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Prediction of Bankruptcy Using Financial Ratios in the Greek Market

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Abstract

This study explores the forecasting ability of bankruptcy prediction models for firms listed on the Athens Stock Exchange. The models have been tested whether they are able to predict bankruptcy one, two and three years prior bankruptcy. The highest bankruptcy predictive accuracy is achieved by the Taffler's and Grammatikos and Gloubos' *Y* models. Early and accurate sign of bankruptcy helps businesses take necessary actions to solve financial distress; hence the Greek bankruptcy prediction models will help companies minimize risk.

Keywords

Bankruptcy, Financial Ratios, Forecasting Ability, Prediction Models

1. Introduction

The research objective of this study is to determine the most accurate bankruptcy prediction model that can be used to predict insolvency of industrialized firms in the Greek market. To do so, this study examines six different well-established bankruptcy prediction models: Altman's [1] Z-score model, Taffler's [2] model, Grammatikos and Gloubos [3] *X* and *Y* models, Zopounidis and Doumpos [4] model and Dimitras *et al.* [5] model. These models are used to predict bankruptcy in firms listed on the Athens Stock Exchange. The sample period of this research is between 2002 and 2012. This study examines the practical application of the aforementioned models by estimating their coefficients using a logit regression framework. The 80% of the sample observations is used to estimate the coefficients of the models and the remaining 20% of the observations (the holdout sample) is used to test the accuracy of the models.

The global financial crisis of 2008 had a severe impact on several countries and Greece is among those affected the hardest. In 2018, Greece comes to the end of its eighth year of external financial assistance, but it has a long way to go on the road to recovery. Greek output is now 3.7 per cent higher than in mid-2015, which makes it 25 per cent below 2007 levels[1]. The European Union has several times interfered and bailed the country out of its on-going economic turmoil [6]. O'Brien [7] reports that the Athens Stock Exchange has fallen over 600% since its peak in November 2007, this makes the fall worse than the fall during the Great Depression in 1933. Numerous Greek companies went bankrupt post-2007 and several pre-bankruptcy procedures have been introduced [8]. According to IMF's 2018 annual health check of the Greek economy: "Greece has successfully eliminated its extraordinarily high fiscal and current account deficits, and restored growth. It must now take action to address crisis legacies and boost inclusive growth"[2].

An early and accurate sign of bankruptcy can help businesses take necessary actions to solve financial distress. Applying the aforementioned bankruptcy prediction models to the Greek market will potentially help companies in Greece minimize risk and avoid bankruptcy in the future.

There is a substantial research on bankruptcy prediction models, but the majority of these have been created before the economic crisis of 2007. Therefore, using a more recent (after the financial crisis) sample period (2002-2012) of 50 companies listed on the Athens Stock Exchange, we estimate the aforementioned models and check whether their predictive accuracy is affected. Safeguarding a valid bankruptcy prediction model is valuable for the Greek capital market. This study may be useful for many internal and external stakeholders such as management, employees, customers, banks, investors and other creditors. In particular, it may assist the managers of corporations to take drastic measures to avoid bankruptcy, it may help employees and customers to identify and associate themselves with companies with low insolvency risk, and it may help banks and investors to allocate capital more efficiently.

The remainder of this study is structured as follows: Section 2 critically evaluates previous literature on corporate bankruptcy studies. Section 3 describes the data collection process and the methodology used in this study; in particular it presents the different models that have been used in the research to predict bankruptcy. Section 4 describes the models with the estimated coefficients for the Greek market. Section 5 analyses the findings, whereas Section 6 concludes the paper and discusses potential areas for future research.

2. Literature Review

Altman [9] stated that four different terms has been used when discussing financial distress in companies: failure, solvency, bankruptcy and default. A common term of financial distress is when a company "*cannot meet its current obligation*" [9]. When this occurs a company normally increases its loans to meet its pay-

[1]See for example Financial Times: https://www.ft.com/content/3067bf9c-8a88-11e8-bf9e-8771d5404543.

[2]Source, International Monetary Fund: www.imf.org/en/News/Articles/2018/07/30/NA07302018.

ments. But, when a firm misses scheduled loan and/or bond payments, a legal default is an option, which results in filing for bankruptcy.

Financial distress cost is classified as either direct or indirect. Direct costs are considered out-of-pocket expenses for accountants, turnaround specialists, lawyers, expert witnesses and other professionals. Indirect costs are all unobservable opportunity costs. These costs include all loss of sales and profits by customers for choosing not to go into business with a company that is entering bankruptcy [9].

Hunter and Isachenkova [10] argue that company distress and company failure is because of their inability to pay debts as they come due. Reasons as to why companies are unable to pay their bills are associated with gearing and insufficiency of liquid assets.

Poston *et al.* [11] present five stages of business failure. The stages are; the incubation stage, the financial embarrassment stage, the financial insolvency stage, the total insolvency stage and finally the confirmed insolvency stage. The first stage will most likely go unnoticed by the company; this is the stage when the financial difficulties are developing. In the second stage, the management and probably others in the company will note the difficulties that the company is suffering from. This is the stage where the company is unable to meet their payments, even though the company have assets that exceed their liabilities. Even though the company have the assets, the assets that the company has is not possible to use for payments as they are not liquidated.

The third stage of business failure, the financial insolvency stage, is when the firm is unable to obtain necessary funds to pay its obligations. From this stage there is still firms that are restored to a healthy state. However, the firms which are not able to return to a healthy state progress to stage four: total insolvency stage. According to Fitspatrick [12] cited in Poston *et al.* [11] the fourth stage *occurs when the liabilities exceed the physical assets. It is, in a number of instances, the time when the general public and those creditors not yet apprised of the firm's true condition first learn that the company is failing. The business can no longer avoid the confession of failure*.

At the fourth stage, the total insolvency stage, creditors may take over the business or restructure the troubled debt. The company may also make an attempt to get extra funds from financing sources. If none of these are successful, the business enters the confirmed insolvency stage, the last/fifth stage. This step includes legal steps to protect the firm's creditors. As mentioned, this is when the company files for bankruptcy. The majority of companies that reaches this final step are liquidated, but some companies are returned to a healthy state through restructuring and reorganization.

The general definition of failure is when a company is not able to pay their lenders, suppliers, preferred stock shareholders and so on, a bill is overdrawn, or the firm is bankrupt according to law. All these situations previously mentioned terminate the firms operations [5].

Taffler [2] states that there are financial indicators or symptoms that can be analysed to predict bankruptcy/corporate failures. The symptoms or indicators can be observed by looking at the financial results of the company over a period of time; e.g. see Slatter (1984) and Hunter and Isachenkova [10].

Altman [1] stated that financial ratios can be used to detect if a company is having operating and financial difficulties. The usage of financial ratios to check the status of the companies' profitability, liquidity, leverage, turnover, variability and size gives the viewer a good understanding of the company [13]. In Beaver's [14] research of financial ratios figured out that by using financial ratios give signs of financial distress about five years prior to bankruptcy.

Throughout the years there have been several different studies that have used different ratios for predicting bankruptcy. According to Bellovary *et al.* [15] bankruptcy prediction literature dates back to the 1930s. The Bureau of Business Research published in 1930 a study in which 8 ratios determined that gave a good indicator of failing firms. The next 30 years bankruptcy prediction models used univariate or single factor analysis to predict future bankruptcy. Using individual ratios for predicting bankruptcy can be misleading and inadequate. Altman [1] was the first research to publish a multivariate discriminate analysis model. Altman's Z-score model uses five financial ratios to calculate a Z-score, which differentiates a *healthy* company with an *unhealthy* company.

In addition to Altman's Z-score model, there were two other models that were developed during the 1960s. After 1960 several other models have been developed. 28 studies were published in the 1970s, 53 studies were published in the 1980s and 70 studies were published in the 1990s. In the period 2000 – 2004 there were 11 studies that were published [15]. These studies are on different research area and therefore different number of ratios is included in the models. Ohlsen [16] developed a logit analysis, Zmijewski (1984) developed probit analysis in the study. Other models that have been developed are Altman *et al.* [9] neural networks, Vermeulen *et al.* (1998) multi-factor model and Messier and Hansen (1988) expert system model. Auditors, bond analysts, insurance companies, banks, and financial institutions make use of such models; *i.e.* see Poston *et al.* [11] and Dimitras *et al.* [5].

The models that have been developed use several different ratios to predict company bankruptcy. Compared to Altman's Z-score which uses five different ratios to analyse company bankruptcy Jo *et al.* [17] uses as many as 57 different ratios in their multivariate discriminant analysis. The more ratios the model use, does not necessary means higher accuracy of the model. For example Jo, Han and Lee's [17] model is 81.94% accurate, while Rose and Kolari [18] model that uses 23 different ratios is 76% accurate and Moses and Liao [19] model which uses three different ratios is 85% accurate. **Table 1** provides detailed information for the competing models.

The models that have been developed have been created for several different sectors; manufacturing firms, banks, airline companies, small firms, oil and gas companies and so on. Additionally, the models have been developed for specific

Table 1. Information for the competing models.

	Application Study Period	Criteria for failed firm	Timeframe	Model Accuracy
Altman model	33 failed and 33 non-failed US manufacturing firms 1946-1965	Firm that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act	5 years	76% for hold-out sample
Taffler model	23 Failed and 45 non-failed UK industrial firms, 1968-1973	Receivership, voluntary liquidation, winding up by court order or equivalent	4 years	96% for failed firms and 100% for non-failed firms
Grammatikos and Gloubos *X* model	29 failed Greek industrial firms and 29 non-failed firms, 1977-1981	Went bankrupt or applied for bankruptcy	3 years	93% for failed firms and 90% for non-failed firms
Grammatikos and Gloubos *Y* model	29 failed Greek industrial firms and 29 non-failed firms, 1977-1981	Went bankrupt or applied for bankruptcy.	3 years	90% for failed firms and 93% for non-failed firms.
Dimitras *et al.* model	80 Greek firms, 40 failed firms and 40 non-failed firms, 1986-1990	Went bankrupt or applied for bankruptcy.	3 years	Hold-out sample: Year 1: Failed firms: 63.2% Healthy firms: 68.4%
Zopounidis and Doumpos model	58 Failed and 58 non-failed firms.	Failed firms.	3 years	Hold-out sample Year-1: 65.79% Year-2: 57.89% Year-3: 55.26%

countries; Gloubos and Grammatikos [3] were developed a model for Greek firms, Taffler [2] were focused on UK manufacturing firms while Rose and Kolari [18] were predicted bankruptcy in banks. Other models were developed for general application, such as Karels and Prakash (1987).

Even though the vast majority of the literature of bankruptcy prediction has focused the research on the US and the UK, there are also models that have been developed for Greek firms. Gloubos and Grammatikos [3] focused their research on Greek firms and created a set of linear probability, probit, logit and multi discriminate analysis models. The most accurate of the developed models were the probit and the linear probability models which both had a 70.8% accuracy. Theodossiou [20] created a linear probability model, a logit model and a probit model for Greek manufacturing firms. The most accurate of these models was the linear probability model which had a 96.4% accuracy. Dimitras *et al.* [5] [21] created three different models for Greek firms, a rough set theory model, a multi discriminate analysis model and a logit model, of these the rough set theory model was the most accurate with 73.7% accuracy one-year prior bankruptcy. Zopounidis and Doumpos [4] created a utilities additives discriminant model, which used twelve different ratios with accuracy varying from 47.37% to 84.21% for bankrupt companies. The models discussed in this section have been developed and used before the financial crisis of 2007. The present study tests whether the multi discriminate analysis models perform well on a more recent (after the 2007 financial crisis) sample period. Therefore the following two hypotheses are investigated:

Hypothesis (1): *Bankruptcy of Greek companies can be predicted using financial ratios.*

Under this hypothesis it is investigated whether bankruptcy in the Greek market can be predicted by analysing the ratios of different companies.

Hypothesis (2): *Altman's Z-score model* [1] *gives a better bankruptcy prediction of Greek companies compared to other models.*

3. Data Collection and Existing Models

The data collected from DataStream™ are the public records from the Athens Stock Exchange, including data from their: balance sheet, income statement and the cash flow statement. The data have been collected for 25 bankrupt companies for the period 2002-2012. To check if the models can differentiate between healthy and unhealthy companies 25 healthy companies have also been chosen. The healthy companies have been matched to the bankrupt companies regarding size and industry. Only companies with a full data set are included in the sample. The models' predictive accuracy is tested one, two and three years prior to bankruptcy. **Table 2** provides information about the financial ratios employed in various studies.

According to Burns and Burns [22] a discriminant analysis model is a linear equation that will divide the results into two groups, in this case bankrupt and non-bankrupt. The different combination of the variables provides a score for each company using the generic formula:

$$Z_i = v_0 + \sum_{j=1}^{N} v_j x_{j,i} + \varepsilon_i \,. \tag{1}$$

where Z_i is the discriminant function, or the score that divides the samples into groups, v_j are the coefficients, $x_{j,i}$ are the scores for the different variables, v_0 is a constant coefficient, N is the number of explanatory variables, and $\varepsilon_i \sim N\left(0, \sigma_\varepsilon^2\right)$. To differentiate between bankrupt and non-bankrupt companies a cut-off score is calculated. Based on this cut-off score and the Z-score of the company, a firm is classified as bankrupt or non-bankrupt. To differentiate between bankrupt and non-bankrupt companies the distribution of the scores is essential. If the scores overlap each other as illustrated in **Figure 1**, it will be hard to differentiate between bankrupt and non-bankrupt companies. However if the distribution is like the bottom figure, misclassification is minimal.

The six multiple discriminant analysis models that have been established in literature are investigated: Altman's [1] Z-score, Taffler's [2], Grammatikos and Gloubos's [3], Dimitras' *et al.* [5] and Zoupounidis and Doumpos's [4] models.

Altman's Z-score

$$Z_i = 0.12x_{1,i} + 0.14x_{2,i} + 0.033x_{3,i} + 0.006x_{4,i} + 0.999x_{5,i} + \varepsilon_i \,, \tag{2}$$

where Z_i denotes the overall index, $x_{1,i}$ is the working capital to total assets, $x_{2,i}$ are the retained earnings to total assets, $x_{3,i}$ are the earnings before interest and tax (EBIT) to total assets, $x_{4,i}$ is the market capitalisation to total liabilities, whereas $x_{5,i}$ denote the sales to total assets. The cut-off score for this model is 2675. If the Z-score is lower than 2675 the company is a bankrupt company. If the Z-score is above 2675 then the company is a non-bankrupt company.

Taffler's Model

$$Z_i = 3.2 + 12.18x_{1,i} + 2.5x_{2,i} - 10.68x_{3,i} + 0.029x_{4,i} + \varepsilon_i \,, \tag{3}$$

Table 2. Information for the financial ratios employed.

Financial Ratios	Altman [1]	Taffler [24]	Grammatikos and Gloubos [3] *X* Model	Grammatikos and Gloubos [4] *Y* Model	Dimitras *et al.* [5]	Zopounidis and Doumpos [4]
Profitability						
EBIT/Total assets	X				X	X
Profit before tax/Current Liabilities		X	X	X		
Earnings after Tax to Current Liabilities			X	X		
Net Income to Gross Profit					X	X
Net income to Total Assets					X	X
Liquidity						
Working Capital/Total Assets	X		X	X		
Current Assets/Total Liabilities		X			X	X
Current liabilities to current assets		X				
Current Assets to Total Assets			X			
Notes payable to total assets			X			
Quick Assets to Current Liabilities					X	X
Current Liabilities To Total Assets					X	X
Leverage						
Equity Market Value to Total Liabilities	X					
Retained Earnings/Total Assets	X					
Net worth to Net worth + Long term debt					X	X
(Long term debt + current liabilities) to total assets					X	X
Net worth to Net fixed assets					X	X
Turnover						
Sales/Total Asset	X					
No-credit interval in days		X				
Inventories/Net working Capital			X		X	X
Net Income to Total Worth					X	X
Working capital to net worth					X	X

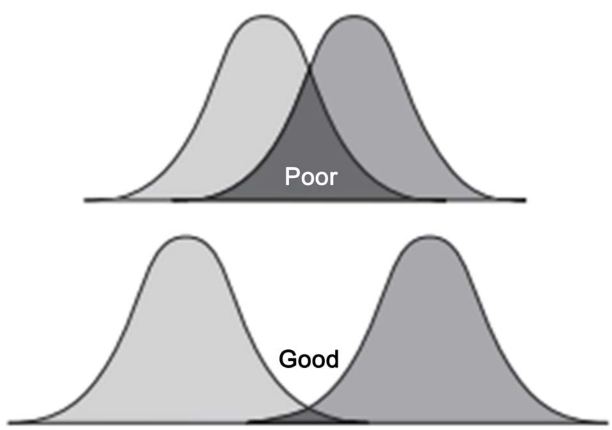

Figure 1. The distribution of the scores [22].

where Z_i is the overall index, $x_{1,i}$ is the profit before tax to current liabilities, $x_{2,i}$ denote the current assets to total liabilities, $x_{3,i}$ are the current liabilities to current assets, $x_{4,i}$ expresses the no-credit interval in days (liquid current assets/daily cash operating expenses) or (quick assets − current liabilities)/((sales − profit before tax)/365). In this model the cut-off score is −1.95. If the Z score is lower then −1.95 the company is a bankrupt company. If the Z score is above −1.95 the company is a non-bankrupt company. The ratio $x_{4,i}$ is the estimated time that a company could finance the expenses of its business with the company's current level of activity [23].

Grammatikos and Gloubos' Model

Grammatikos and Gloubos presented two different models, one with six ratios (X model) and one with three ratios (Y model), therefore two sets of coefficients have been created for the ratios.

$$\begin{aligned} Z_i &= -0.863 - 2.461x_{1,i} + 5.33x_{2,i} - 0.022x_{3,i} + 3.676x_{4,i} \\ &\quad + 3.543x_{5,i} + 4.223x_{6,i} + \varepsilon_i \end{aligned} \tag{4}$$

where Z_i = overall X score, $x_{1,i}$ = current assets to total assets, $x_{2,i}$ = net working capital to total assets, $x_{3,i}$ = inventories to net working capital, $x_{4,i}$ = notes payable to total assets, $x_{5,i}$ = earnings after taxes to current liabilities, $x_{6,i}$ = gross income to total assets. The cut-off score of this model is 0. If the Z score is below 0 the company is a bankrupt company. If the Z score is over 0 the company is a non-bankrupt company.

$$Y_i = 0.313 + 0.546x_{2,i} + 0.805x_{5,i} + 0.979x_{6,i} + \varepsilon_i, \tag{5}$$

where Y_i is the overall Y-score. The cut-off score of this model is 0.5. If the Y score is below 0.5 the company is a bankrupt company, otherwise it is a non-bankrupt company.

Dimitras et al.'s Model

$$\begin{aligned} Z_i &= -1.151 + 0.0093x_{1,i} + 1.9154x_{2,i} + 2.4196x_{3,i} + 0.1245x_{4,i} \\ &\quad + 1.2882x_{5,i} - 0.9008x_{6,i} - 0.7149x_{7,i} + 0.004x_{8,i} + 0.0342x_{9,i} \\ &\quad - 0.0168x_{10,i} + 0.6294x_{11,i} + 0.0022x_{12,i} + \varepsilon_i \end{aligned} \tag{6}$$

where $x_{1,i}$ = Net income to gross profit, $x_{2,i}$ = Gross profit to total assets, $x_{3,i}$ = Net income to total assets, $x_{4,i}$ = Net income to total worth, $x_{5,i}$ = Current assets to current liabilities, $x_{6,i}$ = Quick assets to current liabilities, $x_{7,i}$ = (Long term debt + current liabilities) to total assets, $x_{8,i}$ = Net worth to net worth+long term debt, $x_{9,i}$ = Net worth to net fixed assets, $x_{10,i}$ = Inventories to working capital, $x_{11,i}$ = Current liabilities to total assets, $x_{12,i}$ = Working capital to net worth. The cut-off score for this model is 0.5. If the Z-score is lower (higher) than 0.5 the company is a bankrupt (non-bankrupt) company.

Zopounidis and Doumpos' Model

$$\begin{aligned} U_i^{c1}(a) &= 0.0523x_{1,i} + 0.0079x_{2,i} + 0.8531x_{3,i} + 0.0068x_{4,i} \\ &\quad + 0.0079x_{5,i} + 0.0079x_{6,i} + 0.0281x_{7,i} + 0.005x_{8,i} \\ &\quad + 0.0079x_{9,i} + 0.0079x_{10,i} + 0.0079x_{11,i} + 0.0073x_{12,i} + \varepsilon_i \end{aligned} \tag{7}$$

and

$$\begin{aligned} U_i^{-c1}(a) = {} & 0.0079x_{1,i} + 0.0079x_{2,i} + 0.0385x_{3,i} + 0.0068x_{4,i} \\ & + 0.0079x_{5,i} + 0.0079x_{6,i} + 0.8865x_{7,i} + 0.005x_{8,i} \\ & + 0.0085x_{9,i} + 0.0079x_{10,i} + 0.0079x_{11,i} + 0.0073x_{12,i} + \varepsilon_i \end{aligned} \tag{8}$$

where $x_{j,i}$, for $j = 1, \cdots, 12$, are the same with Equation (6). Instead of the cut-off score this model compares two different scores. If $U_i^{c1}(a) > U_i^{-c1}(a)$ the company is non-bankrupt company, otherwise the company is a bankrupt company.

4. Prediction of Bankruptcy in the Greek Market

This study uses the logit regression framework to estimate the models' coefficients based on the 80% of the observations[3] (the basic sample). The predictive ability of the models with the updated coefficients is tested on the 20% holdout sample. The logit model divides the results into two groups, but instead of a cut-off score it provides a probability score. The companies' ratios of the basic sample were used to estimate the coefficients for the models. The holdout sample is used to check the accuracy of the updated models. The probability scores have been estimated based on the logistic regression presented in Burns and Burns [22]:

$$P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\left(-v_0 - \sum_{j=1}^{N} v_j x_{j,i}\right), \tag{9}$$

where $\Phi(.)$ is the cumulative distribution function for the logistic distribuion, $d_t = 1$ denotes the status of a non-bankrupt company, whereas $d_t = 0$ the status of a bankrupt company, $P(d_t = 1)$ is the probability that a case is in a particular category (*i.e.* $d_t = 1$), v_j are parameters to be estimated and $x_{j,i}$ define the scores of the various ratios. The models with the updated coefficients are listed in the lines follow:

Altman's Z-score

$$P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\left(-3.84x_{1,i} - 0.78x_{2,i} - 12.21x_{3,i} + 0.46x_{4,i} - 0.63x_{5,i}\right). \tag{10}$$

In the original model the cut-off score was 2675, while in the updated model the Z-score is converted into probability as the probability scores are between 0 and 1. If the probability is higher than 0.5 the model predicts that this company will survive. If the probability is lower than 0.5 the model predicts that this company will not survive.

Taffler's Model[4]

$$P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\left(-4.02x_{1,i} - 0.27x_{2,i} + 0.46x_{3,i} - 123.9x_{4,i}\right). \tag{11}$$

Grammatikos and Gloubos' Models

X model

$$\begin{aligned} & P\left(d_t = 1 \setminus x_{j,i}\right) \\ & = 1 - \Phi\left(5.26x_{1,i} - 4.35x_{2,i} - 1.52x_{3,i} - 4.82x_{4,i} - 1.74x_{5,i} - 8.38x_{6,i}\right) \end{aligned} \tag{12}$$

[3]Both logit and probit techniques provide quite similar estimation outputs. The advantage of logit modelling is that its coefficients can be interpreted in terms of odds ratios, whereas the advantage of probit model is its ability to account for non-constant error variances.

[4]The re-estimated model does not include a constant term compared to the original model.

Y model

$$P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\left(-3.93x_{2,i} - 1.18x_{5,i} - 2.44x_{6,i}\right). \quad (13)$$

Dimitras et al.' s-Zopounidis and Doumpos Models[5]

Dimitras *et al.*, employ the same ratios with Zopounidis and Doumpos, therefore one model is re-estimated.

$$\begin{aligned} P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\big(&-1.20x_{1,i} + 6.47x_{2,i} - 89.14x_{3,i} + 9.24x_{4,i} \\ &- 5.21x_{5,i} + 14.59x_{6,i} - 30.04x_{7,i} - 0.32x_{8,i} \\ &- 0.19x_{9,i} - 0.69x_{10,i} + 19.63x_{11,i} - 3.03x_{12,i}\big) \end{aligned} \quad (14)$$

5. Analysis of the Findings

Table 3 explains the presentation format of the models' predictive accuracy results. "Type 0" denotes the bankrupt companies. If the model shows the company as bankrupt the prediction is correct. If the model classifies the company as a non-bankrupt company we have a "Type 0 error". "Type 1" denotes the non-bankrupt companies. As with Type 0, the classification is correct if the model classifies the company as a non-bankrupt company. If on the other hand the model classifies the non-bankrupt company as a bankrupt company we have a Type 1 error. The last line shows the sum of both Type 0 companies and Type 1 companies. This adds up the correct and the incorrect percentage score and gives an overall score, in other words both bankrupt and non-bankrupt companies have been taken into consideration in the final line.

A summary of the predictive ability of the different models is presented in Table 4. Initially Altman's model results are presented. One year prior bankruptcy in the basic sample when considering only bankrupt companies the prediction accuracy is 73.69% and for the non-bankrupt companies the correct classification increases to 90%. The overall accuracy is 82.05%. In the holdout sample the accuracy decreases to 40% when considering only bankrupt companies but it increases to 100% for the non-bankrupt companies making the overall accuracy 70%.

Two-years prior bankruptcy, the overall accuracy is 62% in the basic sample. When considering only bankrupt companies the accuracy is 47.37%, and for non-bankrupt companies the accuracy is 75%.

Three-years prior bankruptcy the overall accuracy of the basic sample declines to 55.88%. Considering only non-bankrupt companies the accuracy is 88.24%. In

Table 3. Explanation of the results.

1 year prior	% of Correct	% of Incorrect
Type 0	XX%	XX%
Type 1	XX%	XX%
Total	XX%	XX%

[5]The coefficients are statistically significant at 5% level.

Table 4. Predictive accuracy.

	1 yr		2 yr		3 yr	
Altman Basic	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type 0	73.68%	26.32%	47.37%	52.63%	23.53%	76.47%
Type 1	90.00%	10.00%	75.00%	25.00%	88.24%	11.76%
Total	82.05%	17.95%	62.00%	38.00%	55.88%	44.12%
Holdout						
Type 0	40.00%	60.00%	20.00%	80.00%	0.00%	100.00%
Type 1	100.00%	0.00%	100.00%	0.00%	100.00%	0.00%
Total	70.00%	30.00%	60.00%	40.00%	50.00%	50.00%
Taffler Basic	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type 0	84.21%	15.79%	68.42%	31.58%	42.11%	57.89%
Type 1	85.00%	15.00%	75.00%	25.00%	75.00%	25.00%
Total	84.62%	15.38%	71.79%	28.21%	58.97%	41.03%
Holdout						
Type 0	80.00%	20.00%	40.00%	60.00%	0.00%	100.00%
Type 1	80.00%	20.00%	100.00%	0.00%	80.00%	20.00%
Total	80.00%	20.00%	70.00%	30.00%	40.00%	60.00%
GG X Basic	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type 0	84.21%	15.79%	72.22%	27.78%	35.29%	64.71%
Type 1	80.00%	20.00%	68.42%	31.58%	77.78%	22.22%
Total	82.05%	17.95%	70.27%	29.73%	57.14%	42.86%
Holdout						
Type 0	60.00%	40.00%	40.00%	60.00%	50.00%	50.00%
Type 1	80.00%	20.00%	40.00%	60.00%	80.00%	20.00%
Total	70.00%	30.00%	40.00%	60.00%	66.67%	33.33%
GG Y Basic	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type 0	63.16%	36.84%	50.00%	50.00%	17.65%	82.35%
Type 1	90.00%	10.00%	84.21%	15.79%	83.33%	16.67%
Total	76.92%	23.08%	67.57%	32.43%	51.43%	48.57%
Holdout						
Type 0	60.00%	40.00%	0.00%	100.00%	0.00%	100.00%
Type 1	100.00%	0.00%	80.00%	20.00%	100.00%	0.00%
Total	80.00%	20.00%	40.00%	60.00%	55.56%	44.44%
DSSZ Basic	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type 0	89.47%	10.53%	52.63%	47.37%	63.16%	36.84%
Type 1	90.00%	10.00%	85.00%	15.00%	70.00%	30.00%
Total	89.74%	10.26%	69.23%	30.77%	66.67%	33.33%
Holdout						
Type 0	60.00%	40.00%	40.00%	60.00%	20.00%	80.00%
Type 1	80.00%	20.00%	80.00%	20.00%	60.00%	40.00%
Total	70.00%	30.00%	60.00%	40.00%	40.00%	60.00%

the holdout sample the overall accuracy declines to 50%.

Using Taffler model one year prior bankruptcy the overall accuracy is 84.62% in the basic sample and 80% in the holdout sample. In the holdout sample the correct classification for both bankrupt and non-bankrupt companies is the same (80%). The overall accuracy of the holdout sample is therefore, 80%, which is the highest predictive accuracy of all the models when focusing on the holdout sample.

Two-years prior bankruptcy the overall accuracy is 70% in the holdout sample. Considering only bankrupt companies the accuracy is 40% and for the non-bankrupt companies the correct classification is 100%.

Three-years prior bankruptcy the overall accuracy declines to 58.97% in the basic sample. In the holdout sample the overall predicting accuracy declines further to 40%.

Regarding Grammatikos and Gloubo's X model the accuracy in the basic sample when considering only bankrupt companies is 84.21% one year prior bankruptcy. Considering only non-bankrupt companies the accuracy is 80% making the overall accuracy for the basic sample 82.05%. In the holdout sample the accuracy when considering only bankrupt companies is 60% and 80% when considering only non-bankrupt companies making the overall accuracy 70%.

Two-years prior bankruptcy the accuracy is 72.22% when considering only bankrupt companies in the basic sample. For non-bankrupt companies the accuracy is 68.42%. The overall accuracy two-years prior bankruptcy in the basic sample is 70.27%. In the holdout sample the accuracy is 60% when considering only bankrupt companies, 60% when considering only non-bankrupt companies making the overall accuracy of the holdout sample two-years prior bankruptcy 60%.

Three-years prior bankruptcy the accuracy declines further to 35.29% in the basic sample when considering only bankrupt companies and 77.78% considering only non-bankrupt companies. The overall accuracy is 57.14% three-years prior bankruptcy in the basic sample. In the holdout sample the accuracy is 50% when considering only bankrupt companies and 80% when considering only non-bankrupt companies. The overall accuracy of the holdout sample is 66.67%.

Concerning Grammatikos and Gloubo's Y model, one-year prior bankruptcy the accuracy is 63.16% when considering only bankrupt companies in the basic sample and 90% considering only non-bankrupt companies. The overall accuracy one-year prior bankruptcy in the basic sample is 76.92%. The holdout sample has a higher overall accuracy with 80%. The accuracy when considering separately bankrupt and non-bankrupt companies is 60% and 100%, respectively.

Two-years prior bankruptcy the accuracy of the model when considering only bankrupt companies is 50%, in the basic sample. For non-bankrupt companies the accuracy is 84.21%. The overall accuracy of the basic sample is therefore 67.57%. The overall accuracy for the holdout sample two-years prior bankruptcy is 40%. Three-years prior bankruptcy the overall accuracy in the basic sample is 51.43%. The overall accuracy in the holdout sample is 66.67%.

Regarding the common model framework of Dimitras *et al.* and Zopounidis and Doumpos the overall accuracy is 89.74% in the basic sample one year prior bankruptcy. This consists of 89.47% accuracy when considering only bankrupt companies and 90% when considering only non-bankrupt companies. In the holdout sample the accuracy of the model is 70%.

Two-years prior bankruptcy the accuracy declines to 69.23% in the basic sample and to 60% in the holdout sample. Three-years prior bankruptcy the accuracy in the basic sample is 66.67% and declines further to 40% in the holdout sample.

Overall these results suggest that bankruptcy can be predicted with an accuracy range between 70% - 90% one-year prior bankruptcy, 40% - 72% two-years prior bankruptcy and 40% - 67% three-years prior bankruptcy. These results confirm the first hypothesis which suggests that bankruptcy of Greek firms can be predicted using financial ratios.

Regarding the second hypothesis test one-year prior bankruptcy the best models to predict bankruptcy and non-bankruptcy in the holdout sample is Taffler's and Grammatikos and Gloubos' *Y* models. Both models have an accuracy of 80%. Dimitras *et al.* model has the highest predictive accuracy in the basic sample.

Two-year prior bankruptcy the best model for predicting bankruptcy and non-bankruptcy is again Taffler's with 70% accuracy.

The best model three-years prior bankruptcy is Grammatikos and Gloubos' X-model with 66.67% accuracy, in the holdout sample. Second best is the Grammatikos and Gloubos' Y-model with 55.56% accuracy. Overall these results suggest that the second hypothesis does not hold *i.e.* Altman's Z-score model does not provide the highest bankruptcy prediction accuracy for Greek firms.

6. Conclusions and Suggestions for Further Research

The main research objective of this study is to determine the most accurate bankruptcy prediction model that can be used to predict insolvency of industrialized firms in the Greek market. This study used six different well-established bankruptcy prediction models Altman's [1] Z-score model, Taffler's [2] model, Grammatikos and Gloubos [3] *X* and *Y* models, Zopounidis and Doumpos [4] model and Dimitras *et al.* [5] model. In particular, this study investigates the practical application of these models by re-estimating their coefficients using a recent sample period (2002-2012) of 50 Greek firms. The main findings of the two hypotheses tests are the following: 1) Financial ratios and accounting information are important in predicting bankruptcy of companies on the Athens Stock Exchange and 2) Altman's [1] Z-score model is not the best predictor model of bankruptcy in Greece. The models with the best total prediction accuracy (including both bankrupt and non-bankrupt companies) are: Taffler's [2] model and Grammatikos and Gloubos'[3] *Y* model.

Financial ratios in multi-discriminate analysis and logit models can predict bankruptcy in the Greek market with relatively high accuracy. It can be concluded that Taffler's [2] model could be used efficiently as a bankruptcy prediction tool in the Greek market to predict bankruptcy and non-bankruptcy of Greek listed firms. The accuracy of the model is as high as 80% in the holdout sample one-year prior bankruptcy. Grammatikos and Gloubos [3] *Y* model is also a good predictor of bankruptcy and non-bankruptcy in the Greek market with 80% accuracy in the holdout sample one-year prior bankruptcy. Similarly these two models maintain high accuracy levels two and three years prior bankruptcy.

Overall this study provides empirical evidence that corporate bankruptcy in the Greek market is predictable. Taffler's [2] and Grammatikos and Gloubos' [3] *Y* models can assist a firm's stakeholders, such as investors, lending banks, auditors to evaluate bankruptcy risk. In 2018, even though Greece comes to the end of its eighth year of external financial assistance, the impact of financial crisis is still evident *i.e.* high unemployment rate of 18% (even though declining from the pick of 27.5% in 2013) due to many corporate insolvencies during the turmoil period. Therefore, by providing the stakeholders with a prediction device to detect companies that are experiencing distress it may assist: i) banks and investors to allocate capital more efficiently ii) the owners and managers of the companies to take drastic measures to avoid bankruptcy iii) employees to identify and work for companies with low insolvency risk.

Future research may focus on testing the predictive accuracy of the models on specific industries, such as banks, airline companies, hospitals etc. This research study focused on companies listed in the Athens Stock Exchange. Given that many Greek non-listed small and medium enterprises (SMEs) got bankrupt it would be also interesting to test the models' accuracy on non-listed SMEs in Greece.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Altman, E.I. (1968) Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, **23**, 589-610. https://doi.org/10.2307/2978933

[2] Taffler, R.J. (1983) The Assessment of Company Solvency and Performance Using a Statistical Model, *Accounting and Business Research*, **13**, 295-308. https://doi.org/10.1080/00014788.1983.9729767

[3] Grammatikos, T. and Gloubos, G. (1984) Predicting Bankruptcy of Industrial Firms in Greece. *Spoudai*, **34**, 421-443.

[4] Zopounidis, C. and Doumpos, M. (2002) Multi-Group Discrimination Using Multi-Criteria Analysis: Illustrations from the Field of Finance. *European Journal of Operational Research*, **139**, 371-389. https://doi.org/10.1016/s0377-2217(01)00360-5

[5] Dimitras, A.I., Slowinski, R., Susamaga, R. and Zopounidis, C. (1999) Business Failure

Prediction Using Rough Sets. *European Journal of Operational Research*, **114**, 262-280. https://doi.org/10.1016/s0377-2217(98)00255-0

[6] Tokic, D. (2012) The Economic and Financial Dimensions of De-Growth. *Ecological Economics*, **84**, 49-56. https://doi.org/10.1016/j.ecolecon.2012.09.011

[7] O'Brien, M (2012) The Greek Stock Market Has Now Fallen Over 88%. *The Atlantic*, 8 May 2012.

[8] Potamitis, S. and Rokas, A. (2012) A New Pre-Bankruptcy Procedure for Greece. *Journal of Business Law*, **3**, 235-247.

[9] Altman, E.I and Hotchkiss, E. (2011) Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt. 3rd Edition, John Wiley & Sons, Hoboken. https://doi.org/10.1002/9781118267806

[10] Hunter, J. and Isachenkova, N. (2001) Failure Risk: A Comparative Study of UK and Russian Firms. *Journal of Policy Modeling*, **23**, 511-521.

[11] Poston, K.M., Harmon, W.K. and Gramlich, J.D. (1994) A Test of Financial Ratios as Predictors of Turnaround versus Failure among Financially Distressed Firms. *Journal of Applied Business Research*, **10**, 41-56. https://doi.org/10.19030/jabr.v10i1.5962

[12] Fitzpatrick, P.J. (1934) Transitional Stages of a Business Failure. *The Accounting Review*, **9**, 337-340.

[13] Leksrisakul, P. and Evans, M. (2005) A Model of Corporate Bankruptcy in Thailand Using Multiple Discriminant Analysis. *Journal Economic and Social Policy*, **10**, 5.

[14] Beaver, W.H. (1966) Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, **4**, 71-111.

[15] Bellovary, J.L. Giacomino, D.E. and Akers, M.D. (2007) A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education*, **33**, 1-42.

[16] Ohlson, J.A. (1980) Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, **18**, 109-131. https://doi.org/10.2307/2490395

[17] Jo, H., Han, I. and Lee, H. (1997) Bankruptcy Prediction Using Case-Based Reasoning, Neural Networks, and Discriminant Analysis. *Expert Systems with Applications*, **13**, 97-108. https://doi.org/10.1016/s0957-4174(97)00011-0

[18] Rose, P. and Kolari, J. (1985) Early Warning Systems as a Monitoring Device for Bank Condition. *Quarterly Journal of Business and Economics*, **24**, 43-60.

[19] Moses, D. and Liao, S. (1987) On Developing Models for Failure Prediction. *Journal of Commercial Bank Lending*, 27-38.

[20] Theodossiou, P. (1991) Alternative Models for Assessing the Financial Condition of Business in Greece. *Journal of Business, Finance and Accounting*, **18**, 697-720. https://doi.org/10.1111/j.1468-5957.1991.tb00233.x

[21] Dimitras, A.I. Zanakis, S.H. and Zopounidis, C. (1996) A Survey of Business Failures with an Emphasis on Prediction Methods and Industrial Applications. *European Journal of Operational Research*, **90**, 487-513. https://doi.org/10.1016/0377-2217(95)00070-4

[22] Burns, R.B. and Burns, R.A. (2008) Business Research Methods and Statistics Using SPSS. SAGE Publications Ltd., London.

[23] Graham, A. (2000) Credit Risk Management: Corporate Credit Analysis. Fitzrov Dearborn Publishers, London.

[24] Taffler, R.J. (1982) Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data. *Journal of Royal Statistical Society, Series A*, **145**, 342-358. https://doi.org/10.2307/2981867