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Applying, updating and comparing bankruptcy forecasting models. The case of Greece

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Abstract

Research Question: This study examines whether bankruptcy prediction models work well during recessionary periods, on an advanced economy, and how their results can be improved, via a methodological approach to change the coefficients of their variables.

Motivation: This is the first study to follow a methodological approach of a simultaneous comparison-update-comparison task, during a recessionary period, for an advanced economy.

Idea: The paper explores, updates and compares the effectiveness of five of the most common bankruptcy prediction models on the listed companies of an advanced economy (Greece), covering the recessionary period of 2010-2019.

Data: The study sample consists of Greek companies, listed in the Athens Stock Exchange, covering the period 2010-2019, classified into viable and non-viable, based on specific criteria. The final sample consists of fifty-two (52) companies, listed in the Athens Stock Exchange during the period from 2010 to 2019.

Tools: We follow a two-stage analysis. First, we apply the original five bankruptcy prediction models of Altman (2000) and Grammatikos and Gloubos (1984), MDA and LPM models, Taffler (1983) and Dimitras *et al.* (1999) Next, we recalculate their coefficients, keeping the variables stable, and we again apply them to the same sample and compare them again.

Findings: We find that the original models are significantly biased against viable companies, but predict with almost perfect accuracy non-viable companies' bankruptcy. Once we update the variables' coefficients, we get significantly improved results as regards correctly predicting viable companies, at the expense of slightly decreased, but still high, non-viable companies' bankruptcy prediction rates. We suggest a similar methodology to be applied in other similar economies, to increase models' accuracy.

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Contribution: The contribution of the paper is threefold. First, we show how we can develop highly accurate bankruptcy prediction models that can be applied in the economic environment of a developed economy. Second, we show that these models work well during recessionary periods as well, and can also be improved when their coefficients are changed. Third, we suggest a methodology of applying, comparing and updating such models, thus showing in detail this improvement process per model.

Keywords: bankruptcy prediction models, forecasting.

JEL codes: G17, G33

1. Introduction

Predicting bankruptcy has always been an attractive issue in the financial academic literature. Since the first attempts to predict bankruptcy in the early decades of the previous century (Fitzpatric, 1932; Smith & Winakor, 1935; Merwin, 1942; Jackendoff, 1962), to the widely known models of Altman (1968), Ohlson (1980) and Taffler (1983), lots of studies have been trying to develop a model that would forecast business bankruptcy as accurately as possible. Over time, forecasting models evolved into skills and complexity; nowadays bankruptcy models involve the application of neural networks in an attempt to offer more sophisticated solutions to the business viability forecasting issue.

In time, researchers realized that there could not exist a perfect and universal model, to be applied in all economies worldwide, since economies are structured in different ways and their distinct features affect in turn the viability of the companies that operate within. It would thus make more sense to develop models that would fit economies with similar characteristics, rather than try to develop a unique and universal model. For example, Psillaki and Daskalakis (2009) refer to the importance of the institutional setting of each economy, as captured by individual features such as the bankruptcy law, fiscal treatment, ownership concentration and accounting standards, and develop a cluster of four European countries, namely France, Greece, Italy and Portugal, based on a specific set of financial and institutional indicators for several countries developed by Beck et al. (2008) Indeed, Psillaki and Daskalakis (2009) found that SMEs in these countries determine their capital structure in similar ways; and even though the capital structure field is not identical to the bankruptcy prediction field, researchers could find the idea of similar firm behaviour in similar contexts interesting in being applied in different contexts as well. In this context, we can assume that companies that operate in similar economies, are expected to behave in a similar way financially, so that a bankruptcy prediction model that works for one country may work for other similar countries as well.

Another dimension that should also be discussed is whether the prediction power of bankruptcy models is affected by differences in the macroeconomic states. Do these models work differently in growth states or in recessionary states? This is something that is highlighted in some studies in the bankruptcy prediction literature. For example, Khoja *et al.* (2019) denote that the financial health of firms should be examined in situ with the local macro environment. Giannopoulos and Sigbjornsen (2019) admit that one should take under consideration that the 2008 crisis should be taken under consideration when analyzing these models; their sample covers the period during 2002-2012, so that some cases they include take place after the crisis, but, still, the majority of the period they cover refers to a growth period.

The purpose of this paper is to investigate the effectiveness of the five most important bankruptcy prediction models in a recessionary period (2010-2019) in a developed economy (Greece) Specifically, we first apply five bankruptcy prediction models as originally designed by their creators and we explore whether they predict bankruptcy during recession, and we then compare their success levels. Second, we update their coefficients, keeping the variables stable, apply them again and compare their effectiveness. To the best of our knowledge, this is the first study to follow this methodological approach of a simultaneous comparison-update-comparison task, during a recessionary period for an advanced economy. Following the discussion above, we suggest that the best model that comes up from our study could be tested in similar economic contexts in other similar economies as well.

The remainder of the paper is structured as follows. Section 2 discusses the academic literature of business viability and business bankruptcy and describes in detail the existing bankruptcy models. Section 3 describes the definition of variables, the data used, and the econometric model employed. Section 4 discusses the empirical results and presents an inter-country comparison. Section 5 concludes the paper.

2. Literature review and hypotheses development

One of the first questions to be answered in the business viability field is under which preconditions a company can be described as “non-viable”. Beaver (1966) was among the first to work on the business viability academic field and gave a broad definition of viability describing companies as "failed" when they are unable to meet their financial obligations. In particular when the following events occur: a. filing for bankruptcy, b. inability to repay a bond loan, c. overdraft in bank accounts and d. non-payment of dividends on preferred shares.

Altman (1968) used the term "bankruptcy", including in his research only companies that were legally bankrupt. In Altman (1977), he extended this definition including cases of companies that had not gone bankrupt despite their high debt, either due to state intervention, or due to their acquisition by banks, or due to a forced merger with other companies. In his later studies, Altman referred to the problems created by state intervention in the correct classification of companies with economic difficulties. The operational support of the companies for a long time after their financial bankruptcy, essentially prevented their legal bankruptcy. The support was mainly in the form of bank loan financing, under state guarantee, to avoid increases in unemployment due to the bankruptcy of large companies. Altman believed that it was wrong to think of the above companies as healthy and viable and also stated that the above state interventions make it difficult to determine the time of the actual bankruptcy of companies. Gloubos and Grammatikos (1988) later referred to the same subject for the case of Greece; they made special reference to the Greek state intervention showing that forecasting models were less accurate in the correct classification of the financial situation of companies in Greece, compared to similar companies in countries that operated without such state support.

Deakin (1972) described companies as "failed" when the following events were observed: a. filing for bankruptcy, b. insolvency due to inability to service their financial obligations, c. liquidation of assets to service debts to creditors. In the Greek context, Vranas (1991) used a more general definition of financial failure, referring to the following: a. filing for bankruptcy, b. bank "takeover" through shareholding of debts following a respective decision of the general meeting of the shareholders of the company, c. severe inability to service financial obligations, such as accumulation of overdue debts and inability to pay interest or amortization, for a period of more than three years, d. all businesses that followed specific procedures under a specific Greek bankruptcy law (law 1386/83)

After defining bankruptcy, the next step is to create relevant models to predict it. The first attempts to create such models were based on the comparison of financial data presented by two separate groups of companies; one group includes viable companies and the other non-viable. These first attempts belong to the general category of univariate analysis, which focuses on the study of economic indicators. According to Beaver (1966), an early study of the object was made by Fitzpatric (1932) The study included 19 pairs of failed or non-failed businesses and concluded that there are strong differences in the ratios presented by the two groups of companies, at least three years before the failure year. A few years later, Smith and Winakor (1935) expanded their research to 10 years before business failure. They found a steady deterioration in the average values presented by business ratios as they approached the failure year. A few years later, Merwin (1942) compared the average values of the indicators displayed by companies with continuous and discontinuous activity, during the period 1926-1936. He noticed differences between the results of the two groups, up to six years before the failure year in the companies of the second group. The tendency for differentiation was increasing as it approached the failure year.

The Beaver (1966) model

Following these early attempts, the first effort to create a bankruptcy prediction model based on financial indicators was that of Beaver (1966) His sample included 79 pairs of failed and non-failed companies that belonged to 38 different industry branches. His research included 30 indicators which he selected based on various criteria, such as popularity in the scientific literature, success in previous research and correlation with cash flow indicators. Applying a series of tests, he calculated the predictive ability of each indicator individually to correctly classify businesses into failed or non-failed. The indicators that showed the lowest error term in ascending order were the following:

- Cash flow / Total debt
- Net income / Total Assets
- Total Debt / Total Assets
- Working capital / Total assets
- Current assets / Current liabilities
- Available + Receivables / Daily operating expenses

Beaver concluded that single-variable analysis could provide reliable information on the course of business and thus business failure.

The Altman (1968) model

In 1968 Edward I. Altman published his research on "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy" and essentially introduced the Multiple Discriminant analysis (MDA) into forecasting models. According to Altman (1968) a first application of MDA was made in 1936 by R. A. Fisher. Its use was then carried out mainly in the field of biological and behavioral sciences, aiming to predict results in problems where the dependent variable appeared in qualitative form. So, the first step in the MDA was to define specific classification groups, while the next step was to collect data for these groups and try to create a linear combination of their characteristics, that would lead to better distinction between groups. In the case of companies, Altman (1968) defined that these characteristics are their financial ratios, so that the MDA can determine a number of rates for the financial indicators, in order to classify companies into specific groups, such as bankrupt and non-bankrupt. This technique has the advantage that it takes into account a number of characteristics of companies as well as the interaction between them. In his research Altman uses a distinct function of the following form:

$Z = V1X1 + V2X2 + \ldots + VnXn$
Where:
$V1, V2\ldots Vn$ = Discrete coefficients
$X1, X2 \ldots Xn$ = Dependent variables

The above discrete function converts the values of the individual variables into a distinct result called the Z value and is used to classify the companies. His sample consisted of sixty-six companies divided equally into two groups. Businesses were classified into categories based on asset size and industry. For each bankrupt company, a non-bankrupt company belonging to the same size and activity category was selected to be included in the sample. In his research, twenty-two financial indicators were studied based on their popularity in previous surveys and their relationship with the conducted research. The variables under investigation were divided into five main categories of indicators such as liquidity, leverage, activity, profitability and solvency. Using various criteria, Altman concluded that from the initial list of variables, the indicators that can best help predict corporate bankruptcies were the following:

X1- Working capital / Total assets
X2- Retained earnings / Total assets
X3- Profits before taxes and interest / Total assets
X4- Market value of funds / Book value of total debt
X5- Sales / total assets

so that the discrete function selected as the optimal for predicting business bankruptcy is the following:

$$Z= 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

where Z is the total index.

His model had a high prediction accuracy with an overall percentage of correct classification of 95%. Type 1 errors (bankrupt companies that were classified by the model as non-bankrupt) occured at 6%. Type 2 errors (non-bankrupt companies that were classified by the model as bankrupt) occured at 3%. There was therefore a slight upward trend of bias in the group of bankrupt companies. Altman also studied the model's ability to predict bankruptcy up to five years before the event, but found deteriorating results while moving to the past at a rate where the model was unreliable after the second year. Thus, he came up with in a Z value zone that showed great inaccuracy of forecasting and was named "Zone of Ignorance" or "Grey Area". Its values ranged from 1.81 to 2.99 and the companies that lied within these values would be characterized as uncertain. Last, the value of 2.675 was set as the optimal price to distinguish between bankrupt and non-bankrupt companies.

The Altman (2000) model

In a later study, Altman (2000) reported that several researchers began using a simpler version of the original Z-Score model. Specifically, over the years researchers and practitioners have gradually moved to a more convenient specification of the model that uses an intuitively simpler set of coefficients, as shown below.

$$Z= 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$$

Specifically, the original coefficients of the first four variables were replaced with a x100 multiple where the coefficient of the last variable was rounded to 1.0 (from 0.99) The critical values and indicators used for the classification of businesses remain the same as in the original model. This new model was named Z-Score 2000.

The Altman (2010) model

The rapid development of computers and their capabilities provided researchers with the tools to develop new methodological approaches. In the years that followed, neural networks emerged helping solve complex problems in the field of bankruptcy forecast as well, while sophisticated bankruptcy tools were developed leading to the creation of several categories of creditworthiness that credit rating agencies still use today. Altman could not fall behind these methodological developments. After his Altman (1994) model that used Neural Networks, his most recent model is that of 2011, which is called the Z-Metrics model. To create this model, Altman (2011) used data from private and public companies based in the US and Canada, covering the period from 1989 to 2009 (Altman E, 2011), and included thirteen variables in total, not only from financial statements but also from the stock market and from the wider macroeconomic environment. His logit model is:

$$CS_{i,t} = \alpha + \Sigma\beta X_{i,t} + \varepsilon_{i,t}$$

Where:
$CS_{i,t}$: The credit calibration value of each business i during time period t
B: The parameters of the variables or otherwise the weights of the variables
$X_{i,t}$: The variables of the model
$\varepsilon_{i,t}$: The error terms

The $CS_{i,t}$ credit calibration value is then converted into a business credit probability as follows:

$$PD_{i,t} = \frac{1}{1 + \exp(\mathrm{CS}_{i,t})}$$

Based on the above credit risk probability, companies are classified into a total of fifteen credit reliability categories. The highest category in reliability is called "ZA" and the lowest respectively "ZF". These classifications were performed with estimation time horizons from one to five years. Compared to the ratings of international rating agencies, Z-Metrics presented results with greater accuracy in business ratings.

The Taffler (1983) linear discriminant model based on industrial firms in the UK

Taffler (1983) also used discriminant analysis to build a model which was applied on financial data of English industrial companies, listed on the stock exchange market. His sample consisted of 23 failed firms and 45 non failed firms during the period 1968-1973. The criteria that he used for the definition of the failed firms was receivership by court order and voluntary liquidation by creditors. The model is as follows:

$$Y = 3.2 + 12.18X1 + 2.5X2 - 10.68X3 + 0,029X4$$

Where:

X1: profit before tax / current liabilities.

X2: current assets / total liabilities.

X3: current liabilities / current assets

X4: (quick assets − current liabilities) / ((sales − profit before tax)/365)

The cut-off value for the classification of companies between bankrupt and non-bankrupt is set at -1.95. According to Giannopoulos and Sigbjørnsen (2019) the model was highly accurate of predicting bankruptcy at 80% for one year before bankruptcy reducing to 70% and 58,97% for two years and three years respectively.

The Grammatikos and Gloubos (1984) MDA model for Greek companies

Grammatikos and Gloubos (1984) built the first MDA model which was based on financial data of Greek industrial companies. They used data from companies' published financial statements for the period 1977-1981. The model has the following format:

$$Z = -0.863 - 2.461X_1 + 5.33X_2 - 0.022X_3 + 3.676X_4 + 3.543X_5 + 4.23X_6$$

Where:

X_1: Current Assets / Total Assets.

X_2: Working capital / Total assets.

X_3: Inventories / Working Capital.

X_4: Bills payable / Total assets.

X_5: Profits after taxes / Total assets.

X_6: Gross Profit / Total assets.

The cut-off value for the classification of companies between bankrupt and non-bankrupt, is set at 0, while the grey area values were between -0.4754 and 0.2747. The above model was highly accurate of predicting bankruptcy at 91%, for one year before bankruptcy, reducing to 78% and 70% for two years and three years respectively. The model also shows a tendency for more inaccurate classification of bankrupt companies than non-bankrupt ones (type 1 error)

The Grammatikos and Gloubos (1984) LPM model for Greek companies

Apart from the above mentioned MDA "Z" model, Grammatikos and Gloubos (1984) also built A Linear Probability Model (LPM) "Y". In the LPM model, linear regression is used to determine the relationship between the dependent quality variable (business viability) and a series of independent variables (economic indicators) The probability of a company to be classified in a given group is a linear function of its financial characteristics. The model has the following format:

$Y_i = \alpha + \beta_j X_{ij} + \varepsilon_i$
Where:
X_{ij} = the values of the characteristic j (j = 1,2,…n) of the enterprise i.
Y_i = 1 if the company is classified in the first group.
Y_i = 0 if the company is classified in the second group.
ε_i = random variable (E (εi) = 0)

The probability of a company being characterized as a failure depends on the prices that its financial indicators receive. In some cases, however, the probability estimates fluctuate outside the probability interval (0.1) resulting in problems in the predictive interpretation of the model. To avoid the above problem, the following are defined:
$P_i = \alpha + \beta_j X_{ij}$ when $0 < \alpha + \beta j Xij < 1$
$P_i = 1$ when $\alpha + \beta_j X_{ij} \geq 0$
$P_i = 0$ when $\alpha + \beta_j X_{ij} \leq 0$

Grammatikos and Gloubos (1984) built the first LPM model which was based on financial data of Greek industrial companies. The source of their data was companies' published financial statements for the period 1977-1981. The model is as follows:
$Y = 0.313 + 0.546X_1 + 0.805X_2 + 0.979X_3$
Where:
X_1: Working capital / Total assets.
X_2: Profits after taxes / Total assets.
X_3: Gross Profit / Total assets.

The cut-off value for the classification of companies between bankrupt and non-bankrupt is set at 0.5, while the grey area values were between 0.4175 and 0.6104. The above model was highly accurate of predicting bankruptcy at 91% for one year before bankruptcy, reducing to 76% and 78% for two years and three years respectively.

The Dimitras et al. (1999) rough set theory model for Greek companies

Dimitras *et al.* (1999) created three different models based on Greek firms, a rough set theory model, a multi discriminate analysis model and a logit model. According to Giannopoulos and Sigbjørnsen (2019) the most successful of these was the rough set theory model with 73.7% accuracy one-year prior bankruptcy. Their sample consisted of 40 failed firms and 40 non failed firms, while the criterion that they used for the definition of the failed firms was companies that went bankrupt or applied for bankruptcy. The model is as follows:

$$Y = -1.151 + 0.0093X1 + 1.9154X2 - 2.4196X3 + 0.1245X4 + 1.28882X5 - - 0.9008X6 + 0.7149X7 + 0.004X8 + 0..0342X9 - 0.0168X10 + 0.6294X11 + + 0.0022X12$$

Where:
X1: Net income / gross profit.
X2: Gross profit / total assets.
X3: Net income / total assets.
X4: Net income / total worth.
X5: Current assets / current liabilities.
X6: Quick assets / current liabilities.
X7: (Long term debt + current liabilities) / total assets.
X8: Net worth / (net worth + long term debt)
X9: Net worth / net fixed assets.
X10: Inventories / working capital.
X11: Current liabilities / total assets.
X12: Working capital / net worth.

The cut-off value for the classification of companies between bankrupt and non-bankrupt is set at 0.5.

A first major and common drawback for all models, is that the variable coefficients were calculated using business financial data, which were valid decades ago; for example, the Altman (1968) model was based on industrial enterprises operating in the US during the period 1946-1965. It is therefore possible that they do not correspond to the modern economic data of any economy, which would be expected to result in the deterioration of their predictability, so that an update process should take place. This update process is described in detail in the methodology section that follows.

3. Research methodology

3.1 The sample

The study sample consists of Greek companies, listed in the Athens Stock Exchange, covering the period 2010-2019, classified into viable and non-viable, based on specific criteria as discussed below. During that time (2010-2019), the total number of listed companies in the Athens Stock Exchange fluctuated from 255 to 152, while the total number of companies that were delisted from the Athens Stock Exchange by the Capital Market Commission was 93. From these 93 companies that were delisted, 8 exited ASE on their own, 19 were acquired by other companies, the financial statements of 28 could not be found, 4 were financial companies, and no appropriate pair for 8 could be found. Regarding the pairing process, a crucial part of the methodology is to pair bankrupt with non-bankrupt (financially healthy) similar companies; this “similarity” implies that the paired companies should be from the same industry, of similar size and data should be taken for both companies from the same year that one of the two went bankrupt. These “similarity” limitations leave out cases of bankrupt companies that cannot be paired with a healthy company; for example, there were five listed companies from the fish farming sector that went bankrupt and only one healthy company from the same sector.

Therefore, we are left with 26 companies that went bankrupt and we included them in our sample. Please bear in mind that both studies of Giannopoulos and Sigbjørnsen (2019) and Grammatikos and Gloubos (1984) use samples of 50 (25/25) and 58 (29/29) companies respectively in their studies. Thus, the non-viable final sample, includes a total of twenty-six (26) non-viable companies from seventeen (17) different industries. For each non-viable enterprise, we selected a sustainable enterprise from the same industry. Therefore, the final sample consists of fifty-two (52) companies, listed in the Athens Stock Exchange during the period from 2010 to 2019[2]. To determine non-viable companies, we follow the literature of Vranas (1991), and Dimitras (1996), according to which for non-viable companies one of the following criteria must apply:

- Declaration of bankruptcy.
- Joining a regime of financial consolidation.
- Negative equity for at least two consecutive years. It is a condition for the inclusion of capital companies in a special management procedure according to the Greek business bankruptcy law
- Insolvency due to inability to service their financial obligations for at least three years.
- Bank "takeover" through shareholding of debts following a special decision of the general meeting of shareholders of the company.

3.2 The models

The models we chose to apply are the following five:

1. Z Score Altman (2000):
   $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$
2. Taffler (1983) T model
   $Y = 3.2 + 12.18X_1 + 2.5X_2 – 10.68X_3 + 0{,}029X_4$
3. Grammatikos & Gloubos (1984) X model
   $X = -0.863 – 2.461X_1 + 5.33X_2 – 0.022X_3 + 3.676X_4 + 3.543X_5 + 4.23X_6$
4. Grammatikos & Gloubos (1984) Y model
   $Y = 0.313 + 0.546X_1 + 0.805X_2 + 0.979X_3$
5. Dimitras et al. (1999) D model
   $D = -1.151 + 0.0093X_1 + 1.9154X_2 – 2.4196X_3 + 0.1245X_4 + 1.28882X_5 -0.9008X_6 + 0.7149X_7 + 0.004X_8 + 0.0342X_9 – 0.0168X_{10} + 0.6294X_{11} + 0.0022X_{12}$

[2] See Appendix 1 for more information about the 26 sample pairs of viable / non-viable companies.

Regarding our decision to apply these specific models, we followed Giannopoulos & Sigbjørnsen (2019) who refer to these specific models as the ones that simultaneously meet the following criteria: a. well-recognized in the scientific community, b. easy to apply in terms of the variables they use, and c. highly reliable on predicting bankruptcy. A fourth reason that stand for the last three models (X, Y and D) is that they were built using Greek data, so that they are expected to fit better the specificities of the Greek market, as analyzed in the introduction.

3.3 The methodology

Stage 1: Apply and Compare the original models

The models were applied to the last three published financial statements of unsustainable companies before their trading on the Athens Stock Exchange was permanently suspended. The same time periods were chosen to apply the models to the respective viable companies, to have uniformity in the macroeconomic conditions they face. Therefore, the year "0" is defined as the year in which the permanent suspension of trading on the stock exchange of listed companies that were experiencing severe financial problems began. Respectively, the previous three years before the permanent suspension are defined as years "-1", "-2" and "-3".

Once the models were applied and we had the bankruptcy predictability results per individual model, we then compared their predictability power. Specifically, we first calculated the success rate of correct predictions of the models, using the data of the financial statements of the companies for one, two and three years before the year "0". Next, we ran a statistical significance check of the forecast percentages displayed by each mode, as follows:

$$\mathrm{t} = \frac{prediction\ rate - 0{,}5}{\sqrt{0{,}5(1-0{,}5)/n}}$$

where n is the sample size

The null hypothesis is that the forecast rate is equal to 50%; if the null hypothesis is rejected, we accept that the forecast rate exceeds 50%, so the forecast model is effective. The significance level is set at 5% and the rejection rule is t>1,675.

Stage 2: Apply and Compare the updated models

As mentioned at the end of section 2, the variables coefficients need to be updated to reflect the current economic situation. We followed the approach of Giannopoulos & Sigbjørnsen (2019) and updated the coefficients of the models without changing the variables. We then applied the updated models again and compared them, as in stage 1. The update process was the following. We first chose randomly (using the RAND Excel function) forty companies (out of the total fifty-two) from the original sample. We then applied the Logit regression in the observations of the new basic sample of companies to recalculate the coefficients of the models. The accuracy of the updated models was then checked using the observations of the remaining twelve companies in the original sample. To distinguish between viable and non-viable companies we used the survival rates. We used the following formula to calculate the probability of survival of each company:

$$Pi = \frac{1}{1 + \exp\left(\beta_0 + \beta_1 X_{1,i} + \beta_2 * X_{2,i} + \cdots + \beta_n * X_{n,i}\right)}$$

where

• P_i is the probability of survival of any business i.

• $\beta_0 + \beta_1 * X_{1,i} + \beta_2 * X_{2,i} + \ldots + \beta_n * X_{n,i}$ are the prediction models and $\beta_0, \ldots, \beta_n$. their updated coefficients.

If the probability of survival exceeds 50% then the company is considered viable.

4. Empirical results

4.1 Results of Stage 1 – The original models

We applied the three original models for each year (i.e. year -1, year -2 and year -3); the results are shown in Table 1.

Table 1 - Success rates of original models (in percentages)

Models	**Z**		**X**		**Y**		**T**		D		
Actual classification of companies	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	**Year**
Non-viable	100.00%	0.00%	100.00%	0.00%	92.31%	7.69%	96.15%	3.85%	100.00%	0.00%	**-1**
Viable	88.46%	11.54%	76.92%	23.08%	46.15%	53.85%	57.69%	42.31%	80.77%	19.23%	
Total accuracy	55.77%		61.54%		73.08% **		69.23% **		59.62%		
Non-viable	96.15%	3.85%	96.15%	3.85%	92.31%	7.69%	96.15%	3.85%	92.31%	7.69%	**-2**
Viable	88.46%	11.54%	80.77%	19.23%	42.31%	57.69%	57.69%	42.31%	73.08%	26.92%	
Total accuracy	53.85%		57.69%		75.00% **		69.23% **		59.62%		
Non-viable	96.15%	3.85%	84.62%	15.38%	76.92%	23.08%	84.62%	15.38%	84.62%	15.38%	**-3**
Viable	88.46%	11.54%	73.08%	26.92%	38.46%	61.54%	50.00%	50.00%	65.38%	34.62%	
Total accuracy	53.85%		55.77%		69.23% **		67.31% **		59.62%		

Looking at the results, we observe that model Z (Altman model) had a 100% success predicting non-viable companies one year before they failed (meaning that it correctly forecasted all 26 non-viable companies that did fail next year), but only forecasted correctly 11.54% (3 out of 26) viable companies, while the remaining 23 actual companies (88.46%) were forecasted as non-viable. Grammatikos & Gloubos' model X also had 100% accuracy of predicting non-viable companies one year before they failed, but also resulted in very low accuracy of viable companies at 23.08%. Their Y model performed better at viable companies' accuracy (53.85%), but was slightly worse in predicting non-viable companies (92.31%) The only statistically significant overall prediction rate was that of model Y at 73.08%. The Taffler (1983) model had the second-best overall accuracy score for year -1, while the accuracy score of the Dimitras et al. (1999) model comes fourth for year -1.

As regards the results for years -2 and -3, we can observe a slight deterioration of the non-viable companies bankruptcy prediction accuracy, while the respective viable companies results still remain at very low levels. The overall total accuracy percentages slightly deteriorate as well, with the percentages of models Y and T being the only statistically significant percentages. The main conclusion therefore, when applying the five original models is that there seems to be a strong downward bias trend against viable companies, that most of them are shown as non-viable (type 2 error)

4.2 Results of Stage 2 – The updated models

We ran the Logit regression to get the updated coefficients for all five models. We were however able to get results only for the first four models (Z, X, Y and T), since the logit application could not produce results for the D model. Thus, our four updated models end up as follows:

1. Z Score Altman (2000) updated model:
$Z = -0.818383 + 7.92673X_1 + 1.62106X_2 + 6.67171X_3 + 7.02802X_4 + 2.4753X_5$

2. Grammatikos & Gloubos (1984) X updated model:
$X = 2.44254 – 3.51571X_1 + 13.6375X_2 – 0.0608883X_3 – 104.194X_4 + 1.41161X_5 + 5.94564X_6$

3. Grammatikos & Gloubos (1984) Y updated model:
$Y = 0.889069 + 10.7901X_1 + 0.677811X_2 + 3.04736X_3$

4. Taffler (1983) T updated model:
$T = 4.06441 – 0.3310003X_1 + 2.20855X_2 – 4.18857X_3 + 0.000278367X_4$

Looking at the success prediction rates (Table 2), a striking conclusion is that the viable companies prediction rates were significantly improved for all models. On the other hand, we now get slightly worse, but still considerably high prediction rates for the non-viable companies. Specifically, it is worth noting that the very low success rates for predicting viable businesses (11.54% for Z, 23.08% for X, 53.85%

for Y and 42.31% for T) are dramatically improved turning 100% for models Z, Y and T and 83.33% for X. Another interesting result is that the success rates for viable companies slightly improve for the year -2 case, which is not uncommon in the literature (Grammatikos and Gloubos, 1984) Last, we also observe significant improvement in the total accuracy percentages, which are now all statistically significant, except for models Z, X and T, and only for year -3. The high prediction success rates reflect the good adaptation level of the respective observations. The financial data of the remaining twelve companies, that were not selected for the basic sample of Logit regression, were used to determine the accuracy of the forecast models (see appendix III)

Table 2 – Success rates of updated models (in percentages)

Models	Z		X		Y		T		
Actual classification of companies	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	Year
Non-viable	83.33%	16.67%	83.33%	16.67%	83.33%	16.67%	66.67%	33.33%	-1
Viable	0.00%	100.00%	16.67%	83.33%	0.00%	100.00%	0.00%	100.00%	
Total accuracy	83.33%**		91.67%**		91.67% **		83.33% **		
Non-viable	100.00%	0.00%	100.00%	0.00%	100.00%	0.00%	83.33%	16.67%	-2
Viable	0.00%	100.00%	16.67%	83.33%	0.00%	100.00%	0.00%	100.00%	
Total accuracy	100.00%**		91.67%**		100.00% **		91.67% **		
Non-viable	50.00%	50.00%	50.00%	50.00%	66.67%	33.33%	33.33%	66.67%	-3
Viable	0.00%	100.00%	0.00%	100.00%	0.00%	100.00%	0.00%	100.00%	
Total accuracy	75.00%		75.00%		91.67% **		66.67%		

5. Conclusion

In this paper, we apply, compare, update and compare again five popular bankruptcy prediction models. We apply this methodological approach for a developed country (Greece), during a mainly recessionary period (2010-2019); we thus test whether prediction models work well in a recessionary macroeconomic state, plus we then show how we can improve these models, by changing their coefficients. We find that the original models are significantly biased against viable companies (type 2 error), while the non-viable companies' bankruptcy prediction rates are very high. Once we update their coefficients without changing the variables used, we get significantly improved results as regards correctly predicting viable companies, at the expense of slightly decreased, but still high, non-viable companies' bankruptcy prediction rates. We thus show, in detail, how the original models are improved, providing researchers with substantial information as regards this improvement process from the original to the updated models. Conclusively, we show that the main bankruptcy prediction models seem to work well during recessions, a concern that was raised by researchers in the field (Khoja *et al.*, 2019; Giannopoulos & Sigbjornsen, 2019)

Additionally, we also show how these models can be improved, within this recessionary environment, by applying a coefficient change methodology, that captures these macroeconomic conditions endogenously. Comparing our results with those of previous studies, we observe that we get relatively better results compared to those of Giannopoulos and Sigbjornsen (2019), which is the study closest to ours. Specifically, they show that their overall accuracy rates range from 70 between 70% - 90% one-year prior bankruptcy, 40% - 72% two-years prior bankruptcy and 40% - 67% three-years prior bankruptcy, while our respective rates are 83%-92% (year 1), 92%-100% (year 2) and 66%-92% (year 3) Earlier studies (Dimitras *et al.*, 1999; Grammatikos & Gloubos, 1984) show similar results to the ones of Giannopoulos and Sigbjornsen (2019), but it should be noted that the overall business environment of their studies differs dramatically to the one we use. Overall, we get slightly better results than all previous studies we cite, and this might be attributed to the fact that we apply these models during a mainly recessionary period; this implies that the models seem to be working better during recessionary periods.

The aim of the paper is threefold. First to come up with highly accurate bankruptcy prediction models that can be applied in the economic environment of a developed economy (Greece), so that they can be used from practitioners as an additional tool in their fundamental analysis. Second, to show that these models work well during recessionary periods as well, and can also be improved when their coefficients are changed. Third, to suggest a methodology of applying, comparing and updating such models, thus showing in detail this improvement process per model. We believe that a similar methodological process can be applied as such in other countries with similar institutional characteristics, in the context discussed in the paper introduction (Psillaki and Daskalakis, 2009), where businesses in similar economies seem to operate in similar ways. We believe that the paper has fulfilled all research objectives and subsequently contributes to the respective specific fields of the academic literature. Future studies could test the idea of applying-updating and comparing bankruptcy prediction models simultaneously in similar countries.

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Appendix: Sample of Greek listed firms during the period 2010-2019

I.

Initial sample

1	Altec Holdings SA	27	Profile A.E.B.E
2	Alpha Grissin SA	28	Byte Computer A.B.E.E.
3	Microcomputer Systems SA	29	Quality A.B.E.E.
4	Compucon A.B.E.E.	30	Ilida SA
5	Marak Electronics SA	31	Space Hellas A.E.
6	Hellenic Fish Farms SA	32	Galaxidi Thal. Crops SA
7	Crete Farm SA	33	Kri Kri Biom. Milk SA
8	Chatzikranioti SA	34	Stelios Kanakis SA
9	Hellenic Sugar Industry SA	35	Loulis Mills SA
10	Nutriart SA	36	Karaolegos Bakery SA
11	I.Boutaris & Son Holding SA	37	Estate K. Lazaridi SA
12	Hellenic Textile SA	38	ELVE. A.B.E.E.
13	ATTI-KAT A.T.E.	39	I.Kloukinas SA
14	Engineering	40	Intracom Constructions SA
15	Folli-Follie A.B.E.T.E.	41	A.S. A.E.
16	Sfakianakis SA	42	Motodynamics SA
17	Euromedica A.E.	43	Iasso SA
18	Alco Hellas SA	44	Elval SA
19	Pegasus Publishing SA	45	Attiki Publications SA
20	N.E.L SA	46	Kyriakoulis Shipping SA
21	Spider A.E.	47	Mevaco Metal. A.B.E.E.

22	M.I. Maillis SA	48	Karatzi SA
23	Selman SA	49	Iktinos SA
24	Alsinco A.E.E.	50	Douros SA
25	Hatziioannou SA	51	Selected SA
26	Tech. Publications SA	52	Kathimerini SA

II.

Basic sample used in Logit regression

1	Altec Holdings SA	21	Profile A.E.B.E
2	Alpha Grissin SA	22	Byte Computer A.B.E.E.
3	Microcomp. Systems SA	23	Quality A.B.E.E.
4	Marak Electronics SA	24	Space Hellas A.E.
5	Hellenic Fish Farms SA	25	Galaxidi Thal. Crops SA
6	Crete Farm SA	26	Kri Kri Biom. Milk SA
7	Chatzikranioti SA	27	Stelios Kanakis SA
8	Nutriart SA	28	Karaolegos Bakery SA
9	I.Boutaris & Son SA	29	Estate K. Lazaridi SA
10	ATTI-KAT A.T.E.	30	I.Kloukinas SA
11	Engineering	31	Intracom Constructions SA
12	Folli-Follie A.B.E.T.E.	32	A.S. A.E.
13	Euromedica A.E.	33	Iasso SA
14	Pegasus Publishing SA	34	Attiki Publications SA
15	N.E.L SA	35	Kyriakoulis Shipping SA
16	Spider A.E.	36	Mevaco Metal. A.B.E.E.
17	Selman SA	37	Iktinos SA
18	Alsinco A.E.E.	38	Douros SA
19	Hatziioannou SA	39	Selected SA
20	Tech. Publications SA	40	Kathimerini SA

III.

Sample of companies chosen to determine the accuracy of the models

1	Compucon A.B.E.E.	7	Ilida SA

2	Hellenic Sugar Ind. SA	8	Loulis Mills SA
3	Hellenic Textile SA	9	ELVE. A.B.E.E.
4	Sfakianakis SA	10	Motodynamics SA
5	Alco Hellas SA	11	Elval SA
6	M.I. Maillis SA	12	Karatzi SA