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Greek Corporate Failure Using a Logit Approach

Toudas Kanellos[1], Giannakopoulos Themistoklis[2] and Boufounou Paraskevi[3]*

[1]Department of Agribusiness and Supply Chain Management, Agricultural University of Athens, Greece

[2]School of Social Sciences, Hellenic Open University, Greece

[3]Department of Economics, National and Kapodistrian University of Athens, Greece

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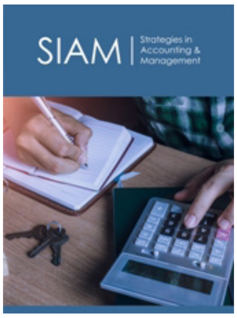

***Corresponding author:** Boufounou Paraskevi, Department of Economics, National and Kapodistrian University of Athens, Greece

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Abstract

The Greek economy's prolonged financial crisis, which began in 2010, has resulted in the corporate bankruptcy of many Greek companies and is one of the most important subjects of scientific research. In this study, we estimate a Logit model to predict the likelihood of Greek company bankruptcy using financial indices for the period 2011-2022. The sample includes 96 firms, with an equal number of healthy and bankrupt firms. The study concludes that predictors representing business profitability (profitability ratios: Cashflow/turnover and EBITDA Margin) and operational efficiency (Net asset turnover and Credit period) lead to the distinction between healthy and bankrupt companies by studying 21 financial indices.

Keywords: Corporate failure; Logit, Financial crisis; SMEs; Financial indices

Introduction

According to EC [1], Small and Medium-Sized Enterprises (SMEs) play an important role in the Greek economy. They account for 63.5% of value added and have an unusually high labour share of 87.9%. Greek SMEs employ 2.6 workers on average, which is about a third less than the European Union average of 3.9 and have suffered disproportionately as a result of the crisis, unable to cope with changing spending patterns and unavailable credit [2]. Business failure is a contingency for business owners Pratten [3] and is a more likely outcome for new businesses, but there is little evidence-based knowledge of how/when it occurs. Such studies offer both useful insights into the conditions required for small businesses to succeed in times of economic hardship, and support for the development of government support strategies [4]. Abdelsamad [5] support the view that "while failures in a free-market system cannot be completely avoided, the failure rate can be reduced if some of the stimuli are identified and preventive measures are taken". In this study, utilizing financial indices, we construct a Logit model to predict the likelihood of Greek company bankruptcy over the years 2011–2022. The sample consists of 96 businesses, with an equal proportion of profitable and unsuccessful businesses. The study, which looked at 21 financial indices, came to the conclusion that the predictors that represent operational profitability (profitability ratios of Cashflow/turnover and EBITDA Margin) and operational efficiency (Net asset turnover and Credit period) are what distinguish healthy from bankrupt companies. This study is organized as follows: At the beginning, a brief description of the basic definitions of corporate failure and the methods of its prediction that have been developed is given and a brief overview of the main studies on corporate failure in Greece is provided. The presentation of the methodological approach followed and the sample used follows. The main results of the research are then presented. Finally, the main conclusions of the study, the practical implications that could be drawn from its use and the possibilities for further research extension are critically commented upon.

Literature Review

Altman [6] stated that four different terms has been used when discussing financial distress in companies: failure, solvency, bankruptcy and default. Many conceptual discussions have focused on the different ways in which bankruptcy can be described. Everett [7] and "includes liquidation of insolvent companies and personal bankruptcy. According to Fredland [8], "bankruptcy suggests that resources have been shifted to more profitable opportunities". He notes that "bankruptcy must mean an inability to 'make ends meet' whether the losses involve one's own capital or someone else's" [9]. Watson [10] defined five types of business failure:

A. Business interruption (for any reason),

B. Discontinuance or change of ownership.

C. Declaration of bankruptcy, discontinuance of business

D. Closure to prevent further losses; and

E. Failure to achieve financial objectives.

While many firms close due to a profitable takeover [11], many more close due to insolvency [12], which is especially common in Greece following the recent financial crisis of 2010 and on. Failure is defined by Dimitras et al. [13] as a company's inability to repay creditors, vendors, preferred stockholders, and other creditors, or when a bank loan cannot be repaid or the company has been declared bankrupt by law. All of the preceding events caused the company's operations to be halted. Poston et al. [14] identified five stages of survival business failure: incubation, financial insolvency, total insolvency, and confirmed insolvency. Financial indicators or signs, according to Taffler [15], can be analyzed to predict bankruptcy or organizational failures. The signs or indicators will appear if the company's financial statements are examined during a specific time period [16,17]. He studied 45 healthy and 23 failed firms in the UK for four years, from 1968 to 1973, and has a predictive accuracy of 96% for failed firms and 100% for healthy firms. Financial ratios, according to Altman [18], should be used to determine whether an organization is experiencing operational and financial difficulties. Financial ratio analysis can predict financial distress five years before bankruptcy by determining a company's earnings growth, liquidity, leverage, turnover, volatility, and size [19,20]. Many experiments have been conducted over the years to predict bankruptcy using various indicators. According to Bellovary et al. [21], the literature on bankruptcy prediction dates back to the 1930s, when the Bureau of Market Research published a report that identified eight indicators as successful indicators for failing firms. For the next 30 years, bankruptcy prediction models relied on univariate or univariate regression to forecast potential losses. Simple indicators (without multivariate regression) can be deceptive and insufficient for predicting default. Altman [18] was the first to apply a Multiple Discriminant Analysis (MDA) Model which calculates a Z-score based on five economic indicators, distinguishing between healthy and non-healthy firms. He studied 33 healthy and 33 failing U.S. firms (included in Chapter X). for 3 years in the period 1946-1965 and has a predictive accuracy of 76%. Subsequent studies also use a larger number of indicators, but this does not necessarily mean that better predictive ability is achieved. For example, the model of Jo et al. [22] achieves 81.94% predictive ability using 57 different indicators, while the model of Rose [23] achieves 76% predictive ability using 23 different indicators, and the model of Moses [24] achieves 85% predictive ability using 3 different indicators. These models are for various countries and time periods. To predict a company's bankruptcy, models based on various ratios have been developed. When compared to Altman's Z-score, which uses five different ratios to analyze a company's bankruptcy, their MDA used more ratios, but this did not always result in higher predictive accuracy. Jo et al. [22] 's model with 57 variables/indices has an 81.94% predictive accuracy, while the model of Rose [23] with 23 variables/indices has a 76% predictive accuracy, and the model of Moses [24] with 3 variables/indices has an 85% predictive accuracy.

In order to assess the impact of the Greek financial crisis of 2010, Benetatos [25] developed an Altman Z-score Multiple Discriminant Analysis (MDA) bankruptcy prediction model evaluating 21 financial indicators (19 used in previous studies and 2 new proposed by their study), studying more 350 healthy and 105 bankrupt Companies for the period 2006-08; and 350 healthy and 86 bankrupt Companies for the period 2010-12. Using discrete analysis methodology, a model for each of the time intervals was developed, which served as the primary tool for predicting classification into one of the two predefined groups (healthy and bankrupt companies). Following the crisis, the overall prediction rate for healthy companies was 98.9% in 2012. A number of new models followed, according to Bellovary et al. [21]. In the 1970s, 28 studies were published, followed by 53 in the 1980s and 70 in the 1990s. Eleven studies were published between 2000 and 2004. Neural network models and other Artificial Intelligence techniques [26-28] and Logit (Ohlson [29] and Probit (Zavgen 1983; Zmijewski [30] models have also been used to predict bankruptcy. As developed by Poston [14] and Dimitras et al. [13] these models are used by audit firms, financial consultants, insurance companies, insurers and financial institutions,

Although the majority of bankruptcy prediction literature has focused on the United States and the United Kingdom, several Discriminant Analysis bankruptcy prediction models for Greece have been developed, according to Giannopoulos [31]:

A. Grammatikos [32] analyzed 29 healthy and 29 bankrupt companies for the period 1986-1990 compared the performance of Probit, logit and MDA linear probability analysis prediction models. Probit and Linear Probability models had the best predictive ability of 70.8%.

B. Theodossiou [33] compared the performance of a linear probability model, a logit model and a Probit model and the Linear Probability model had the best predictive ability 96.4%.

C. Dimitras et al. [34] and Dimitras et al. [13] compared the performance of a rough set theory model, a multi-discriminate analysis model, and a logit model and the rough theory model had the best predictive ability of 73.7%

D. Zopounidis [35] developed a Multi-Criteria Decision Aid (MCDA) discriminant model using twelve variables/indices to study 58 healthy and another 58 bankrupt Companies for the period 1990-1995 which had a predictive accuracy of 47.37% to 84.21% for the bankrupt Companies.

E. Boufounou [36] compared the predictive ability of Logit and Probit Models using financial ratios to predict corporate bankruptcy for Greek companies listed and unlisted in the Athens Stock Exchange (ASE) for the period 2005-2018 and they concluded that duration is important. The shorter the study time period before bankruptcy, the better the results. The Logit Model was the better fit. The Probit method is deemed, based on the reviewed literature, able to yield much better results if the company's Board of Directors were given the opportunity to complete a questionnaire of the company in question, to create an Ordered Probit Model. Excessive lending was found to increase dramatically 3 years before bankruptcy [37].

Materials and Methods

Sample characteristics

This study's data sample consists of 92 firms, with 46 in each of the two categories of Bankrupt and Healthy. Companies in the Bankrupt category have declared bankruptcy under Greek law and have had their last year of operation between 2011 and 2021, and the sample consists of 96 firms, evenly distributed between healthy and bankrupt (i.e., 46 in each category). The data for the study came from financial statements dated one year before the bankruptcy. At the time of the study, the companies in the healthy group were still in operation. Financial ratios, by definition, deflate data by scale, removing a significant portion of the size effect, as is widely accepted. The logit model, discussed further below, tends to be stable enough to support large companies. The logit model estimated includes large bankrupt firms and undoubtedly applies to both small and medium sized firms. In theory, it would be desirable to analyze a set of indicators at time t to make predictions for companies in the future (t+1). This could not be explored due to data limitations.

Indices option

Based on the literature and the availability of data, a total of 21 indices were selected for bankruptcy prediction, classified into four categories, as shown in Table 1 below, which were classified into four general categories: profitability, efficiency, management structure and human resource management. The data necessary for their assessment were obtained from the financial statements (balance sheet and income statement) of each company in the two samples (Healthy and Bankrupt).

Table 1: Categories of Financial Indices.

Categories of Ratios	Indices
Profitability Ratios	A1, A2, A3, A4, A5, A6, A7
Operational Efficiency Ratios	A8, A9, A10, A11, A12
Management Structure Ratios	A13, A14, A15, A16, A17
Human Resource Management Ratios	A18, A19, A20, A21

Logit model

The Logit model is a probability methodology within certain conditions used to investigate the relationship between a set of characteristics of an individual (or company) and its tendency to belong to previously defined classes, a key feature of which is that the dependent variable can only have a value of 0 or 1 (dichotomous variable). To determine the parameters of the model, the maximum likelihood approach is used. Maximum likelihood estimation is one of the methods created by statisticians to estimate the parameters in a mathematical model. This approach can be used to estimate both complex nonlinear and linear models. Some multivariate statistical methods, such as discrete regression, are used to estimate a dichotomous dependent variable from a variety of independent variables. Linear discriminant analysis predicts the category to which the characteristic-bankrupt/non-bankrupt - corresponds directly. Although it is an optimal prediction rule, this strategy involves the assumption of multivariate normality of the independent variables and tables of variance-covariance is equal in both classes.

In the logit model there are no restrictions on the normality of the explanatory variables. Therefore, it seems less restrictive in its application. When applied to the logit model, the main objective of the maximum likelihood estimation method is to find the value of the parameters β and σ2 that maximize the probability given by the likelihood function. Thus, in the Logit model, the relationship between the probability of a business failure (p) and the price of financial indicators is a curve in S ranging between 0 and 1. The logit model is well known because it corresponds to the general sigmoid form of the accounting equation. If the vector Zi is interpreted as an index that incorporates the contributions of various risk factors, then F(Zi) represents the risk for a given value of Z. As a result, risk is small for low values of Z, increases over a range of intermediate Z values, and remains close to one until Z is high enough. The structure of a logit model is based on a logistic cumulative probability function, defined as:

$$p_i = F(Z_i) = F(\alpha + \sum_j \beta_j * X_{ij}) = \frac{1}{1+e^{-Zi}} = \frac{1}{1+e^{-(\alpha+\Sigma_j \beta_j * X_{ij})}} \quad (1)$$

in which it holds that:

$$Z_i = \alpha + \sum_j \beta_j * X_{ij} \quad (2)$$

p_i: Probability of bankruptcy

i: Observation number

β_j: Coefficient for each of the independent variables

X: Financial-financial company ratios

The parameters β of the equation define the rate of increase or decrease of the S-shaped curve for p(i). The sign of the parameter indicates whether the curve is rising (β > 0) or falling (β < 0), and the level of change increases as |β| increases. The right-hand side of equation (1) simplifies to a constant when β = 0. The curve then becomes a horizontal line when p(i) is equal to i. Equation

(1) is suitable for modeling a probability since the values of F(Zi) range from 0 to 1 as it varies from -∞ to +∞. The probability of default is obtained by the product of the ratios and an index Z, which transforms the previous expression, allowing for a certain probability of default. Explanatory variables with negative coefficients reduce the probability of default by reducing *ey* to zero. Similarly, independent variables with a positive coefficient increase the risk of default.

The Logit methodology may present the problems that it requires the groups to be clearly well separated; and the explanatory variables to be independent, however it has important advantages, including that:

A. It does not limit the researcher to assuming that the dependent and independent variables have a linear relationship.

B. It does not require the variables to conform to a normal distribution.

C. It is more robust than discriminant analysis, as it is applicable outside the normal distribution.

D. The dependent variable can be thought of as the probability that the firm will declare bankruptcy.

E. It gives a visually appealing S-shaped representation of the cumulative effect of several risk factors on the probability of an event.

Results

t-test

Table 2 below presents the average values of all Indices in the Healthy and Bankrupt companies in the sample. The table shows the individual sample t-test statistics and the relative p-values for the two groups. The analysis of the mean profitability indices of the two groups reveals that the bankrupt group had less potential to generate profits before bankruptcy. The t-tests also show a large change in the operating return ratio. In addition, the t-test results indicate that there is no significant variation between the two groups in terms of management organization and human capital ratios.

Table 2: Sample Characteristics.

Ratio Category	No	Indices	Healthy Companies Mean	Bankrupt Companies Mean	T Statistic	p- Value	p-Value 2-Tailed
Profitability	A1	Return on shareholders fund	8.67315	-17.720672	-1.761	0.001	0.005
	A2	Return on capital employed	15.135076	-1.732324	-1.581	0.024	0.007
	A3	Return on total assets	3.000802	-2.770824	-2.168	0.003	0.001
	A4	Cash flow/ turnover	2.670343	-1.201	-1.62	0	0.006
	A5	Profit margin	1.406703	-4.630802	-1.443	0	0.011
	A6	EBITDA Margin	6.4344	1.481324	-1.021	0.001	0.025
	A7	EBIT Margin	3.146846	-1.5004	-1.16	0	0.015
Operational Efficiency	A8	Net asset turnover	3.031606	8.357672	1.207	0.01	0.183
	A9	Interest cover	5.235737	10.10076	0.415	0.083	0.5
	A10	Stock turnover	16.500737	28.337628	1.642	0.006	0.072
	A11	Collection period	110.1005623	137.305054	1.072	0.001	0.13
	A12	Credit period	75.820672	126.320812	1.142	0	0.023
Management Structure	A13	Current ratio	1.203802	1.346076	1.08	0.02	0.126
	A14	Liquidity ratio	0.823	1.0483202	1.212	0.027	0.182
	A15	Shareholders liquidity ratio	12.08526	26.04378	0.604	0.231	0.365
	A16	Solvency ratio	17.041703	15.1424	-2.1	0	0.028
	A17	Gearing ratio	151.435454	183.514011	0.637	0.02	0.345
Human Resource Management	A18	Operating profit per employee	111.777278	135.18414	0.211	0.105	0.645
	A19	Share funds per employee	41.860811	56.525082	1.065	0.07	0.132
	A20	Working capital per employee	50.756	30.116748	-1.131	0.822	0.107
	A21	Total assets per employee	100.207881	148.071474	1.028	0.412	0.201

The p-value (2-tailed) can be used to control for group variation:

a) If the p (2-tailed) value is equal to or less than 0.05, the mean scores on categorical variables vary significantly between the two groups.

b) If the p (2-tailed) value is above 0.05, there is no statistically significant difference between the two groups.

As a result, Table 2 shows that the two groups of companies (Healthy/Bankrupt) differ in 10 indicators: A1 (Return on shareholders fund), A2 (Return on capital employed), A3 (Return on total assets), A4 (Cash flow/turnover), A5 (Profit margin), A6 (EBITDA margin), A7 (EBIT margin), A10 (Stock turnover), A12 (Credit period) and A16 (Solvency ratio).

Model results

Table 3 presents the estimated Logit Model's fit with cut-off point 0.5. The Wald test, presented in Table 3 below, which is widely used to test the importance of each predictor in a Logit model, shows the top four predictors with the most significant effects on the dependent variable. The stepwise forward Logit method selected and retained four predictors from 21 candidate variables/ indices that could be filtered to distinguish healthy from bankrupt firms, with the significance level set at p-value=0.05. A4 (Cash flow/ turnover)

A. A6 (EBITDA Margin)

B. A8 (Net asset turnover)

C. A12 (Credit period)

Table 3: Model Fit Wald-test.

		Coefficient B	Standard Error	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Low	High
Step 1	A4 Cash flow/ turnover	2.221	0.377	4.057	1	0.012	2.024	0.054	6.804
	A6 EBITDA Margin	-0.856	0.354	3.216	1	0.027	0.27	0.042	0.835
	A8 Net asset turnover	-0.051	0.067	3.137	1	0.028	0.74	0.62	0.881
	A12 Credit period	-0.01	0.008	3.28	1	0.025	0.87	0.851	0.888
	Constant	3.15	1.034	2.836	1	0.036	60.773		

Indices in step 1: A1, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11, A12, A13, A14, A15, A16, A17, A18, A19, A20, A21.

This does not mean that the bankrupt firms differ from the healthier ones only in these four predictors/indices, but that these four indices combined will best differentiate the two groups. The odds ratios for each selected index are represented by the values in the Exp column (B). When the value of the predictor increases by one unit, the odds ratio increases (or decreases if it is less than one unit) the probability of a firm being in an outcome group (healthy/ bankrupt). Four variables/indices from the original set of 21 are selected to achieve the best possible prediction of corporate failure. As a result, the logit model for predicting bankruptcy can be written in logit(y) as follows.

$$Logit(y)=3.150+2.221\times A_4-0.856\times A_6-0.051\times A_8-0.01\times A_{12}$$

The values in the Exp column represent the odds ratios for each selected indicator (B). The odds ratio increases (or decreases if it is less than one) the probability of finding a firm in an outcome group when the value of the predictive indicator increases by one unit. In this case, the likelihood ratio of stable firms is distributed as 1, the cash flow/turnover ratio of bankrupt firms is 2,024 times greater, and all other predictors are held constant. The 95% confidence interval (95% CI for Exp (B)) for each likelihood ratio is shown in the last column, along with a lower and upper bound. The set of predictors selected by the progressive stepwise method differs from the independent-sample test set, from which a total of nine variables are drawn. This does not mean that the bankrupt firms differ from the healthier firms only in these four predictors. Rather, it simply implies that these four indicators combined will better differentiate the two groups. This model uses important financial indicators in the areas of profitability and operating performance. Therefore, according to the above, the reasons why SMEs fail are as follows:

a) Reduction in profit generating capacity.

b) Insufficient labor resources and loss of interest payment capacity, which contributes to greater financial distress; and

c) The lack of maintaining relationships with customers, as evidenced by the longer time for a firm's customer to extend credit.

Table 4 below illustrates the utility of the model, while the Cox & Snell R Square and Nagelkerke R values reflect the magnitude of the difference in the dependent variable explained by the model; this range of variables explains 37.1% and 53.2% of the uncertainty, respectively. Table 5 below presents the Model's goodness of fit test. Overall, the significance is less than .05, indicating that the approximate Logit model provides a good fit with the data and that the parameters of the estimated variables are significant. The Hosmer and Lemeshow goodness of fit test presented in Table 6 below, also confirms that the model has a good fit to the data (sig. value is 0.402 in this analysis with an x-squared value of 6.208 with 7 degrees of freedom), indicating that the final four-prediction model fits the results well, so there is no substantial difference between the observed and predicted classification. Table 7 below, presents the Classification Table with cut-off point 0.5, according to which the overall prediction rate is 73.15%, where the prediction rates for bankrupt and healthy firms are 70.3% and 76.0% respectively. Table 8 below presents the Pearson Correlation Table of the predictor variables/indices in the entire sample. There is a moderate correlation between A4(Cash flow/ turnover) and A6 (EBITDA Margin) at 1% significance level. This is explained by the nature of the two indices, as they are both Profitability Ratios and they "serve the same cause", as if we have high cash flow cycles, it means that the company's cash periods are moving fast (i.e. they can easily replenish and use cash on a more extensive basis), therefore they are efficient and therefore with high operating profit. Furthermore, it should be noted that coefficient Pearson between A4 (cashflow/turnover) and A12 (credit period) is -0.100, indicating negative correlation significant at 5% level, which is the only negative correlation that is significant at a 5% level. The following are the main findings of the analysis for each category of firms separately.

Table 4: Model Synopsis.

Step	-2 Log likelihood (1)	Cox & Snell R Square	Nagelkerke R Square
1	66.0141	0.371	0.532

(1) The estimation was terminated at iteration number 9 because the parameter estimates changed by less than .001.

Table 5: Goodness of Fit Test.

		Chi-square	df	Sig.
Step1	Step	59.413	10	.000
	Block	59.413	10	.000
	Model	59.413	10	.000

Table 6: Hosmer and Lemeshow Goodness of Fit Test

Step	Chi-square	df	Sig.
1	6.208	7	0.402

Table 7: Classification Table.

Observed		Predicted		
		Bankrupt		Percentage Correct
		Bankrupt	Healthy	
Bankrupt variable	Bankrupt	26	20	70.3
	Healthy	5	41	76
Overall Percentage				73.15
The cut-off point is 0.5				

Table 8: Pearson Correlation Table.

		A4 Cash Flow/ Turnover	A6 EBITDA Margin	A8 Net Asset Turnover	A12 Credit Period
A4 Cash flow/ turnover	Pearson Correlation	1	0.741**	-0.002	*-0.100**
	Sig.(2-tailed)		0.000	0.220	0.033
	N	92	92	92	92
A6 EBITDA Margin	Pearson Correlation	0.741**	1	-0.135	-0.156
	Sig.(2-tailed)	0.000		0.154	0.001
	N	92	92	92	92
A8 Net asset turnover	Pearson Correlation	-0.002	-0.135	1	-0.027
	Sig.(2-tailed)	0.220	0.154		0.606
	N	92	92	92	92
A12 Credit period	Pearson Correlation	*-0.100**	-0.156	-0.027	1
	Sig.(2-tailed)	0.033	0.001	0.606	
	N	92	92	92	92

*The correlation is statistically significant at level 0,05 (2-tailed).

**The correlation is statistically significant at level 0,01 (2-tailed).

Bankrupt companies

Table 9 below presents the basic sample characteristics for the sample of 46 bankrupt companies, where the following can be observed:

A. Regarding the average cash flow cycle, it is at -2.30. This ratio expresses how quickly the company goes through its cash cycles in order to put cash to better use. It assesses the company's overall cash efficiency. There are more companies that are above the industry average. This means that just because a company has high profits but low cash does not always imply that it is in a strong position. Companies with low cash reserves, on the other hand, may require short-term financing in the near future to meet their commitments.

B. The average EBITDA margin is currently at 0.5. This ratio represents a company's earnings before taxes and depreciation. It calculates the gross operating profit as a percentage of sales. As can be seen, there are slightly more companies that are above the industry average, but the percentage is still relatively low. This means that businesses are having problems with sustainability and cash flow.

C. A company's strong EBITDA does not always mean that it is profitable. This is because EBITDA does not have improvements in working capital, which is usually necessary for business growth. In addition, it does not take into account the capital investments used to cover assets on the balance sheet.

D. The average credit period is currently 126.32 days. This indicates how many days a customer takes to pay an invoice. It determines how much operating capital a company is willing to spend on the open balances of its customers in order to generate revenue. There are more companies that are below the industry average. This means that businesses are collecting payments more quickly. The disadvantage of this is that it may indicate that a company's credit policies are overly strict, and consumers may seek out suppliers or service providers with more favorable payment terms.

Table 9: Basic sample characteristics of Bankrupt Companies.

	N	(Min)	(Max)	(Mean)	(Std. Deviation)	(Skewness)		(Kurtosis)	
	Statistic					Statistic	Std. Error	Statistic	Std. Error
A4 Cash flow/ turnover	46	-57.28	20.113	-2.301	17.7811361	-1.486	0.24	2.208	0.577
A6 EBITDA Margin	46	-53.6	25.242	0.481324	16.601887	-1.4	0.24	3.168	0.577
A8 Net asset turnover	46	0	127.616	8.367672	17.5334577	3.21	0.24	17.1	0.577
A12 Credit period	46	0	604.847	126.320802	140.340001	1.887	0.24	3.188	0.577
Valid N (listwise)	46								

Healthy companies

Table 10: Basic sample characteristics of Healthy Companies.

	N	(Min)	(Max)	(Mean)	(Std. Deviation)	(Skewness)		(Kurtosis)	
	Statistic					Statistic	Std. Error	Statistic	Std. Error
A4 Cash flow/ turnover	46	-8.48	16.427	3.780454	4.8440436	0.15	0.24	3.515	0.577
A6 EBITDA Margin	46	-5.4	18.487	6.4344	5.6238161	0.123	0.24	2.068	0.577
A8 Net asset turnover	46	0.556	20.62	3.031606	4.0788727	2.601	0.24	15.064	0.577
A12 Credit period	46	8.414	216.744	75.820672	40.6200187	1.118	0.24	8.328	0.577
Valid N (listwise)	46								

Table 10 below presents the basic sample characteristics for the sample of 46 healthy companies where the following can be observed:

A. Observing the mean of each independent variable and focusing primarily on the values obtained, we can conclude that the mean values are all positive but not very close to zero. When analyzing companies that are deemed healthy, it makes sense for this value to be positive or close to zero.

B. The average cash flow cycle is currently 3.78. As previously stated, this ratio reflects how quickly the company moves through its cash cycles in order to use cash for better purposes. It assesses the company's overall cash efficiency. With a positive sign, we can see that there are more companies that are almost evenly divided above and below the industry average. This means that the majority of businesses have a high cash turnover, indicating a higher frequency of cash replenishment through revenue.

C. In terms of average EBITDA margin, it is at 6.43, much higher than the insolvent companies. As mentioned earlier, this ratio reflects a company's earnings before taxes and depreciation and amortization. It estimates gross operating profit as a percentage of sales. We note that there are slightly more companies below the industry average, but still close to the industry average. This means that companies have profitability issues as well as cash flow issues. Positive EBITDA suggests that company earnings are stable but remain relatively low with most companies below 6.43%. The profitability and cash flow issues are indicative of low EBITDA margins. This is due to the fact that EBITDA has no improvements in working capital, which is usually necessary for business growth. In addition, it does not take into account capital investments used to cover assets on the balance sheet.

D. In terms of net turnover of assets, it is at 3.03. As mentioned earlier, this ratio compares the value of a company's profits with the value of its real estate. Net asset turnover is an indicator of how efficiently a company uses its assets to generate sales. We can see that there are more companies below the industry average, but still have a positive sign. This means that most companies are not effectively using their assets to generate revenue or that the potential for sales is not being maximized. On the other hand, companies that are above average have a surplus of capital compared to their actual needs.

E. In terms of average credit period, it is 75.82, which is significantly less than that of insolvent companies. As previously stated, this rate expresses the number of days a customer must wait before paying an invoice. It establishes how much operating capital a company is willing to invest in accounts receivable in order to generate revenue. We notice that there are more businesses that are below the industry average. This means that businesses can collect more quickly.

F. A drawback of this is that it may mean that a company's credit rules are too strict and consumers may seek suppliers or service providers with more favorable payment terms. The striking thing about this is that healthy companies collect payments faster than insolvent or problematic companies.

Conclusion

At a time when companies are facing increasing difficulties, it is especially important to develop mechanisms to detect whether or not a company is on the verge of insolvency. In this context, the goal of this research was to examine the Greek economy, which has been in a deep economic slump since 2010. This study estimated a four-variable logit model with a cut-off point of 0.5 for predicting Greek firm insolvency, with a 73% overall predictive ability. According to the results of the t-test, the bankrupt group of companies (bankrupt companies) has a lower ability to generate profit before bankruptcy and there is a significant gap in the operating efficiency index. According to the findings of this study, the predictors of operational profitability (profitability ratios: Cashflow/turnover and EBITDA Margin) and operational efficiency (Net asset turnover and Credit period) lead to the distinction between healthy and bankrupt companies, leading to the conclusion that the causes of bankruptcy in Greece during the study period can be attributed to

a) To the reduction of the profit generating capacity.

b) To insufficient resources and loss of ability to pay interest.

c) The lack of control of relations with customers; and

d) The existence of a relatively slow collection mechanism, weak credit practices and/or consumers/customers who are not financially viable due to the recession.

A direct comparison of the findings of the corporate failure studies with each other is, as expected, not effective as they relate to different countries and/or different time periods. The study conducted helps to identify the warning signs of insolvency, as it provides information on the insolvency risk position of each company in Greece for the period 2011-2022. Its application can have significant practical consequences for banks, financial institutions, government action, and financial system regulators. The out-of-sample test is not included in all corporate failure studies (including this one) due to a lack of data from the failing firm. At the academic level, the current study could be expanded by investigating the significance of non-financial indicators, such as key firm characteristics, in predicting bankruptcy (size, age, capital investment and depreciation). It would also be an interesting extension of this study to conduct a similar study of corporate failures in other EU countries over the same time period, incorporating state-level risk indicators to determine the scope of the study.

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