



“Bankruptcy prediction model for listed companies in Greece”

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BANKRUPTCY PREDICTION MODEL FOR LISTED COMPANIES IN GREECE

Abstract

This paper deals with the ever-increasing issue of bankruptcy prediction in distressed economies. Specifically, the aim of this study is to create a model by establishing a new set of predictor variables, which achieves significant discrimination among listed manufacturing firms in Greece, by using multivariate discriminant analysis (MDA). An equally balanced matched sample of 28 Greek-listed manufacturing firms was used in this study covering the distressed period from 2008 to 2015 (including all firms that went bankrupt between 2008–2015). It is found that the quick ratio, cash flow interest coverage, and economic value added (EVA) divided by total assets are significant for predicting bankruptcy in Greece. The discriminant analysis (DA) model comprised the aforementioned variables and correctly classified 96.43% of grouped cases 1 year before bankruptcy. The adjusted DA prediction model for two and three years before bankruptcy used the same variables and correctly classified 92.86% and 89.29% of grouped cases, respectively. Consequently, this mix of financial ratios achieved strong classification accuracy even three years before bankruptcy, captivating an overall picture of a firm's financial health and providing a powerful tool for decision making to investors and risk managers in the banking section and economic policy makers.

Keywords

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

JEL Classification

C52, G33, M41

INTRODUCTION

The year 2008 is seen by many as the beginning of the global financial crisis, when the subprime crisis bubble burst in the United States, affecting most economies throughout the world. Greece was already distressed, dealing with increasingly massive debt and waiting for a trigger to burst. That trigger was transatlantic, plunging the entire country into one of the greatest financial crises of its recent history. The unbearable austerity measures imposed led a significant number of Greek firms to either flirt with bankruptcy or eventually go bankrupt. In addition, huge fiscal mismanagement in the wake of the 2008 crisis and continued downward pressures in the Greek economy have wiped out stock market valuations, led to a structural shift in stock market performance, and radically changed the way investors, locals and foreigners see evolution of Greek equities (Papanastasopoulos et al., 2016). The stressed condition of the Greek economy provides a good opportunity to study the variables that may help forecast better bankruptcy under special economic conditions. In fact, during that time, Greece was the absolute definition of a stressed economy, as this was reflected on the international economic news. Thus, the above stressed period may be the case of a natural experiment, providing the framework for financial ratio analysis and the potential to develop an alternative bankruptcy prediction model.

Bankruptcy prediction has always been one of the most important and challenging tasks in finance and accounting. Over the last 50

years, an impressive body of theoretical and empirical research has been developed on this topic. During financial crises, the importance of predicting a potential bankruptcy and recognizing a distressed firm is felt strongly by stakeholders. Investors want to be sure about a company's creditworthiness and default rate before investing in one. The same applies to the firm's creditors and debtors. For this purpose, many bankruptcy models have been developed. Methods such as discriminant analysis (DA), probit analysis, neural networks, and others have been broadly used to create new models. The more famous of these models is Altman's Z-score model (1968), based on discriminant analysis.

The purpose of this study is to establish an alternative set of predictor variables that achieve significant discrimination accuracy between bankrupt and non-bankrupt firms based on Multivariate Discriminant Analysis (MDA), during stressed periods even three years before the event of bankruptcy.

1. LITERATURE REVIEW

Bankruptcy modeling studies originated with univariate discriminant analysis and progressed to multivariate discriminant analysis. Beaver (1966) used univariate discriminant analysis (UDA) for a set of selected financial ratios and found that some had very good predictive power. Altman (1968), in his novel study, using multivariate discriminant analysis (MDA), developed the Z-Score model. This approach has been replicated in several countries using a country-specific dataset. In particular, Altman (1968), Altman et al. (1977), Altman (2000), and Bhandari and Iyer (2013) used U.S. firms; Taffler (1982) and Almamy et al. (2016) used U.K. firms; Pozzoli and Paolone (2016) used Italian firms; Tung and Phung (2019) and Thinh et al. (2020) used Vietnamese firms. Kliestik et al. (2018) used firms from Visegrad group (Slovakia, Czech Republic, Poland, and Hungary) and formed a prediction model for each V4 country. Also, Kovacova et al. (2019) confirmed that each V4 country prefers different explanatory variables while developing a bankruptcy prediction model. Regarding Greek firms, previous research (2018) used the MDA technique on Greek-listed firms from the Food and Drinks industry.

Altman (2017) used a dataset that includes mostly private companies in all industrial sectors, with the exception of financial companies from 31 European countries, as well as China, Colombia and the United States. The model used is based on the original model developed by Altman (1983) for

private and public manufacturing and non-manufacturing firms, using different modifications. This is the first study offering such a comprehensive international analysis.

Some researchers restricted their sample to firms in a particular industry. As an illustration, Curry et al. (2007) and Chiaramonte et al. (2016) used banks, Ciampi (2017) and Ma'aji (2018) used SMEs firms, Altman (1968), Khoury and Beaino (2014) and Sfakianakis (2018) used firms from the manufacturing industry, and Bhunia et al. (2011) and Panigrahi (2019) used retail enterprises.

Although DA was a widely incorporated technique, conditional probability models such as logit and probit were also applied. Ohlson (1980), Glezakos et al. (2010), Cultrera and Bredart (2016) and Abdullah et al. (2019) used logit analysis, whereas Benos and Papanastasopoulos (2007) attempted probit analysis.

Other authors developed and compared various bankruptcy models using multiple analytical methods. More particularly, Lennox (1999) employed discriminant, logit, and probit analysis, and Bunyaminu and Issah (2012) and Mihalovic (2016) used discriminant and logit analysis.

However, none of the aforementioned studies evaluated performance indicators, such as economic value added (EVA), as predictor variables. Most such studies relied solely on the typical five ratios – liquidity, solvency, profitability, leverage, and activity.

Several performance measurement methods can be applied to business organizations. Nevertheless,

when using traditional indicators, most companies appear profitable even if, in reality, they are not. EVA¹ corrects this error by explicitly recognizing that when management use capital, they must pay for it. Given the cost of equity, EVA indicates the profit or loss during each reporting period (Vasilescu & Popa, 2011). In other words, EVA is an indicator of the actual profitability of company projects; therefore, it serves as a reflection of management performance. Thus, many authors, such as Sharma and Kumar (2010), Parvaei and Farhadi (2013), and Ioachim and Ionela (2017) considered EVA to be a crucial tool to measure performance.

Regarding the incorporation of EVA in a bankruptcy model, Timo and Virtanen (2001) indicated that EVA can act as a bankruptcy warning device because an economic bankruptcy appears when a firm's value turns from positive to negative. Pasaribu (2008) showed that public companies that do not create EVA are at high risk of distress, and Anvarkhatibi et al. (2013) argued that the likelihood of bankruptcy decreases as economic value increases. Last but not least, Beros et al. (2018) refer that EVA is the most utilized modern indicator in assessing a company's financial health. Consideration of all of the aforementioned studies shows strong evidence that EVA and a firm's overall financial health are closely related. Thus, attempting to incorporate EVA into a bankruptcy prediction model is of strong interest.

2. METHODOLOGY AND DATA

The aim of this study is to use approaches based on discriminant analysis (DA) to establish an alternative set of predictor variables that achieve significant distinction regarding bankruptcy for Greek-listed manufacturing firms. The proposed bankruptcy prediction model is developed in a way that adjusts itself on the basis of the period approaching bankruptcy ($t-1$, $t-2$, $t-3$), always using the same set of selected variables.

2.1. Discriminant analysis

Both the univariate and multivariate approaches to DA were used to find a set of variables that best

discriminates bankrupt from non-bankrupt firms. DA is a statistical technique used to classify observations into non-overlapping groups on the basis of scores for one or more quantitative predictor variables. The greater the information provided by the predictor variables, the better the classification outcome of the model. Mathematically, the objective in discriminant analysis is to obtain a set of coefficients (a_i 's) of the financial ratios (x_i 's) in a linear equation, $z = a_0 + a_1x_1 + a_2x_2 + \dots + a_nx_n$, which maximizes the discriminant criterion, where

$$\lambda = \frac{\text{Between group variance on } z\text{-scores}}{\text{Within group variance on } z\text{-scores}} \quad (1)$$

First, the univariate approach of DA was employed to observe the classification power of each ratio at the univariate level. The majority of the selected ratios presented strong classification power even at a univariate level. Moreover, univariate analysis contributed to distinguishing the type of ratios with stronger classification power from the weaker ones. Liquidity, solvency, and performance ratios stand out as the most significant indicators. Important to highlight at this point is the fact that the univariate approach of DA has significant disadvantages relative to MDA because it can only view the measurements used for group assignments, one at a time. In contrast, MDA has been considered by many authors (Altman, Taffler, and others) to be the best technique for developing bankruptcy prediction models, since it has the advantage of considering an entire profile of characteristics common to the relevant firms and the interaction of these properties. A poor indicator at the univariate level may be a significant indicator at the multivariate level. Thus, univariate analysis has been used only as a form of further information ancillary to a multivariate analysis rather than as a deciding factor.

Consequently, MDA was conducted for one to three years before bankruptcy to find a set of variables that, combined, can achieve significant discrimination even three years before bankruptcy. In this study, after a thorough analysis, three variables were selected as predictor variables in an attempt to correctly classify firms into two groups – bankrupt and non-bankrupt.

¹ Stern Stewart and Co. (now known as Stern Value Management) developed the EVA concept in 1991 to evaluate the performance of business organizations expressed as value generation for shareholders.

2.2. Sample selection and variables employed

The sample consists of Greek listed manufacturing firms for the 2008–2015 period because the implications of the recent financial crisis are of interest. Indeed, the Greek financial crisis appeared in 2008 and has yet to be fully confronted. As a result, the selected period is exactly within the crisis and effectively represents its consequences. Another important point to underline is that the manufacturing sector plays one of the leading roles in the Greek economy, capturing a third of Greek GDP (31%), according to the Greek Foundation for Economic and Industrial Research (IOBE). The final sample consists of all Greek manufacturing public firms using available data from the Datastream International and Bloomberg databases to compute the explanatory variables of this study (Table 1). Specifically, the sample includes 14 non-bankrupt firms and 14 firms, from a total of seven sectors, that went bankrupt during the 2008–2015 period (with no exceptions). The validity of the status of each firm (active, bankrupt) was cross-checked through the Greek General Commercial Registry (G.E.MI) to fully exclude firms that are neither active nor bankrupt. The two groups were matched on the basis of industry and asset size, resulting in a paired sample of 14 firms (28 in total). The year of the last listed financial statement is the year before bankruptcy ($t-1$). Examining the behavior of the selected variables not only during the year before the event but also two and three years before is important, since discriminating healthy from bankrupt firms three years before the bankruptcy indicates the overall statistical validity of the model and the excellent discriminating power of the selected variables. Therefore, the analysis was conducted separately for each year before the bankruptcy i.e., $t-1$, $t-2$ and $t-3$.

2.3. Predictor variables

Most of bankruptcy prediction models used the same accrual accounting-based measures without adding new information during the overall discriminating process. Thus, the purpose of this study is to examine and find a small set of variables with significant classification power to approach

bankruptcy prediction from a slightly different perspective (introducing new unconventional ratios on the basis of a firm's overall performance).

Following both recent literature and common practice techniques, a list of potentially helpful ratios was compiled for evaluation (Table 1). The potential variables were classified into six ratio categories, as shown in Table 1. Most of the studies conducted on bankruptcy prediction analyzed only five ratio categories, as previously stated in the literature review section. No study to date has tested performance-indicating ratios (such as EVA). However, this type of ratio carries an important amount of information regarding firms' effectiveness and their overall strength and health, as previously stated.

As has been the practice of most researchers in previous studies, the choice of financial ratios as variables is based on a series of trial-and-error processes. The number one priority in selecting predictor variables in this study is to approach the problem both theoretically and practically. Thus, a series of potential variables with an outstanding theoretical background were tested.

From the beginning, a significant number of liquidity, solvency, and performance ratios stood out at a univariate level (UDA). Some of this phenomenon was foreseeable because liquidity and solvency ratios are widely used in the bankruptcy prediction literature and play the leading role. MDA was conducted multiple times on different combinations that seemed promising. However, a specific set of variables projected strong classification accuracy, approaching bankruptcy from a well-rounded perspective. This set consisted of three variables, each providing information on the firm from a different angle and exporting a significant amount of information on the firm's integrity. However, examining the behavior of the selected variables not only during the year before failure but also two and three years before its occurrence is important. Therefore, MDA is used separately for each year before bankruptcy ($t-1$, $t-2$, $t-3$). The selected set of predictor variables produced models that achieved strong discrimination even three years before the bankruptcy, confirming their significance and their overall classification power.

Table 1. 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 $t-1$
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

Notes: Table 1 consists of the potential variables compiled for evaluation. Most of the studies on bankruptcy prediction used only five ratio categories for analysis. However, in this study, six ratio categories were tested. Specifically, liquidity, solvency, leverage, profitability, efficiency, and performance ratios were selected for evaluation. The list was created based on both the recent literature and common practice techniques.

The proposed set of variables consists of:

- EVA/total assets

EVA is a performance indicator that attempts to capture a company's true economic profit. EVA measures financial performance using residual wealth calculated by deducting the cost of equity from its operating profit adjusted for taxes on a cash basis. This measure was developed by Stern Stewart and Co. in 1991 to assess the performance of business organizations. As previously stated in the literature review, several important studies acknowledge the interconnection between EVA and financial distress, such as Timo and Virtanen (2001), who indicated that EVA can warn about an approaching bankruptcy, and Pasaribu (2008), who showed that public companies that do not create EVA are at high risk of distress. EVA is scaled by total assets for regularization and to project significant classification accuracy at both the univariate and multivariate levels. Thus, EVA is essential for inclusion in the model, with the full awareness that no other study has previously attempted to as-

sess its contribution in a discriminant bankruptcy prediction model.

- Quick ratio: (current assets – inventory – prepaid expenses) / current liabilities

The relevant literature indicated conflicting empirical evidence on the strong relationship between liquidity ratios and financial distress. Theoretically, liquidity difficulties that arise from the inability of current assets to cover current liabilities can cause financial distress. Thus, the analysis incorporates liquidity ratios that are most commonly used in the relevant literature (Table 1). The quick ratio stands out as the most important liquidity ratio, with strong classification power at both the univariate and multivariate levels.

The quick ratio indicates the ability of a company to pay its current obligations without having to sell its inventory or receive additional financing. A higher ratio indicates that the company has better liquidity and financial health; the opposite is true for a lower ratio. When a firm is unable to meet its

current obligation, it may face the strong possibility of financial distress. Therefore, the quick ratio is an important determinant of financial distress.

- Cash interest coverage ratio: (operating cash flow + interest + taxes) / interest

The solvency ratio selected derives from the cash flow statement and not from accrual accounting-based measures. As stated in Bhandari and Iyer (2013), few studies used cash flow measures and with limited success. Cash flow measures are very important for predicting financial distress or default because cash inadequacy is an often-cited reason for bankruptcy. Beaver (1966) stated that the most important ratio is operating cash flows divided by total debt for use in discriminating a going bankrupt firm from a healthy one.

However, a company's total debt cannot represent a clear picture of its ability to meet its obligations, which is what the interest coverage ratio aims to accomplish. This ratio showcases the company's ability to meet interest payments. A company that cannot cover its interest obligations from the operating cash that it generates is certainly in a distressed situation. Uncovered interest expenses may lead to rapidly increasing debt that can easily become unsustainable. Thus, the interest coverage ratio indeed reveals potential bankruptcy candidates.

These three variables combined achieve impressive classification accuracy even three years before a bankruptcy, as shown in the following section. The key to their success arises from the well-rounded information that they manage to convey when they are used in a combined manner.

Table 2. Descriptive group statistics (t-1)

Variables	Bankrupt firms (14)			Non-bankrupt firms (14)			Total firms (28)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0.1077	-0.0964	0.6724	0.0000	0.0000	0.0001	-0.0539	-0.0001	0.4785
Quick ratio	0.3410	0.2088	0.3200	1.0548	1.0291	0.2048	0.6979	0.7596	0.4467
(OCF+INT+TAX) / INT	-3.6645	-1.3889	8.5496	1.2287	-0.3467	7.7563	-1.2179	-0.7071	8.5214

Notes: Table 2 provides descriptive 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 total firms for the t-1 period. The matched sample consists of 28 firms, taking into account all manufacturing firms listed on the Greek Stock Exchange with sufficient data from the Datastream and Bloomberg databases to compute financial statement variables over the t-1 year-period (one year before bankruptcy). In addition, the validity of the status of each firm (bankrupt, non-bankrupt) was cross-checked through the Greek General Commercial Registry (G.E.MI) to fully exclude firms that are neither bankrupt nor active.

3. RESULTS AND ANALYSIS

MDA, correlation and collinearity tests have been conducted for each year before bankruptcy for the selected variables. The selected ratios had no missing values and no significant correlation or collinearity between them, thus providing the advantage of yielding a model with a relatively small number of selected measurements. These measurements give the model the potential to convey a significant volume of information.

This section is divided into three separate subsections (for three years) because the analysis was conducted individually for each year before bankruptcy. The selected set of variables used in the following models consists of the following:

$$X_1 = EVA \text{ scaled by total assets} = \frac{EVA}{Total \ assets}$$

$$X_2 = \text{Quick ratio} = \frac{Current \ Assets - Inventories}{Current \ Liabilities}$$

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

3.1. Results one year before bankruptcy (t-1)

Descriptive statistics (mean, median, standard deviation) for each selected variable are provided in Table 2 for both bankrupt (14) and non-bank-

Table 3. Outline of canonical discriminant functions (*t*-1)

Function	Eigen values				Wilks' λ	X ²	df	Sig.
	Eigen value	Percentage of variance	Cumulative percentage	Canonical correlation				
1	1.921	100	100	0.811	0.342	26.264	3	0.000

Notes: Table 3 outlines the canonical discriminant functions of the proposed model for *t*-1. The model is highly significant with great overall levels, which indicates effectiveness and significant discrimination ability.

rupt (14) firms and for all (28) firms of the sample. MDA was conducted using the StatGraphics statistical software.

Table 3 outlines the canonical discriminant functions of our model. The X²-statistic of the estimated discriminant function is highly significant (at the 0.000 level), which indicates the effectiveness of the proposed bankruptcy forecasting model. In addition, the high level of canonical correlation achieved (0.811) represents the model's strong ability to discriminate among the groups.

The standardized coefficients in Table 4 provide evidence of the relative importance of each variable in predicting business bankruptcies. That said, the quick ratio (0.968) is the most important variable for the one year before actual bankruptcy measurement. Unstandardized coefficients are the coefficients used in the model to calculate each firm's discriminant score. If the firm's score is close to -1.336, the firm is classified as bankrupt. Otherwise, if the firm's score is close to 1.336, the firm is classified as non-bankrupt. These centroids are presented in Table 5. The average discriminant score of a bankrupt firm is -1.336, and is 1.336 for a non-bankrupt one. A score close to zero (middle point) means indifference.

Table 4. Coefficients of the discriminant function (*t*-1)

Variables	Standardized coefficients	Unstandardized coefficients
EVA/TA	0.140	0.283
Quick ratio	0.968	3.474
(OCF+INT+TAX) / INT	0.279	0.033
Constant		-2.369

Notes: Table 4 consists of the standardized and unstandardized coefficients of the model, providing evidence on the relative importance of each variable in predicting business bankruptcies during the *t*-1 period. Specifically, the quick ratio variable is the most important one for predicting bankruptcy one year prior based on its high standardized coefficient (0.968). The unstandardized coefficients are the betas of the equation of the proposed model for *t*-1.

Table 5. Group centroids (*t*-1)

Groups	Discriminant function Group centroids
Bankrupt (B=0)	-1.336
Non-Bankrupt (B=1)	1.336

Notes: Table 5 projects the group centroids of the proposed model for *t*-1. In detail, a firm with a discriminant score close to -1.336 is classified as bankrupt (B = 0) because bankrupt firms tend to project a score close to that number. Conversely, a firm with a discriminant score close to 1.336 is classified as non-bankrupt (B = 1) because non-bankrupt firms tend to project a score close to that number, respectively.

The previous finding is considered to develop the resulting equation of the discriminant model for bankruptcy prediction one year before, as follows:

$$Z = -2.369 + 0.238 \cdot X_1 + 3.474 \cdot X_2 + 0.033 \cdot X_3,$$

where *Z* – discriminant score.

The model correctly re-classified 96.43% of all given cases. In greater detail, the model correctly predicted 13 out of 14 bankrupt firms and 14 out of 14 non-bankrupt firms, as shown in Table 6.

Table 6. Classification results (*t*-1)

Actual	Group size	Predicted 0	Predicted 1
Bankrupt (B=0)	14	13 (92.86%)	1 (7.14%)
Non-bankrupt (B=1)	14	0 (0.00%)	14 (100.00%)
Percent of cases correctly classified: 96.43%			

Notes: Table 6 displays the classification results of the model for the *t*-1 period. The proposed model correctly re-classified 96.43% of all given cases. In detail, the model correctly predicted 13 out of 14 bankrupt firms and 14 out of 14 non-bankrupt firms one year before bankruptcy. In other words, the model correctly re-classified 27 out of 28 cases, indicating strong discriminating power.

In summary, the proposed model correctly re-classified 27 out of 28 cases (96.43%), indicating strong discriminating power and introducing a new set

of variables with significant potentiality for bankruptcy prediction. In the following subsections, the same set of variables is examined to further evaluate their behavior two and three years before the actual bankruptcy. Thus, the overall predictability of the proposed set is measured throughout time, and the model was adjusted accordingly for each period.

3.2. Results two years before bankruptcy ($t-2$)

The descriptive statistics two years before bankruptcy for each selected variable are provided in Table 7 for both bankrupt (14) and non-bankrupt (14) firms, as well as for all (28) firms in the sample. MDA was conducted once again using the StatGraphics statistical software.

Table 8 encapsulates the canonical discriminant functions that provide valuable information on the significance and effectiveness of the chosen variables and the overall model for $t-2$. The X^2 -statistic of the estimated discriminant function is highly significant (at the 0.002 level), which indicates the effectiveness of the proposed bankruptcy prediction model for $t-2$. Additionally, the model achieved a high level of canonical correlations for $t-2$ as well (0.669), representing its ability to discriminate among the groups.

On the basis of the standardized coefficients provided in Table 9, the most important variable to correctly predict bankruptcy two years before is EVA/TA (0.757), which should be considered comparatively with the results of Table 4 for $t-1$ to further analyze the entire nature of bankruptcy itself. In most cases, a company does not go bankrupt overnight. Bankruptcy is the result of a long, fluctuating procedure. A potential bankruptcy in the short run should not be handled in the same way that it is handled in the long run, which is why the proposed model adjusts itself depending on the period from which bankruptcy approached ($t-1$, $t-2$, $t-3$). When dealing with a potential bankruptcy in the coming year, liquidity ratios carry the most valuable information. Otherwise, the analysis must focus on performance ratios, such as EVA/TA, because these types of ratios extract more thorough information on firms' overall picture than do liquidity ratios (which only examine firms' liquidity and look past their overall performance). The proposed model incorporates both liquidity and performance ratios in an attempt to reflect in the most efficient way to a company's overall financial health.

The resulting equation for the discriminant model for bankruptcy prediction two years before, on the basis of unstandardized coefficients, is as follows:

Table 7. Descriptive group statistics ($t-2$)

Variables	Bankrupt firms (14)			Non-bankrupt firms (14)			Total firms (28)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0.2145	-0.1212	0.2693	0.0000	0.0000	0.0001	-0.1073	-0.0001	0.2185
Quick ratio	0.4346	0.3487	0.3537	1.4427	1.0232	1.1981	0.9386	0.7394	1.0170
(OCF+INT+TAX) / INT	-2.5878	-0.0429	8.5179	1.7134	-0.3448	4.8182	-0.4372	-0.1731	7.2464

Notes: Table 7 provides descriptive statistics (mean, median, standard deviation) for EVA/TA, the quick ratio, and the (OCF+INT+TAX)/INT ratio across bankrupt firms, non-bankrupt firms, and total firms for the $t-2$ period. The matched sample consists of 28 firms, taking into account all manufacturing firms listed on the Greek Stock Exchange with sufficient data from the DataStream and Bloomberg databases to compute financial statement variables over the $t-2$ year-period (two years before bankruptcy). In addition, the validity of the status of each firm (bankrupt, non-bankrupt) was cross-checked through the Greek General Commercial Registry (G.E.MI) to fully exclude firms that are neither bankrupt nor active.

Table 8. Outline of canonical discriminant functions ($t-2$)

Function	Eigen value	Percentage of variance	Eigen values			Wilks' λ	χ^2	df	Sig.
			Cumulative percentage	Canonical correlation					
1	0.808	100	100	0.669	0.553	14.515	3	0.002	

Notes: Table 8 outlines the canonical discriminant functions of the proposed model for $t-2$. The model is highly significant with strong overall levels, indicating effectiveness and strong discrimination ability.

Table 9. Coefficients of the discriminant function ($t-2$)

Variables	Standardized coefficients	Unstandardized coefficients
EVA/TA	0.757	3.833
Quick ratio	0.518	0.565
(OCF+INT+TAX) / INT	0.570	0.079
Constant		-0.084

Notes: Table 9 consists of the standardized and unstandardized coefficients of the model, providing evidence on the relative importance of each variable in predicting business bankruptcies during the $t-2$ period. Specifically, EVA/TA is the most important variable for predicting bankruptcy two years earlier based on its high standardized coefficient (0.757). The unstandardized coefficients are the betas of the equation of the proposed model for $t-2$.

$$Z = -0.084 + 3.833 \cdot X_1 + 0.565 \cdot X_2 + 0.079 \cdot X_3,$$

where Z – discriminant score.

Depending on the firm's score, the firm is classified as either bankrupt or non-bankrupt based on the group centroids presented in Table 10.

Table 10. Group centroids ($t-2$)

Groups	Discriminant function Group centroids
Bankrupt (B=0)	-0.866
Non-Bankrupt (B=1)	0.866

Notes: Table 10 projects the group centroids of the proposed model for $t-2$. In detail, a firm with a discriminant score close to -0.866 is classified as bankrupt ($B = 0$) because bankrupt firms tend to project a score close to that number. Conversely, a firm with a discriminant score close to 0.866 is classified as non-bankrupt ($B = 1$) because non-bankrupt firms tend to project a score close to that number, respectively.

If the firm's score is close to -0.866 (average discriminant score of a bankrupt firm), the firm is classified as bankrupt. Otherwise, if the firm's score is close to 0.866 (average discriminant score of a non-bankrupt firm), it is classified as non-bankrupt. A score close to zero (middle point) means indifference.

Table 12. Descriptive group statistics ($t-3$)

Variables	Bankrupt firms (14)			Non-bankrupt firms (14)			Total firms (28)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
EVA/TA	-0.1512	-0.0617	0.2211	0.0000	0.0000	0.0001	-0.0756	-0.0001	0.1736
Quick ratio	0.6157	0.5857	0.4871	1.2885	1.0705	0.6601	0.9521	0.8506	0.6706
(OCF+INT+TAX) / INT	1.8840	-0.0336	4.1916	8.3533	0.9094	23.2393	5.1186	0.8030	17.0082

Notes: Table 12 provides descriptive statistics (mean, median, standard deviation) for EVA/TA, the quick ratio, and the (OCF+INT+TAX)/INT ratio across bankrupt firms, non-bankrupt firms, and total firms for the $t-3$ period. The matched sample consists of 28 firms, taking into account all manufacturing firms listed on the Greek Stock Exchange with sufficient data from the Datastream and Bloomberg databases to compute financial statement variables over the $t-3$ year-period (three years before bankruptcy). In addition, the validity of the status of each firm (bankrupt, non-bankrupt) was cross-checked through the Greek General Commercial Registry (G.E.MI) to fully exclude firms that are neither bankrupt nor active.

Table 11. Classification results ($t-2$)

Actual	Group size	Predicted 0	Predicted 1
Bankrupt (B=0)	14	13 (92.86%)	1 (7.14%)
Non-bankrupt (B=1)	14	1 (7.14%)	13 (92.86%)
Percent of cases correctly classified: 92.86%			

Notes: Table 11 displays the classification results of the model for the $t-2$ period. The proposed model correctly re-classified 92.86% of all given cases. In detail, the model correctly predicted 13 out of 14 bankrupt firms and 13 out of 14 non-bankrupt firms two years before bankruptcy. In conclusion, the proposed model for $t-2$ achieved exceptional classification accuracy, managing to predict correctly 26 out of 28 given cases two years before bankruptcy.

The model correctly re-classified 92.86% of all given cases two years before a bankruptcy event, confirming once again the strong discriminating power of the selected variables. Analytically, the model correctly predicted 13 out of 14 bankrupt firms and 13 out of 14 non-bankrupt ones, as shown in Table 11.

In summary, the proposed model for $t-2$ correctly predicted 26 out of 28 cases (92.86%) – a result that is commendable and further confirms the strong potentiality of the blend of the selected set of variables to make bankruptcy predictions.

3.3. Results three years before bankruptcy ($t-3$)

The descriptive statistics three years before bankruptcy for each selected variable are provided in Table 12 for both bankrupt (14) and non-bankrupt (14) firms and for all (28) firms in the sample. MDA was conducted once again using the StatGraphics statistical software.

Table 13 summarizes the canonical discriminant functions that provide valuable information on the significance and effectiveness of the selected variables and the overall model for $t-3$. The X^2 -statistic of the estimated discriminant function is highly significant (at the 0.001 level), indicating the effectiveness of the proposed bankruptcy prediction model for $t-3$. Moreover, the model achieved a high level of canonical correlation for $t-3$ as well (0.687), representing once again its strong ability to discriminate among the groups.

However, it should be emphasized that the X_3 variable does not contribute significantly to the discrimination process at this time point ($t-3$). Variable X_3 symbolizes the interest coverage ratio [(OCF+INT+TAX)/INT]. One of the top priorities of every firm is to cover its interest expenses. Uncovered interest expenses may lead to rapidly increasing debt that can easily become unsustainable, as previously mentioned in section 3. Because bankrupt firms three years before their bankruptcy are borderline healthy, a variable (X_3) that reflects such fragile information has limited discriminating power and does not contribute as significantly to the overall discrimination capability of the model at this time point ($t-3$).

The X_1 and X_2 variables are shown to have equally strong importance (0.855 and 0.989, respectively) on the basis of the standardized coefficients provided in Table 14.

Table 14. Coefficients of the discriminant function ($t-3$)

Variables	Standardized coefficients	Unstandardized coefficients
EVA/TA	0.855	5.270
Quick ratio	0.989	1.643
(OCF+INT+TAX) / INT	-0.219	-0.013
Constant		-1.101

Notes: Table 14 consists of the standardized and unstandardized coefficients of the model, providing evidence of the relative importance of each variable in predicting business bankruptcies during the $t-3$ period. Specifically, the quick ratio and EVA/TA variables are equally important for predicting bankruptcy three years earlier based on their high standardized coefficients (0.989 and 0.855, respectively). However, the EVA/TA variable plays the leading role in the equation because it has a significant larger unstandardized coefficient than the quick ratio variable. The unstandardized coefficients are the betas of the equation of the proposed model.

In addition, the unstandardized coefficients that emerged in Table 14 indicate that the resulting equation of the discriminant model for bankruptcy prediction three years before bankruptcy is as follows:

$$Z = -1.101 + 5.270 \cdot X_1 + 1.643 \cdot X_2 - 0.013 \cdot X_3,$$

where Z – discriminant score.

Depending on the firm's score, the firm is classified as either bankrupt or non-bankrupt on the basis of the group centroids presented in Table 15.

Table 15. Group centroids ($t-3$)

Groups	Discriminant function Group centroids
Bankrupt (B=0)	-0.910
Non-bankrupt (B=1)	0.910

Notes: Table 15 projects the group centroids of the proposed model for $t-3$. In detail, a firm with a discriminant score close to -0.910 is classified as bankrupt (B = 0) because bankrupt firms tend to project a score close to that number. Conversely, a firm with a discriminant score close to 0.910 is classified as non-bankrupt (B = 1) because non-bankrupt firms tend to project a score close to that number.

Table 13. Outline of canonical discriminant functions ($t-3$)

Function	Eigen values							
	Eigen value	Percentage of variance	Cumulative percentage	Canonical correlation	Wilks' λ	χ^2	df	Sig.
1	0.892	100	100	0.687	0.529	15.623	3	0.001

Notes: Table 13 outlines the canonical discriminant functions of the proposed model for $t-3$. The model is highly significant with decent overall levels, indicating effectiveness and a substantial discrimination ability three years before bankruptcy ($t-3$).

If the firm's score is close to -0.892 (average discriminant score of a bankrupt firm), the firm is classified as bankrupt. Otherwise, if the firm's score is close to 0.892 (average discriminant score of a non-bankrupt firm), it is classified as non-bankrupt. Again, a score close to zero (middle point) means indifference.

Table 16. Classification results ($t-3$)

Actual	Group size	Predicted	
		0	1
Bankrupt (B=0)	14	12 (85.71%)	2 (14.29%)
Non-bankrupt (B=1)	14	1 (7.14%)	13 (92.86%)
Percent of cases correctly classified: 89.29%			

Notes: Table 16 displays the classification results of the model for the $t-3$ period. The proposed model correctly re-classified 89.29% of all given cases. In detail, the model correctly predicted 12 out of 14 bankrupt firms and 13 out of 14 non-bankrupt firms three years before bankruptcy. In total, the model predicted correctly 25 out of 28 cases, indicating strong discriminating power and classification accuracy.

The model correctly re-classified 89.29% of all given cases three years before the bankruptcy event. In depth, the model correctly predicted 12 out of 14 bankrupt firms and 13 out of 14 non-bankrupt ones, as shown in Table 16.

In summary, the proposed model for $t-3$ correctly predicted 25 out of 28 cases (89.29%), validating once again the discrimination capabilities of the selected blend of variables throughout time.

4. DISCUSSION

The selected set of predictor variables created a model that can successfully predict bankruptcy over time. The model can adjust itself on the basis of the period during which bankruptcy is approached ($t-1$, $t-2$, $t-3$), hedging the weights of its variables accordingly. When dealing with a potential bankruptcy in the short run ($t-1$), the liquidity ratios are the most important indicators. Conversely, when dealing with a potential bankruptcy in the long run ($t-2$, $t-3$), the importance of liquidity ratios subsides, and performance-indi-

cating ratios are brought to the fore. The selected set of variables of the proposed model combines the short-run predicting capabilities of the liquidity ratios with the long-run capabilities of the performance-indicating ratios. When these two types of ratios are combined with the selected solvency ratio (cash flow coverage of interest ratio), they successfully predict bankruptcy in 96.43% of cases for $t-1$, 92.86% of cases for $t-2$, and 89.29% of cases for $t-3$.

Gerantonis et al. (2009), examined the effectiveness of original Altman's (1968) "Z-score" on predicting bankruptcies up to three years before its occurrence for Greek publicly listed firms and found that the model correctly predicted 66% of given cases one year prior to bankruptcy ($t-1$), 52% of given cases two years prior and just 39% of given cases three years prior the event of bankruptcy, respectively ($t-2$, $t-3$). In addition, Glezakos et al. (2010) applied Logit Analysis using a predetermined set of ratios on Greek publicly listed firms to study its ability and effectiveness on bankruptcy prediction three years before its occurrence. Although the Type II error of the model developed (i.e. misclassification of a healthy firm as a bankrupt one) was fairly low ranging from 5% to 10%, Type I error (i.e. misclassification of a bankrupt firm as a healthy one) was proven to be significantly high ranging from 40% to 70%. The proposed model of this study produced considerably superior results than both aforementioned studies.

This study adds to the international evidence of bankruptcy prediction in many respects. First, the period selected is exactly during the Greek financial crisis and effectively represents its consequences.² Second, unconventional performance indicators, such as EVA, were used to predict bankruptcy. According to the available information, limited studies manage to successfully predict bankruptcy not only a year before but also two and three years before an eventual bankruptcy. Finally, an additional advantage of the model proposed is its simplicity, since the proposed set of predictor variables consists only of three financial ratios that are justified a priori in an economic

² According to Malliaris (2016), a modern mixed capitalist economy (such as the Greek economy) is divided into the following four phases: expansion, upper turning period, recession, and a lower turning period. The last phase (lower turning period) of the economic cycle in the United States began in July 2009 and lasted until November 2010. In contrast, Greece went through a recession (third phase) but remained in the last phase of the economic cycle throughout our selected time sample (2008–2015). Thus, the period was selected on purpose to further analyze an economy that experiences the recession phases of its economic cycle.

sense and are not the outcome of a step-wise procedure, providing an overall status of the firm and achieving significant classification accuracy.

This analysis is subject to limitations that are commonly encountered in bankruptcy prediction bibliography. First, the explanatory variables of the model (financial ratios and EVA) are based on ac-

counting data, making them susceptible to measurement errors. Last but not least, factors such as macroeconomic and industry specific conditions, variability of business conditions and competitiveness have not been considered due to potential difficulties regarding their measurement, even if their contribution to the overall classification accuracy of the model may be of great significance.

CONCLUSION

The purpose of this study was to approach bankruptcy prediction among listed manufacturing companies in Greece from a different, revitalized perspective on the basis of the recent literature. Most past attempts with respect to bankruptcy prediction models used predictor variables derived mostly from accrual accounting-based financial statements. No other study considered pure performance indicators, such as EVA, as variables. In addition, according to Bhandari and Iyer (2013), few studies used cash flow measures but with limited success. This study introduces and exposes the significant potentiality and impressive classification power of a new blend of variables on bankruptcy prediction during stressed periods.

An equally balanced matched sample of 28 Greek-listed manufacturing firms was used in this study (including all firms that went bankrupt between 2008-2015 in its entirety). Greece was purposefully selected for its fruitful ground for bankruptcy analysis, created from its recent great economic depression. Multivariate DA was applied to the matched sample using data from one year ($t-1$), two years ($t-2$), and three years ($t-3$) before bankruptcy, resulting into a model that adjusts itself depending on the period before which bankruptcy is approached ($t-1$, $t-2$, $t-3$) and that always uses the same set of selected variables. The selected variables used are EVA/TA, quick ratio, and cash flow coverage of interest, and the model correctly classified 96.43% of cases in $t-1$, 92.86% of cases in $t-2$, and a remarkable 89.29% of cases three years before the bankruptcy event ($t-3$).

In summary, the selected set of predictor variables achieved strong classification accuracy even three years before the bankruptcy. Consequently, this mix of financial ratios captivated an overall picture of a firm's financial health, achieving strong predictability for Greece.

With respect to future research, this study focused on companies listed on the Athens Stock Exchange. Given that many Greek non-listed small and medium enterprises (SMEs) have also gone bankrupt, it would also be interesting to test the accuracy of the models on non-listed SMEs in Greece. In addition, it is of great interest to further evaluate the efficiency and predictability of the proposed set for other countries that are similar to those of Greece (for example, Italy). This approach may allow discussion of whether the success of the proposed set is a nationwide or a worldwide phenomenon.

AUTHOR CONTRIBUTIONS

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