amount of information relevant to a company's effectiveness, overall strength, and health.

Table II: Initial list of potential predictor variables

Ratio's category	Name	Definition
Liquidity	Working Capital ratio	Working Capital / Total Assets
Liquidity	Current ratio	Current Assets / Current Liabilities
Liquidity	Quick ratio	Quick Assets / Current Liabilities
Liquidity	Cash ratio	Cash / Current Liabilities
Liquidity	Δ(liquidity) ratio	Current ratio t – Current ratio t–1
Solvency	OCF / CL ratio	Operating Cash Flow / Current Liabilities
Solvency	OCF / CE ratio	Operating Cash Flow / Capital Expenditure
Solvency	Interest coverage ratio	Operating Cash Flow / Interest Expense
Solvency	Interest coverage ratio	EBIT / Interest Expense
Solvency	OCF / TD ratio	Operating Cash Flow / Total Debt
Leverage	Debt ratio	Total Debt / Total Assets
Leverage	Δ(Debt) ratio	Debt ratio t – Debt ratio t–1

[21] Sfakianakis (no 12).

Profitability	Return on Capital Employed	EBIT / Capital employed
Profitability	EBIT margin	EBIT margin / Total Sales
Profitability	Basic Earning power (ROI)	EBIT / Total Assets
Profitability	Internal growth rate	Retained earnings / Total Assets
Efficiency	Asset Turnover ratio	Total Sales / Total Assets
Efficiency	Δ(Asset Turnover) ratio	Asset ratio t – Asset ratio t–1
Efficiency	Equity Turnover ratio	Total Sales / Total Equity
Performance	EVA / TA	EVA / Total Assets
Performance	EVA / MV	EVA / Market Value
Performance	RI / TA	Residual Income / Total Assets
Performance	RI / MV	Residual Income / Market Value

The potential variables assembled for evaluation are listed in Table II. According to the literature, the majority of studies on bankruptcy prediction used only five ratio categories for analysis. However, six ratio categories were examined in this research. The following ratios were chosen for analysis: liquidity, solvency, leverage, profitability, efficiency, and performance. The list was compiled using both recent studies and common practice methods.

The variable selection process – as evidenced by other researchers – involves trial and error. We follow this route as well to select the appropriate set of predictor variables – both from a theoretical and a practical perspective. Consequently, candidate variables supported by the relevant theoretical background were tested.

UDA, initially, unveiled the significance of several liquidity, solvency, and performance indicators, which was, to a certain extent, anticipated, as liquidity and solvency ratios seem to be broadly included and even prevail in the models studied in the available literature. MDA followed and was performed on a series of combinations of candidate variables that were considered promising. The combination that exhibited strong classification accuracy, tackling bankruptcy in a comprehensive manner, involved three variables – EVA/ total assets, quick ratio, and cash interest coverage ratio - each of which revealed information about the company under investigation (each from a different angle) as well as its integrity. In predicting potential bankruptcies, it is crucial to be able to tell well in advance whether a company will go bankrupt or not. Consequently, MDA was applied separately for each year before bankruptcy (t–1, t–2, and t–3), to generate models that showed strong discrimination ability even three years before the bankruptcy, attesting to their significance and their global classification capacity.

The variables that qualified as per our tests are:

- EVA/total assets

EVA - developed by Stern Stewart and Co. in 1991 to evaluate the performance of business organisations - is a performance indicator that (i) reflects the genuine profitability of a company; (ii) gauges financial performance with net wealth (estimated as operating profit less the cost of capital adjusted for taxes on a cash basis). As realised in the literature review section, EVA is interrelated with financial distress, as EVA can signal upcoming bankruptcy ,[22] and public companies that do not generate EVA face high distress risk .[23] EVA is scaled by total assets so as to normalise and project significant classification accuracy when either UDA or MDA are employed.

• Quick ratio = (current assets – inventory – prepaid expenses) / current liabilities

The available research provides conflicting results with regards to the strength of the relationship between liquidity ratios and financial distress. In theory, lack of liquidity can lead to financial distress as the current assets do not suffice to cover the current liabilities. Following this rationale, the analysis undertaken in this research also encompasses the most frequently used liquidity ratios (Table II). The quick ratio is probably the most proclaimed liquidity ratio as it shows superior classification capacity when either UDA or MDA are employed.

The quick ratio reflects whether a firm is capable of paying its current liabilities without resorting to its inventory or reaching to additional funding; the higher (lower) its value the higher (lower) the liquidity and the financial health of the firm. As elaborated above, the quick ratio captures financial distress, as, when a firm cannot cover its current liabilities, then this is potentially a prelude of future bankruptcy.

• Cash interest coverage ratio = (operating cash flow + interest + taxes) / interest

The chosen solvency ratio comes from the cash flow statement and not from accrual accounting-based metrics. Bhandari and Iyer[24] note that a small number of research papers has relied on cash flow metrics, and that, moreover, they demonstrate questionable success. However, as cash inadequacy can lead to bankruptcy (as is often cited in the relevant literature), one can infer that cash flow metrics are key to predicting financial distress or default. Beaver (1966) realises that the predominant indicator in discriminating going-bankrupt from healthy firms is operating cash flows divided by total debt.

Nevertheless, before a company becomes unable to meet its total debt obligations, it has to be in place to meet its interest obligations from its operating cash flows.

[22] Timo, Virtanen (no 15).

[23] Pasaribu (no 16).

[24] S. B Bhandari, R. Iyer, 'Predicting Business Failure Using Cash Flow Statement Based Measures' (2013) 39(7) *Managerial Finance* 667-676.

Consequently, the interest coverage ratio provides a clearer picture of a firm's ability to make interest payments than the operating cash, which is clearly an indication of a healthy or distressed entity. Before becoming unable to meet debt obligations, a firm is most likely unable to meet interest expense, which, if accumulated, can lead to unserviceable debt. Therefore, the interest coverage can signal firms that are in the verge of bankruptcy.

The analysis that follows will provide evidence that these three variables combined can deliver superior classification accuracy even three years before a bankruptcy as they embed comprehensive information that can be carried over to the interested parties when used altogether.

Results and Analysis

In applying MDA, we first tested for correlation and collinearity for each year prior to bankruptcy for all variables. The capacity of the model to carry this comprehensive information that was mentioned in the previous section is justified by the fact that the chosen ratios exhibit no material correlation or collinearity, and thus a model with a small number of chosen measurements was developed.

To facilitate the presentation of our models, this section is divided into three subsections, one for each of the years preceding bankruptcy. The collection of variables that has been chosen for our models $\frac{EVA}{\quad}$

X_1 = EVA scaled by

X_2 = Quick ratio = $\frac{(Current\ Assets - Inventories)}{Current\ Liab}$

X_3 = Cash flow coverage of interest = $\frac{(Operating\ Cash\ Flow + Interest + Tax)}{Interest}$

Results One Year Before Bankruptcy (t–1)

Table III displays the descriptive statistics (mean, median, and standard deviation) for each selected variable for the bankrupt (21) as well as the non-bankrupt (21) firms and for all (42) firms of the sample. We used the StatGraphics statistical software in order to perform MDA.

Table III: Descriptive group statistics (t–1)

Variables	Bankrupt firms (21)			Non-Bankrupt firms (21)			Total firms (42)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0,3593	-0,0568	1,1434	0,0520	0,0000	0,1857	-0,1536	-0,0001	0,8445
Quick ratio	0,2419	0,1861	0,2077	2,2536	1,3015	3,6879	1,2477	0,6358	2,7988
(OCF+INT+TAX)/INT	-2,5753	-1,3526	6,5737	0,3553	0,3103	4,3384	-1,1100	-0,4641	5,7589

Table III presents summary statistics (mean, median, standard deviation) on EVA/TA, the quick ratio, and the (OCF+INT+TAX)/INT ratio across bankrupt firms, non-bankrupt firms, and the entire sample of firms for the t–1 period. The matched sample consists of 42 manufacturing enterprises listed on the Greek and Cypriot Stock Exchanges with sufficient data from the Datastream and Bloomberg databases to compute accounting variables over the t–1 year-period (one year before bankruptcy). Furthermore, the legitimacy of each firm's status (bankrupt, non-bankrupt) was double-checked using the Greek General Commercial Registry (G.E.MI) and its Cypriot counterpart to completely eliminate firms that are neither bankrupt nor operating.

The canonical discriminant functions of our model are shown in Table IV. The effectiveness of the recommended bankruptcy prediction model is evidenced by the high significance of the X2-statistic of the estimated discriminant function (at the 0.0032 level), as well as the notable level of canonical correlation observed (0.549), indicating an efficient model in discriminating among the groups.

Table IV: Outline of canonical discriminant functions (t-1)

Eigen Values								
Function	Eigen value	Percentage of variance	Cumulative percentage	Canonical correlation	Wilks' λ	X^2	df	Sig.
1	0.431	100	100	0.549	0.699	13,792	3	0.0032

Table IV demonstrates the proposed model's canonical discriminant functions for t–1. The model is highly significant, with high overall levels of efficacy and discrimination ability.

Table V presents the standardised and unstandardised coefficients. The former show the relative importance of each variable in predicting business bankruptcies; the quick ratio with a value of 0.876 appears to be the most important variable for one year prior to the actual bankruptcy. The latter are utilised in the model in order to estimate the firm discriminant score. Table VI displays the centroid scores; the average discriminant score for a bankrupt (non-bankrupt) company is -0.641 (0.641 respectively). Consequently, for a score close to –0.641 (0.641) the firm is classified as bankrupt (non-bankrupt respectively).

Table V: Coefficients of the discriminant function (t–1)

	Standardised coefficients	Unstandardised coefficients
EVA/TA	0.447	0.533
Quick ratio	0.876	0.327
(OCF+INT+TAX)/INT	0.785	0.138
Constant		-0,174

Table V presents the standardised and unstandardised coefficients of the model, indicating the relative significance of each variable in forecasting business bankruptcies during the t–1 period. Due to its large standardised coefficient, the quick ratio variable is the most crucial variable for forecasting *bankruptcy one year before (0.876). The betas in the proposed model's equation for t–1 are the unstandardised coefficients.*

Table VI: Group centroids (t–1)

	Discriminant function
Groups	Group centroids
Bankrupt (B=0)	-0,641
Non-Bankrupt (B=1)	0,641

Table VI displays the suggested model's group centroids for t–1. In more detail, a company with a discriminant score of –0.641 is classified as bankrupt (B=0) since bankrupt companies tend to project a score near that figure. Non-bankrupt firms, on the other hand, tend to project a score near 0.641, hence a firm with a discriminant score close to that number is classified as non-bankrupt (B=1).

The previous discussion leads to the equation of our discriminant model for bankruptcy prediction one year prior to its occurrence:

$Z = -0.174 + 0.533 * X_1 + 0.327 * X_2 + 0.138 * X_3$

where:

Z is the discriminant score.

95.24% of all given cases were re-classified accurately, corresponding to an accurate prediction of 20 out of the 21 bankrupt firms and 20 out of the 21 non-bankrupt firm. Table VII captures the model performance.

Table VII: Classification results (t–1)

Actual	Group Size	Predicted 0	Predicted 1
Bankrupt (B=0)	21	20	1
		(95.24%)	(4.76%)
Non-Bankrupt (B=1)	21	1	20
		(4.76%)	(95.24%)
Percent of cases correctly classified: 95.24 %			

Table VII presents the model's classification results for the t–1 period. 95.24 % of all cases were successfully reclassified using the proposed model. One year before bankruptcy, the model correctly predicted 20 out of 21 bankrupt enterprises and 20 out of 21 non-bankrupt enterprises. To put it differently, the model successfully reclassified 40 out of 42 cases, suggesting strong discriminating ability.

As a result, the recommended model demonstrates strong discriminating capability as it correctly re-classified 40 out of 42 firms (95.24%). Furthermore, it shows that the combination of the selected variables encompasses significant information with regards to the firms under investigation.

In what follows, the same analysis is repeated to assess the behavior of these variables two and three years prior to the occurrence of the bankruptcy –mapping in this way the predicting capacity of the variables with the passage of time.

Results Two Years Before Bankruptcy (t–2)

Table VIII displays the descriptive statistics two years before bankruptcy for each selected variable for both bankrupt (21) and non-bankrupt (21) companies, and for all (42) companies of our sample. To perform the MDA we used the StatGraphics statistical software this time as well

Table VIII: Descriptive group statistics (t–2)

Variables	Bankrupt firms (21)			Non-Bankrupt firms (21)			Total firms (42)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0,1874	-0,0487	0,7163	0,4126	0,0001	0,7318	0,1126	0,0000	0,8417
Quick ratio	0,5938	0,5423	0,4702	1,3127	1,3419	0,8101	0,9465	0,7679	0,7546
(OCF+INT+TAX)/INT	-1,8101	-0,0079	7,2158	1,4258	0,6964	5,1430	-0,1921	0,0486	6,4712

Table VIII presents summary statistics (mean, median, standard deviation) on EVA/TA, the quick ratio, and the (OCF+INT+TAX)/INT ratio across bankrupt firms, non-bankrupt firms, and the entire sample of firms for the t–2 period. The matched sample consists of 42 manufacturing enterprises listed on the Greek and Cypriot Stock Exchanges with sufficient data from the Datastream and Bloomberg databases to compute accounting variables over the t–2 year-period (two years before bankruptcy). Furthermore, the legitimacy of each firm's status (bankrupt, non-bankrupt) was double-checked using the Greek General Commercial Registry (G.E.MI) and its Cypriot counterpart to completely eliminate firms that are neither bankrupt nor operating.

The canonical discriminant functions, which incorporate valuable information on the significance and effectiveness of the selected variables and the model employed at time t–2 years, are depicted in Table IX. This is evidenced by the X2-statistic which posts a high significance (at the 0.000 level), as well as the high level of the canonical correlation for t–2 (0.706), which is indicative of its capacity to discriminate among the groups.

Table IX: Outline of canonical discriminant functions (t–2)

Eigen Values								
Function	Eigen value	Percentage of variance	Cumulative percentage	Canonical correlation	Wilks' λ	X^2	df	Sig.
1	0.995	100	100	0.706	0.501	26,593	3	0,0000

Table IX demonstrates the proposed model's canonical discriminant functions for t–2. The model is highly significant, with high overall levels of efficacy and discrimination ability.

Table X presents the standardised coefficients, which indicate that the most important variable to accurately predict bankruptcy two years in advance is EVA/TA (with a value of 0.718). This indicator can be used along with the results of Table V for t−1 year to elaborate on the nature of bankruptcy itself. This is a consequence of the realisation that in most cases, a company does not file for bankruptcy suddenly. On the contrary, bankruptcy is the outcome of a rather long and volatile/ bumpy process. One needs to treat a potential bankruptcy in the short-term differently from a bankruptcy in the long-term. For short-term periods (such as one year) the liquidity ratios can be quite efficient into conveying the relevant information. For long(er)-term periods (2 or 3 years) performance ratios – such as EVA/TA - seem to be more suitable, as they carry more information than liquidity ratios pertaining to the global financial status of a firm. The proposed model adjusts itself depending on the period when bankruptcy approached (t−1, t−2, and t−3) and encompasses both liquidity and performance ratios so as to better capture the firm's overall financial health.

Table X: Coefficients of the discriminant function (t–2)

	Standardised coefficients	Unstandardised coefficients
EVA/TA	0.718	0.620
Quick ratio	0.539	0.798
(OCF+INT+TAX)/INT	0.484	0.075
Constant		-0,886

The standardised and unstandardised coefficients of the model are provided in Table X, indicating the relative importance of each variable in predicting business bankruptcies during the t–2 period. Because of its high standardised coefficient, EVA/TA is the most crucial variable for forecasting bankruptcy two years earlier (0.718). The unstandardised coefficients are the betas of the proposed model's t–2 equation.

The previous discussion leads to the equation of our discriminant model for bankruptcy prediction two years prior to its occurrence – based on the unstandardised coefficients:

$Z = -0.886+0.620*X_1+0.798* X_2+0.075*X_3$

where:

Z is the discriminant score.

Table XI shows the group centroids, which can assist in classifying a firm as either bankrupt or non-bankrupt – depending on its score (in a way similar to the 1-year prior bankruptcy case).

Table XI: Group centroids (t–2)

	Discriminant function
Groups	Group centroids
Bankrupt (B=0)	-0,974
Non-Bankrupt (B=1)	0,974

Table XI provides the proposed model's group centroids for t–2. A firm with a discriminant score of –0.974 is classified as bankrupt (B=0), because bankrupt enterprises tend to project a score near that value. Non-bankrupt firms, on the other hand, tend to project a score close to 0.974, hence a firm with a discriminant score near that number is classified as non-bankrupt (B=1).

This classification is done based on the proximity to the centroid values; if a company posts a score close to –0.974 – the average discriminant score of a bankrupt firm (0.974 - the average discriminant score of a non-bankrupt firm respectively), then the firm is categorised as bankrupt (non-bankrupt respectively). A score that is close to zero (middle point) indicates indifference.

Table XII: Classification results (t–2)

Actual	Group Size	Predicted 0	Predicted 1
Bankrupt (B=0)	21	20	1
		(95.24%)	(4.76%)
Non-Bankrupt (B=1)	21	2	19
		(9.52%)	(90.48%)
Percent of cases correctly classified: 92.86 %			

The model's classification results for the t–2 period are shown in Table XII. 92.86 % of all cases were correctly reclassified using the proposed model. Two years before bankruptcy, the model correctly predicted 20 out of 21 bankrupt firms and 19 out of 21 non-bankrupt firms. As a result, the suggested t–2 model demonstrated excellent classification accuracy, correctly predicting 39 of 42 given cases two years before bankruptcy.

92.86% of all firms were re-classified accurately, corresponding to an accurate prediction of 20 out of the 21 bankrupt firms and 19 out of the 21 non-bankrupt firms. Table XII captures the model performance.

All in all, the recommended model for t-2 (2 years before bankruptcy) accurately re-classified 39 out of 42 firms (92.86%). This outcome is noteworthy and subscribes to the overall contribution of the proposed set of variables in bankruptcy prediction.

Results Three Years Before Bankruptcy (t–3)

Table XIII displays the descriptive statistics three years before bankruptcy for each selected variable for both bankrupt (21) and non-bankrupt (21) companies, and for all (42) companies of our sample. To perform MDA we used the StatGraphics statistical software this time as well.

Table XIII: Descriptive group statistics (t–3)

Variables	Bankrupt firms (21)			Non-Bankrupt firms (21)			Total firms (42)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0,1601	-0,0416	0,2659	0,3019	0,0001	0,5355	0,0709	0,0000	0,4818
Quick ratio	0,6240	0,5447	0,5079	1,6647	1,4634	0,9787	1,1443	0,8945	0,9374
(OCF+INT+TAX)/INT	1,5790	0,1119	3,9599	1,7907	0,9841	8,4871	1,6848	0,8188	6,6232

Table XIII presents summary statistics (mean, median, standard deviation) on EVA/TA, the quick ratio, and the (OCF+INT+TAX)/INT ratio across bankrupt firms, non-bankrupt firms, and the entire sample of firms for the t–3 period. The matched sample consists of 42 manufacturing enterprises listed on the Greek and Cypriot Stock Exchanges with sufficient data from the Datastream and Bloomberg databases to compute accounting variables over the t–3 year-period (three years before bankruptcy). Furthermore, the legitimacy of each firm's status (bankrupt, non-bankrupt) was double-checked using the Greek General Commercial Registry (G.E.MI) and its Cypriot counterpart to completely eliminate firms that are neither bankrupt nor operating.

The canonical discriminant functions - displayed in Table XIV - incorporate valuable information on the significance and effectiveness of the chosen variables and the model employed at time t–3 years. This is evidenced by the X2-statistic which posts a high significance (at the 0.000 level), as well as the high level of the canonical correlation for t–3 (0.728), which is indicative of its capacity to discriminate among the groups.

Table XIV: Outline of canonical discriminant functions (t–3)

Eigen Values								
Function	Eigen value	Percentage of variance	Cumulative percentage	Canonical correlation	Wilks' λ	X²	df	Sig.
1	1,128	100	100	0.728	0.470	29,078	3	0,0000

Table XIV demonstrates the proposed model's canonical discriminant functions for t–3. Three years before bankruptcy (t–3), the model is quite significant with high overall levels, indicating effectiveness and a great discrimination ability.The standardised coefficients (with values of 0.830 and 0.902, respectively) – reported below in Table XV – indicate that the variables X_1 *and* X_2 *exhibit a strong importance as well.*

Table XV: Coefficients of the discriminant function (t–3)

	Standardised coefficients	Unstandardised coefficients
EVA/TA	0.830	1,915

Quick ratio	0.902	1,130
(OCF+INT+TAX)/INT	0.411	0,061
Constant		-1,530

The standardised and unstandardised coefficients of the model are shown in Table XV, demonstrating the relative importance of each variable in predicting business bankruptcies during the t–3 period. Because of their high standardised coefficients, the quick ratio and EVA/TA variables are equally useful for forecasting bankruptcy three years earlier (0.902 and 0.830, respectively). However, because the EVA/TA variable has a greater unstandardised coefficient than the quick ratio variable, it takes the lead in the equation. The betas in the proposed model's equation are the unstandardised coefficients.

The previous discussion leads to the equation of our discriminant model for bankruptcy prediction three years prior to its occurrence – based on the unstandardised coefficients as demonstrated in Table XV:

$Z = -1.530 + 1.915 * X_1 + 1.130 * X_2 + 0.061 * X_3$

where:

Z is the discriminant score.

Table XVI shows the group centroids, which can assist in classifying a firm as either bankrupt or non-bankrupt – depending on its score (in a way similar to the 2-year prior bankruptcy case).

Table XVI: Group centroids (t–3)

	Discriminant function
Groups	Group centroids
Bankrupt (B=0)	-1,037
Non-Bankrupt (B=1)	1,037

Table XVI demonstrates the proposed model's group centroids for t–3. A firm with a discriminant score near –1.037 is classified as bankrupt (B=0), because bankrupt enterprises tend to project a score near that value. Non-bankrupt enterprises, on the other hand, tend to project a score close to 1.037, so a firm with a discriminant score near that number is classified as non-bankrupt (B=1).

This classification (for the t-3 case) stems from the proximity to the centroid values; if a company receives a score close to –1.037 – the average discriminant score of a bankrupt firm (1.037 - the average discriminant score of a non-bankrupt firm respectively), then the firm is sorted as bankrupt (non-bankrupt respectively). Similarly to the t-2 case, a score in the area of zero (middle point) denotes indifference.

Table XVII: Classification results (t–3)

Actual	Group Size	Predicted 0	Predicted 1

Bankrupt (B=0)	21	19 (90.48%)	2 (9.52%)
Non-Bankrupt (B=1)	21	4 (19.05%)	17 (80.95%)
Percent of cases correctly classified: 85.71 %			

The model's classification results for the t–3 period are shown in Table XVII. 85.71 % of all cases were successfully reclassified using the proposed model. Three years before bankruptcy, the model correctly predicted 19 out of 21 bankrupt firms and 17 out of 21 non-bankrupt firms. The model successfully predicted 36 of 42 cases, suggesting high discriminating power and classification accuracy.

85.71% of all firms were re-classified accurately, corresponding to a precise prediction of 19 out of the 21 bankrupt firms and 17 out of the 21 non-bankrupt firms. Table XVII captures the model performance. It is important to note that the model faced greater difficulty in discriminating the non-bankrupt from the bankrupt firms. This clearly showcases the negative impact that the economic crisis had to the core fundamentals of the majority of the firms, even the non-bankrupt ones.

All in all, the recommended model for t-3 (3 years before bankruptcy) accurately re-classified 36 out of 42 firms (85.71%). This outcome outlines the appropriateness of the proposed mix of variables in discriminating firms throughout time.

Discussion

A similar study[25] was conducted on a solely Greek sample that resulted in a different model that nevertheless uses the same set of predictor variables. Both models (of the present study and of the study for Greek firms only) adjust themselves to reflect the number of years before bankruptcy (t-1, t-2, and t-3); the weights of the incorporated variables adapt as necessary. Both models conclude that the liquidity ratios seem to be the most important indicators when a (probable) bankruptcy is tested in the short term (t-1). Nonetheless, the performance indicators prevail (over liquidity ratios) when a long(er)-term (probable) bankruptcy is tested. The chosen combination of variables, used in both models, blends the predicting efficiency of the liquidity ratios (for the short-term) and of the performance indicators (for the long-term). Further blending of the previous ratios with the chosen solvency ratio (cash flow coverage of interest ratio) leads to a model that posts highly significant classification accuracy between bankrupt and non-bankrupt firms, even in times of distress.

[25] Sfakianakis (no 12).

A relevant study is this of Gerantonis & Ors[26]that examines the success of the Z-score, as initially developed by Altman in 1968, to predict the bankruptcies of Greek publicly-listed firms up to 3 years prior to them taking place. They realised that the model correctly predicted 66%, 52% and 39% of the cases under investigation for (t-1), (t-2) and (t-3), i.e. one year, two years and three years before the bankruptcy actually happened. Even though the results of the model of this study are significantly superior (compared to Altman's), it is of great interest to test the classification accuracy and overall performance of the respective model developed for Greek firms[27] that uses the same set of predictor variables, on this study's mixed sample of publicly-listed Greek and Cypriot firms.

As far as bankruptcy prediction one year before (t-1) bankruptcy is concerned, the equation for the model developed for Greek firms[28]is:

$$Z = -2.369+0.283*X_1+3.474*X_2+0.033*X_3$$

where:

Z is the discriminant score.

If the firm's discriminant score turns out to be negative (positive), then the firm is classified as bankrupt (non-bankrupt). The greater ––in absolute value– the score is, the healthier (if positive)/ more troubled (if negative) the firm is.

Throughout the mixed sample of the current study, the model developed for Greek firms[29]managed to predict correctly 38 out of 42 given cases (90,48%) one year prior to their bankruptcy, even thought it was supposed to achieve perfect fit exclusively for Greek listed firms.

As far as bankruptcy prediction two years before (t-2) bankruptcy is concerned, the equation for the model developed for Greek firms[30] is:

$$Z = -0.084+3.833*X_1+0.565*X_2+0.079*X_3$$

where:

Z is the discriminant score.

Again, depending on the firm's score, the firm is classified as either bankrupt (negative score) or non-bankrupt (positive score).

[26] Nikolaos Gerantonis, Konstantinos Vergos, Apostolos Christopoulos 'Can Altman Z-Score Model Predict Business Failure in Greece?' (2009) 12 *Research Journal of International Studies* 1 - 11.

[27] Sfakianakis (no 12).

[28] Ibid.

[29] Ibid.

[30] Ibid.

The Z-scores provided by the model developed for Greek firms,[31] correctly classified 35 out of 42 (83,33%) cases under investigation of the mixed sample of the current study, two years prior to bankruptcy, proving its strong predictability once again, regardless the non-Greek-firm-only sample.

Last but not least, as far as bankruptcy prediction three years before (t-3) bankruptcy is concerned, the equation for the model developed for Greek firms (Sfakianakis, 2021) is

$Z = -1.101+5.270*X_1+1.643*X_2+0.013*X_3$

where:

Z is the discriminant score.

Once again, depending on the firm's score, the firm is classified as either bankrupt (negative score) or non-bankrupt (positive score).

The model developed for Greek firms[32]continued to produce great results three years prior to bankruptcy too, managing to correctly predict 34 out of 42 (80,95%) given cases.

Consequently, the model developed for Greek firms[33]showcased great predictability even throughout its application to a combined sample of two distressed economies (Greece's and Cyprus's) rather than strictly to the Greek listed firms only. That mainly happened due to the fact that both economies share an adequate amount of characteristics and were both distressed during the same 2008-2015 period. The Greek model, unlike the existing bankruptcy models, was destined for a wide application on a distressed economy. As a result, showcasing good predictability on a dataset that consists of firms taken from distressed economies makes sense, even if it is not strictly Greek firms. However, the proposed model of the present study surely achieves greater classification accuracy than the model developed for Greek firms[34]when applied to the sample that blends both distressed economies. Nevertheless, both models manage to produce far superior results through their application to distressed economies compared to those delivered by Altman's (1968) 'Z-score'. Regarding the selection and applicability of the models, if one is to investigates bankruptcy strictly on Greek firms, the Greek model appears to bemore appropriate. On the other hand, if one is to analyse the possibility of a potential bankruptcy in a more generic frame-

[31] Ibid.
[32] Ibid.
[33] Ibid.
[34] Ibid.

work using a dataset based on distressed economies (like the Greek and the Cypriot one), then the proposed model of the current study is the more appropriate one.

The present paper contributes to the available literature on bankruptcy prediction in three directions: (i) it captures the impact of the financial crisis on the evolution of bankruptcies in Greece and Cyprus, the two countries that were probably hit the most; (ii) it employs novel performance metrics, e.g. EVA, in order to predict bankruptcies not only one but even two and three years before their occurrence, thus offering a comparative advantage to our approach over the available approaches (at least to the best of our knowledge); and (iii) it offers a simple model involving three predictor variables that are based on an equal number of financial ratios —established independently of the model in advance and not for the needs of the model— that capture the global status of a company and offer significant classification accuracy.

Conclusion

This analysis aims at offering a fresh approach to the bankruptcy prediction effort among listed manufacturing companies compared to the available literature in the field. To do so, it involved a sample of such companies in Greece and Cyprus. The recorded efforts so far have involved predictor variables taken from financial statements that relied to accrual accounting solely. The first attempt to incorporate performance ratios (such as EVA) among the model variables was our study on the Greek listed manufacturing firms.[35]The recommended array of variables unveils the superiority of our models in classifying firms at distressed times. This success is noteworthy as Bhandari and Iyer[36] note that only limited papers have employed cash flow metrics and with mediocre results.

This paper relied on an equally balanced matched sample of 42 Greek and Cypriot listed manufacturing firms (including all firms that filed for bankruptcy in the period 2008-2015). The choice of Greece and Cyprus is justified by the fact that on the one hand they have similar economic and social structures, and on the other they both underwent the 2008 financial crisis in a rather harsh manner, which makes them the appropriate candidates for bankruptcy studies. The method applied to our dataset was MDA for periods of one year (t–1), two years (t–2), and three years (t–3) prior to bankruptcy. This led to a model that relies on the same combination of variables (EVA/TA, quick ratio and cash flow coverage of interest) and that adjusts itself depending on the time period that elapsed before bankruptcy (t–1, t–2, and t–3). The

35 Ibid.

36 Bhandari, Iyer (no 23).

model correctly classified 95.84%, 92.86% and 85.71% of cases one, two and three years prior to the occurrence of bankruptcy respectively.

These percentages indicate that the chosen combination of variables exhibits superior classification capacity even three years before the bankruptcy took place. Judging from this result, we infer that the selected blend of financial ratios captures globally the financial health of a company and thus predicts bankruptcies in a reliable manner for Greek and Cypriot firms.

As is the case in all studies, our analysis reveals some limitations, which are not new to the bankruptcy prediction research. We note that the explanatory variables employed (financial ratios and EVA) are derived from accounting data, which means that they are subject to potential calculation errors. Furthermore, a series of possibly significant —for the classification accuracy— determinants have not been taken into account, as their quantification is not always straightforward. Such determinants may be (relevant to) macroeconomic and industry specific conditions, the variability of business conditions, as well as competitiveness.

Future research is envisaged in two different directions. One is to extend the models to Greek and Cypriot non-listed small and medium enterprises (SMEs), considering the fact that the firms studied in the present paper were listed in the stock exchanges of the two countries. Another is to augment the sample space to manufacturing firms from all European countries with distressed economies, thus testing the efficacy of the selected variables to Eastern European countries.

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