

Article

Corporate Bankruptcy Prediction Models: A Comparative Study for the Construction Sector in Greece

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Abstract: This study focuses on testing the efficiency of alternative bankruptcy prediction models (Altman, Ohlson, Zmijewski) and on assessing the possible reasons that led to the confirmation or not of the prevailing model. Data from financial statements of listed (Greek) construction companies before the economic crisis were utilized. The results showed that Altman's main predictive model as well as the revised models have low overall predictability for all three years before bankruptcy.

Keywords: corporate bankruptcy; construction sector; accounting indicators; Altman Z-score; Logit; Probit

1. Introduction

Construction activity is a key component of both the Greek and the European economy. It is closely linked to various sectors ranging from the industry of construction and other materials used in construction projects to architectural/study activities and trade. The fundamental contribution of construction to the implementation of investment projects in sectors such as Public Infrastructure, Tourism, Industry, and Trade, as well as to residential/urban development, emphasizes construction as a key component in the country's economic development [1].

In Greece, the construction sector grew rapidly from the early 1990s until 2007, contributing substantially to the growth of the Greek economy. However, the adverse impact of the global economic crisis and the weakness of the real Greek economy due to the 2010–2018 economic crisis had a catalytic effect on the sector's performance, leading many construction companies to bankruptcy [2]. Indicatively, in 2006 the value added of the construction sector reached 22.5 billion Euros (or 11% of the Greek GDP), and in 2013 it had fallen to 8.1 billion Euros (or 4% of the Greek GDP). The impact of the economic crisis was also huge on employment in the sector's professions and specializations since, in 2013, 287.000 people were employed (8.7% of total employment) compared to 589.000 in 2008 (when the crisis had not yet fully spread to Greece) [3]. Similarly, corporate failure multiplied exponentially with the financial crisis and Greece's entry into the Memoranda; as Eurostat data show, the number of companies in the construction sector fell from 112,952 in 2009 to 77,229 in 2016 [4].

In order to deal effectively with the risk of corporate failure, the need for valid methods of predicting potential failure becomes absolutely essential. The recent Greek financial crisis, which resulted in the implementation of the capital control measures, had significant implications for businesses, which were initially faced with a lack of liquidity to finance the import of imported products [5]. Some of these businesses were eventually led to bankruptcy (indicatively, [6,7]), therefore attracting significant research interest (indicatively, [8,9]).



Citation: Toudas, K.; Archontakis, S.; Boufounou, P. Corporate Bankruptcy Prediction Models: A Comparative Study for the Construction Sector in Greece. *Computation* **2024**, *12*, 9. <https://doi.org/10.3390/computation12010009>

Academic Editor: Pedro G. Lind

Received: 27 September 2023

Revised: 31 December 2023

Accepted: 2 January 2024

Published: 9 January 2024



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This study focuses on studying bankruptcy prediction in the construction sector in Greece during the economic crisis. Three (3) alternative models for predicting corporate bankruptcy are applied and compared: (a) the Altman Model (using three different variations, namely the Altman Z-Score model [10], the Altman Z'-Score [10], and the Altman Z''-Score [11]); (b) the Ohlson Model [12]; and (c) the Zmijewski Model [13]. These are applied to construction companies listed in the Athens Greek Stock Exchange. The study aims (i) to measure the predictability of the models considered by comparing their performance and (ii) to ascertain whether, for the companies that went bankrupt, it was possible to predict the event or not and whether the healthy ones should indeed be classified in the category in which the models in question classify them. This is the first time such a comparative study has been conducted for Greece and internationally. The study's importance is further enhanced by the fact that Greece is still in "turmoil" (as the economic crisis/recession was succeeded by the pandemic crisis, followed by the Ukrainian crisis, the energy crisis, etc.) and, therefore, the use of effective bankruptcy forecasting models has become a necessity.

The study is structured as follows: At the beginning, an overview of the concepts of the theoretical background is given, accompanied by a brief literature review of the topic. This is followed by a presentation and analysis of the characteristics of the research sample. Subsequently, we present the corporate bankruptcy models that were evaluated and a comparative evaluation of their performance in classifying firms as bankrupt or healthy. Finally, the conclusions are presented and suggestions for further research on the subject are provided.

2. Literature Review

This section presents the theoretical background of bankruptcy prediction and provides a brief survey of the main alternative methods applied, coupled with relative empirical applications in Greece and internationally.

The ability to predict corporate bankruptcy is particularly important for successful corporate finance as it is directly related to improving risk management [14]. According to [15], we can distinguish the concepts as follows (although, in the literature, all of the following are used with the same meaning):

- *Corporate Failure*: In economic terms, failure indicates that, for a certain amount of risk, the invested amount in return is lower (both in significance and duration) than the usual returns on similar investments. Other economic criteria that have been used to describe the term include insufficient revenues to cover the firm's costs and a fall in the value of the average return on investment (ROI) below the value of the capital cost over a long period of time. However, these factors cannot justify the decision to continue or to discontinue the business. The expected return and the ability of the firm to cover its variable costs should be included. It could be noted here that a firm may be chronically in financial failure, but this may not be detected due to low short-term liabilities.
- *Corporate Insolvency/Bankruptcy*: The term insolvency implies a negative return for a business and tends to be used for more technical matters. Specifically, insolvency refers to when a company is unable to meet its current obligations, indicating a lack of liquidity. According to [16], the basic criterion for the technical measurement of bankruptcy should be net cash flow in relation to short-term liabilities and not the Working Capital measure. According to Greek Law, insolvency can be a temporary situation, although it is usually the main reason for inclusion in the Bankruptcy Code. The term bankruptcy denotes a more critical situation that is perpetuated. A business may find itself in this situation if its Total Liabilities exceed the fair value of its total Assets, which implies a negative net worth. Technically, the bankruptcy of a firm is easily detectable. In more complex cases, however, an in-depth analysis is necessary, which is usually not carried out until the liquidation of Assets has been considered.

- *Corporate Default*: This term is indisputably linked to corporate financial distress. Corporate default can have both technical and legal dimensions, but it always involves both the lender and the borrower. For example, a breach of the terms of a loan agreement or an alteration of the Current Liquidity Ratio would be triggers for a default. However, a payment default can be renegotiated and simply means limited activity for the company. It is rare that this category of financial distress can lead to formal bankruptcy, as mentioned above.

Empirical studies in the literature have come to various conclusions regarding the factors that lead to the bankruptcy of a firm. Ref. [17] distinguishes the factors that lead a firm to bankruptcy in eight (8) categories: financial, informational, physical, human, reputational, criminal, and natural disasters. Ref. [18] divides the causes of financial distress into endogenous and exogenous. In their study, they emphasize that exogenous factors can affect the firm to a small extent, although the firm cannot be unaffected by the current dynamic environment. Of particular interest could be the research of [19], in which he identifies three cases as causes of economic distress: First, according to the neoclassical model, declaring bankruptcy is considered a positive event because it essentially releases investment goods (Assets) into the market which have not been allocated to healthy firms. The financial model argues that although the investment Assets were allocated in a correct way, the composition of the WACC was not satisfactory, resulting in a rather high WACC. Finally, the corporate governance model takes as a given that both investment goods and liabilities are properly allocated, but considers management inefficient. Refs. [15,20] summarize the factors that can lead to bankruptcy as follows:

- Economic sectors that suffer from long-term ailments (agriculture, textiles, etc.) mainly due to their dependence on external factors.
- The deregulation of key sectors of the economy (energy, telecommunications, etc.), resulting in more incoming and outgoing companies in various sectors.
- High real interest rates on borrowing, especially in certain periods (such as the period 2009–2019), resulting in unserviceable liabilities.
- International competition resulting in increased costs for businesses (for advertising, etc.).
- Overcapacity in certain sectors of the economy.
- Increased leverage in domestic companies resulting in a vertiginous increase in liabilities.

Furthermore, [15] concluded that the management factor was the one that scored close to 90%. Also, in the same study, the age of the firm seemed to be an important factor. Ref. [20] showed that more than 50% of the firms that had declared bankruptcy were new firms under 5 years of operation. Indicative actors that can lead a firm to failure were developed by [21–25].

Regarding the methodological approaches used over time to assess the factors that contribute to corporate failure, special reference could be made among distinct categories. *The Univariate Analysis* approach (1930–1965) was used after the Great Crash of the New York Stock Exchange in 1929, which was the occasion for economists of that time to start investigating the components that led to corporate failure. The research of this period, analyzing various financial ratios of bankrupt firms (e.g., Working Capital to Total Assets; Surplus and Reserves to Total Assets; Net Worth to Fixed Assets; Fixed Assets to Total Assets; Current Ratio; Net Worth to Total Assets; Sales to Total Assets; Cash to Total Assets; etc.), aimed to identify common characteristics or trends by comparing them with their average. According to [26], these studies were the foundations for the transition to Multivariate Analysis (indicatively, [27–34]).

As the necessity for even more valid default prediction models grew, further development of models was imperative for several reasons: Researchers were often led to conflicting observations or could not agree on their conclusions. Furthermore, manipulated accounting situations and differences in generally accepted principles contributed to the evolution of other methods that succeeded Univariate Analysis [4].

Multivariate Discriminant Analysis considered the possibility that multiple ratios considered simultaneously may have a higher predictive ability than single ratios. The first study published by [10] is the most popular and is still applied in numerous studies, as presented in the literature survey by [26], which reviewed 165 bankruptcy studies. The advantages of Altman's Z-Score model include the ease of use and the reliability of the results in combination with the free availability of the model. The disadvantages of the model have been noted by several scholars, concluding that the model is not as accurate when used for firms that do not belong to the industrial sector. Other disadvantages mentioned by scholars include the small number of samples used in the original model, the static nature of the financial ratios, and the falsification of the financial statements of the firms. Indicative studies for Greece are [35–43].

The *Regression Models* include the *Linear Probability Models (LPMs)*, the *Logit models*, and the *Probit models*. The need to use these models stemmed from the use of non-linear probability maximization. The main disadvantage of the LPM is that the dependent variable exclusively takes values 0 and 1 even though the probability of bankruptcy may be above 1, creating problems of interpretation.

The *Logit model* is a development of the LPM, where the linear relationship was developed using logistic transformation. First, [12] used the Logit model in his study. His sample consisted of 105 listed firms that had failed and 2058 that had not failed in the period 1970–1976. For the bankrupt firms, the sample was collected three years earlier, while for the non-bankrupt firms it was collected one year earlier. He concluded that nine variables had the highest statistical significance in his study, which constructed the O-Score, namely the Total Assets/GNP price-level index as an indicator of the company's size; Total Liabilities/Total Assets; Working Capital/Total Assets; Current Liabilities/Current Assets; Net Income/Total Assets; Funds provided by Operations/Total Liabilities; the Net Profit year to year as a percentage of the yearly Net Profits; a dummy showing if Total Liabilities > Total Assets; and a dummy showing if Net Profits < 0 for the last 2 years. The main difference between the two Logit and Probit models is that the logistic regression has thicker tails. This difference, however, is considered negligible unless the sample includes multiple observations with extremely large values [44]. Ref. [45] conducted a review of Logit model applications in corporate failures and [46] presented the application of a Logit model in NYSE-listed firms.

The first to apply the *Probit model* was [13]. Based on financial ratios measuring both the profitability and liquidity of the firm, he used his own model to calculate the probability of failure. The sample consisted of 40 bankrupt firms and 800 non-bankrupt firms between 1972 and 1978. The indicators used were the following: Net Income/Total Assets (Return on Assets, ROA); Total Debt/Total Assets (Financial Leverage; Current Assets/Current Liabilities) [47]. The higher the score, the higher the chances of bankruptcy. Ref. [13] identified two errors in the procedure: the first error stemmed from the selection of firms of which the failure was known in advance, while the second error stemmed from the fact that only firms whose data were available had to be used.

Many studies focusing on Greece have been conducted using Logit and Probit models. In the study of [48], the LPM was used in comparison with the MDA model in the context of predicting the bankruptcy of Greek industrial firms. In the findings of their study, it was reported that both models successfully predicted companies that were going to fail or had failed. The LPM's rates were 91.4%, 76%, and 78% for the 1st, 2nd, and 3rd year before bankruptcy, respectively, while the MDA model's rates were 91%, 78%, and 70% for similar years. Also, [49] used the LPD model compared to the Logit model to predict bankruptcy in a sample of 35 firms in the industrial sector. In his findings, he concluded that both of these models gave very satisfactory results regarding the viability analysis of firms in the industrial sector in Greece. In fact, in his research [49] found a success rate of 87.4% for the LPM. Ref. [50] compared the performance of Logit and Probit models for predicting corporate failure at the macro level in Greece. Ref. [51], using data from 64 companies listed in the Athens Stock Exchange for the period 2004–2016, compared the

performance of the Z-Score Altman Model versus the Logit model and concluded that the Logit model had the best results (93.8%) for bankrupt and non-bankrupt companies one year prior to bankruptcy [52], using a sample of 50 companies listed on the Athens Stock Exchange for 2002–2012, compared the forecasting ability of the bankruptcy prediction models of [10,40,45,48,53]. They showed that financial ratios and accounting information are important in predicting the bankruptcy of companies on the Athens Stock Exchange and that Altman's [10] Z-score model was not the best predictor model of bankruptcy in Greece, while Taffler's [53] model and Gloubos and Grammatikos' model [48] had the best total prediction accuracy (including both bankrupt and non-bankrupt companies). Ref. [54] compared the performance of the Logit and Probit models, examining the usefulness of financial ratios in predicting corporate bankruptcy for Greek companies both listed and unlisted in the Athens Stock Exchange (ASE) for the period 2005–2018, and the Logit model was proven the better fit. Ref. [55] estimated a Logit model to predict the likelihood of Greek company bankruptcy using financial indices for the period 2011–2022. The sample included 96 firms, with an equal number of healthy and bankrupt firms. Studying 21 financial indices, they concluded that predictors representing business profitability (profitability ratios: Cash-flow/Turnover and EBITDA Margin) and operational efficiency (Net Asset Turnover and Credit period) led to the distinction between healthy and bankrupt companies.

In recent years, other methods have been applied, e.g., *Data Envelopment Analysis—DEA* (indicatively for Greece, [8,56,57]) and the *Gradient Boosting Approach* (indicatively, [58–60]). *Machine Learning techniques* are increasingly being used to predict bankruptcy (indicative literature reviews include [61–63]). Among them, the most commonly used is the *Artificial Neural Network* (ANN) method (for example, [64,65]). Indicative studies of corporate bankruptcy prediction using ANN methods for Greece are [66–69]. Other most-often-used methods involve *Neuro-fuzzy systems* (indicatively, [70–72]); KNN (indicatively, [62,73,74]); Support Vector Machines [75]; the Ensemble Method (indicatively, [76,77]); and deep learning methods such as convolutional neural networks (indicatively, [78–80]). Late studies that compare the performance of alternative Machine Learning techniques include [62,81–86].

As specifically stated by [63], “although some papers have studied credit default and machine learning [87–91], new studies, exploring different models, contexts and datasets, are relevant, since results regarding the superiority of models are still inconclusive. The debate over the best models for predicting failure will probably continue in the short and medium terms, as new techniques are frequently being suggested and, particularly for the study of corporate bankruptcy, failure events are subject to myriad variables. In this context, for instance, with the advancement of technology, data scraping will allow the observation of new variables that could be relevant inputs to machine learning models and lead to different results”. They also concluded that “the Altman and Ohlson models are still relevant, due not only to their predictive power but also to their simple, practical, and consistent frameworks”. Furthermore, [92] noted that “despite its “old age”, the Altman Z-score is still the standard against which most other bankruptcy or default prediction models are measured and is clearly the most used by financial market practitioners and academic scholars for a variety of purposes”.

Finally, it should be noted that such bankruptcy prediction studies referred to either specific economic sectors of a country (such as the banking sector [93–96]; the telecoms [97]; the trading sector [98]; the cement industry [99]; the pharmaceutical sector [100]; the construction sector [101–103]; or specific companies [104–106]); the present study concentrated on the construction sector due to its importance for the Greek economy, as illustrated above.

The Altman Z-score model has been widely applied all over the world; for instance, it has been applied to Greece [36–38,46,48–57,66–69]; to Pakistan [107]; to China [108]; to the USA [25,95]; to Indonesia [97,101,102,106,109]; to India [110,111]; to Bangladesh [93,99]; to Malaysia [98]; and to Serbia [96].

Many researchers have compared the predictive performance of Altman's model over Olshon's, Smijewski's, Springate, and/or AI techniques (indicatively, [112–120]). As stated by [121], "some resulted in favour of Altman Z Score model's validity some others revised the model or offered more state of art technology added methods".

Hence, the present study focused on the comparison of the bankruptcy forecasting ability of the Altman Model (using three different variations, namely the Altman Z-Score model of Altman [10], the Altman Z'-Score of Altman [10], and the Altman Z''-Score of Altman [11]); the Ohlson Model of Ohlson [12]; and the Zmijewski Model of Zmijewski [13] of the Greek construction sector.

3. Materials

This section presents the data used. The study examines the forecasting potential of alternative bankruptcy prediction of companies listed in the Athens Stock Exchange in the construction sector (as this is a sector of major importance for the Greek economy [2,8,9]), focusing on the period before the Greek financial crisis, i.e., before the Greek bailout and the relative Memorandums' introduction in 2010. Starting then (2010), Greece entered a prolonged recession period that coupled with other crises that occurred (i.e., the COVID-19 pandemic, the energy crisis, etc.), resulting in a domino of company failures. Thus, the pre-Memorandum period sample choice offered a better representation of the country's normal economic activity (strengthening the importance of the results obtained). Furthermore, this fact prevented the study of panel data of European countries that would include Greece.

The Athens Stock Exchange is a relatively small stock exchange, both in terms of number of listed companies and in valuation terms, and the number of 148 companies listed in total was further reduced due to the prolonged economic crisis. This was a major restricting factor to the sample size used, consisting of 10 construction companies that went bankrupt before 2010 and 10 healthy construction companies in 2010. Data availability for all bankrupt companies was a further restricting factor. More specifically, financial data from one year before the company's failure (year -1) were not available for many companies. These companies either could not produce financial statements or had not published them, therefore restricting the sample size.

We defined "Bankrupt" as firms that in the year of bankruptcy (year 0) had either filed for bankruptcy or were under trading suspension. The healthy firms are still being traded on ATHEX today (the total number of the listed construction companies is 16). To enhance the sample's homogeneity effect, specific companies were included in the healthy companies group (e.g., Halcor, due to its important impact on the construction sector and the supply chain). It should be noted that some of the firms that at that time were defined as failed/bankrupt managed to restart their activities at a later stage. Annual financial data were used which were derived from the relevant accounting statements for all companies, except for the company 'Babis Vovos', where half-yearly data were used for year -1 . Data were collected for a total of three years prior to bankruptcy (-1 , -2 , -3), further stressing the difficulty of collecting the data necessary. The final list of bankrupt firms was confirmed by their website. Data were primarily gathered from the ATHEX website and also from the companies' websites. The basic characteristics of the companies studied are presented in Table 1 below.

Table 1. Dataset presentation.

Non-Healthy Companies					Healthy Companies			
Years	Company Name		Average of (3 Year) Total Assets	Average of (3 Year) Sales		Company Name	Average of (3 Year) Total Assets	Average of (3 Year) Sales
2007-2006-2005	N1	Gener	37,596,333.33	7,431,333.33	H1	Proodeftiki	85,278,290.58	27,744,261.40
2007-2006-2005	N2	Diekat	124,070,876.35	94,762,849.78	H2	Intrakat	164,557,789.52	101,017,143.67
2007-2006-2005	N3	Betanet	115,002,000.27	25,444,333.34	H3	Kloykinas-Lappas	98,136,987.89	57,112,892.28
2005-2004-2003	N4	Themeliodomi	261,351,995.20	107,522,225.62	H4	Bitros	224,559,409.33	132,520,855.89
2007-2006-2005	N5	Mesochoriti	37,172,717.60	29,037,427.95	H5	Ekter	40,869,890.74	13,856,053.57
2008-2007-2006	N6	Xaly Sheet Steel	14,341,687.32	2,878,685.23	H6	Domiki	53,365,747.05	16,291,512.06
2009-2008-2007	N7	Attikat S.A.	411,171,644.87	181,357,374.10	H7	Alumil	409,851,552.67	260,875,799.33
2009-2008-2007	N8	Edrasis S.A.	205,658,000.00	94,002,666.67	H8	Vioter	203,722,666.67	65,873,666.67
2010-2009-2008	N9	Michaniki S.A.	569,271,333.33	150,217,000.00	H9	Halcor	771,129,787.00	974,555,201.33
2010-2009-2008	N10	Mpampis Vovos	1,297,693,666.67	30,741,666.67	H10	Avax	1,334,140,333.33	909,126,666.67

Table 2 below shows that the averages of the Assets of the two categories of firms are similar, indicating an unbiased comparison between the failed and healthy firms. Looking at the rest of the data, we can conclude that the ratio of the average Sales divided by the average Assets of the failed firms was much lower, respectively, than that of the healthy firms (23.53% vs. 75.58%). This difference is logical, as in the failed firms the average Sales decreased significantly before they went bankrupt. The median value of Assets and Sales was also considerably higher in healthy firms. The minimum and maximum values of the Asset and Sales totals show a wide range in both failed and healthy firms. This range suggests that the sample collected is composed of firms of different capital structures, but which have relatively similar coefficients of variation with respect to their Asset totals.

Table 2. Sample characteristics.

	Non-Healthy Companies		Healthy Companies	
	Assets	Sales	Assets	Sales
Mean	307,333,025.50	72,339,556.27	338,561,245.78	255,897,405.29
Median	163,515,500.00	36,941,103.61	194,296,673.55	69,844,500.00
Minimum	8,179,707.79	1,097,000.00	40,254,928.32	7,513,599.38
Maximum	1,375,911,000.00	250,455,603.00	1,378,155,000.00	1,200,295,367.00
Standard Deviation	371,946,226.77	68,377,659.98	392,738,600.54	358,421,483.01
Coefficient of Variance	1.21	0.95	1.16	1.4

4. Methods and Results

In the present study, the bankruptcy forecasting ability of three models was compared: the Altman Model (using three different variations, namely the Altman Z-Score model of Altman [10], the Altman Z'-Score of Altman [10], and the Altman Z''-Score of Altman [11]); the Ohlson Model of Ohlson [12]; and the Zmijewski Model of Zmijewski [13]. For each of the three bankruptcy prediction models, a brief presentation of the model is followed by the obtained predictability results for the years -1 , -2 m and -3 and by the obtained model scores and their critical discussion. For the variables obtained in all models, Analysis of (ANOVA) was applied to study the within- and between-sample variables to verify the statistical significance, as in relevant previous studies (indicatively [93] A prerequisite for this application, was to consider the means between them equal $H_0 (\mu_1 = \mu_2 \dots \mu_n)$ and reject H_1 (at least one mean differs) [122]. The significance level was set at 0.05 and all the results obtained were statistically significant, as presented in Appendix A.

4.1. Altman Model

In the following, the results from the application of three different variations of the Altman Model, namely the Z-Score Model of Altman [10], the Z'-Score of Altman [10], and the Z''-Score of Altman [11], are presented.

4.1.1. Altman Z-Score

Altman's classic linear regression model [10] is the first to be examined, as many studies in the international literature have verified the high predictability of the model. The equation used is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (1)$$

The equation variables denote indicators, the data for which are taken from the published accounts of the companies.

X_1 = Working Capital/Total Assets: Working Capital is defined as the difference between Current Assets and Current Liabilities. This ratio measures the net liquidity of the company in relation to its total capitalization. According to [10], this ratio showed greater statistical significance when compared with two other liquidity ratios (Current Ratio, Quick ratio).

X_2 = Retained Earnings/Total Assets: This ratio is a measure of the cumulative profitability of the firm, i.e., it indicates financial leverage over time. It is an indicator that is directly linked to reality, since it favors older firms which, having established themselves in the environment, are less likely to go bankrupt than younger firms.

X_3 = Earnings before Interest and Taxes/Total Assets: This ratio reflects the net productivity of the firm, or the net of various taxes or interest. Although this indicator can be easily manipulated, it is considered essential for business viability studies, since each company bases its existence on its ability to generate profits [42].

X_4 = Market Value of Equity/Book Value of Total Liabilities: the Market Value of Equity, in this thesis, is obtained by multiplying the average price of shares outstanding in the reference year by the price of the company's share on the last day it was traded. This ratio indicates the magnitude of the decline in the value of the firm's Assets before Total Liabilities exceed Assets.

X_5 = Sales/Total Assets: Although this ratio did not prove to be statistically significant in Altman's analysis, it ranks second in the utility of complementing the overall model. It indicates the main effect of Sales on the firm's Assets.

The variables above were used in the sample to construct the final equation and derive the scores, which were obtained from the application of the model. A firm was considered healthy if it scored above 2.99 and non-healthy/bankrupt if it scored below 1.81. The values $1.81 < Z < 2.99$ constitute the gray zone (controversial) according to [10]. Also, given the results, there was the possibility that a firm could fall into one of the two error categories: Type I (when a failing firm is categorized as healthy), and Type II (when a healthy firm is categorized as non-healthy/bankrupt).

After applying the classical Altman Z-Score model to the sample of 10 bankrupt and 10 healthy firms of the construction sector operating in ATHEX 3 years before the bankruptcy date studied in this study, the predictability results for years −1, −2, and −3 were calculated and are shown in Table 3 below. The number of correctly forecasted companies in each category (Type I/Type II error) is indicated and the relative percentages of correct and error predictions are shown. The total number of companies (size n) is also shown in the last column.

Table 3. Altman Model forecasting ability.

		Errors	No Correct	% Correct	% Error	Size n	
Altman Model	Altman Z	1 year before bankruptcy altman Z (−1)	Type I	10	100%	0%	10
			Type II	0	0%	100%	10
			Total	10	50%	50%	20
		2 years before bankruptcy altman Z (−2)	Type I	10	100%	0%	10
			Type II	0	0%	100%	10
			Total	10	50%	50%	20
		3 years before bankruptcy altman Z (−3)	Type I	10	100%	0%	10
			Type II	0	0%	100%	10
			Total	10	50%	50%	20
	Altman Z'	1 year before bankruptcy altman Z' (−1)	Type I	10	100%	0%	10
			Type II	0	0%	100%	10
			Total	10	50%	50%	20
		2 years before bankruptcy altman Z' (−2)	Type I	9	90%	10%	10
			Type II	0	0%	100%	10
			Total	9	45%	55%	20
		3 years before bankruptcy altman Z' (−3)	Type I	10	100%	0%	10
			Type II	0	0%	100%	10
			Total	10	50%	50%	20
	Altman Z''	1 year before bankruptcy altman Z'' (−1)	Type I	9	90%	10%	10
			Type II	2	20%	80%	10
			Total	11	55%	45%	20
		2 years before bankruptcy altman Z'' (−2)	Type I	7	70%	30%	10
			Type II	5	50%	50%	10
			Total	12	60%	40%	20
		3 years before bankruptcy altman Z'' (−3)	Type I	5	50%	50%	10
			Type II	2	20%	80%	10
			Total	7	35%	65%	20

The results of the Altman Z-Score model applied in this study suggest 50% accuracy of the model for all years. This conclusion is drawn from the fact that the model presented all healthy matched firms as bankrupt. Therefore, as compared to the percentages (95%) predicted by [10], the model has low forecasting ability. The economic situation and the upcoming financial turmoil that decimated the Greek economy is probably the reason for this discrepancy. The Altman Z-Scores of the sample are depicted in Table 4 below:

Table 4. Altman Model scores.

		Non-Healthy Companies									Healthy Companies									
		Altman Z			Altman Z'			Altman Z''			Altman Z			Altman Z'			Altman Z''			
		Year −1	Year −2	Year −3	Year −1	Year −2	Year −3	Year −1	Year −2	Year −3		Year −1	Year −2	Year −3	Year −1	Year −2	Year −3	Year −1	Year −2	Year −3
Altman Model	N1	(1.88)	(3.03)	0.72	(1.17)	(2.28)	0.86	(4.35)	(7.80)	3.10	H1	0.19	0.28	1.19	0.45	0.57	0.78	0.51	1.01	0.70
	N2	0.41	0.91	0.39	0.53	0.94	0.59	(1.89)	0.14	(1.57)	H2	0.93	0.55	1.66	1.29	1.07	0.92	2.32	2.39	1.95
	N3	0.54	0.85	0.85	1.09	1.01	1.02	2.82	3.21	2.38	H3	1.67	1.19	1.06	2.00	2.93	1.50	4.53	4.54	2.56
	N4	(0.69)	(0.94)	0.90	(0.38)	(0.64)	1.20	(3.63)	(3.18)	2.54	H4	1.09	0.80	0.18	0.85	1.38	0.51	1.48	3.32	2.43
	N5	0.74	1.25	0.31	1.10	1.52	1.01	0.72	2.14	(0.31)	H5	0.57	0.77	0.57	1.16	1.08	1.32	3.23	3.14	2.42
	N6	(4.30)	(1.33)	(0.84)	(2.83)	(0.34)	(0.47)	(12.11)	(2.24)	(1.72)	H6	0.98	0.73	0.87	0.90	1.37	1.04	1.57	3.36	2.76
	N7	0.20	0.96	0.98	0.32	1.02	1.00	0.75	2.09	2.81	H7	1.27	0.91	0.21	0.97	1.32	1.12	1.94	2.77	0.93
	N8	(1.25)	0.61	0.72	(0.83)	0.73	0.94	(4.97)	0.84	0.74	H8	0.40	1.08	1.31	0.46	0.65	1.06	0.37	0.79	4.39
	N9	(0.11)	(0.07)	1.00	0.12	0.19	1.19	0.11	0.32	2.80	H9	1.00	1.61	0.85	1.43	1.13	1.67	0.31	0.73	1.40
	N10	0.10	0.06	0.11	0.21	0.14	0.18	0.00	0.08	0.46	H10	0.91	1.05	-	0.93	0.97	1.09	1.12	0.90	1.25

4.1.2. Altman Z'-Score

While this paper refers to listed firms, the revised Z-score model was applied, which was designed for firms that are not traded on the stock exchange and wish to conduct bankruptcy forecasting. The reasons were the relatively low predictability of the classical model and to answer the question of whether the years of updating the model have had a tangible effect on the viability analysis. The main differences with the original model were found in the weights of the variables while replacing the variable X4 with the Accounting Value of Equity. The resulting final function is as follows:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \quad (2)$$

The cut-off points were also revised. Now, firms predicted to fail must have a score below 1.23 (as opposed to 1.81), the gray zone was placed between 1.23 and 2.90, and the safe zone includes scores of 2.90 and above. After applying the Altman Z'-Score model, the results were obtained, which are presented in Table 3 above. In this application, low predictability of the model was also obtained which, for the three years, ranged from 45% to 50%. Note that the Type II error also includes the results classified in the gray zone [42]. It should be underlined that, relative to the previous model, some healthy firms were classified closer to reality in that, in total for all three years of examination, 10 firms (3 in year −1, 4 in year −2, and 3 in year −3) were classified in the gray zone and not as failures. The exact Altman Z-scores calculated are shown in Table 4 above.

4.1.3. Altman Z''-Score

For the comprehensiveness of the research, it was considered appropriate to apply the latest revision of Altman. This model was used to minimize the industry effect and to make it more applicable to firms operating in developing markets, such as Mexico [11]. Again, differences were found in the weights of the variables, while the variable X5 was omitted altogether. The resulting final function is as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (3)$$

The cut-off points were also revised. Now, firms that are predicted to fail must have a score below 1.10 (as opposed to 1.26), the gray zone was placed between 1.11 and 2.59, and the safe zone includes scores of 2.60 and above [11]. After applying the Altman Z'-Score model, the results presented in Table 3 above were obtained. Although the predictability (forecasting) of the Altman Z-Score model ranged between 35 and 60%, it had better explanatory power than the other models, in that the basic error of ranking healthy firms to bankrupt ones was reduced. In year −1, two firms were correctly identified as healthy, while seven of the healthy ones were classified in the gray zone. Similarly, in year −3, although only two were correctly classified, six firms were in the gray zone, touching more closely to reality. Finally, the use of this model gave us the best predictability so far at 60%. The Altman Z-scores estimated are depicted in Table 4 above.

4.2. Ohlson Model

The next approach examined in this study is the Logit model of [12]. The application of this model was considered imperative as it is ranked among the most valid by the international literature. The model analysis was based on nine variables, which were analyzed as they were used to process the data of the study:

- X₁: Log[Total Assets/Gross National Product Price Index]. This indicator is the logarithm of a fraction, which consists of Total Assets in its numerator and the Gross National Product Price Index in the reference year.
- X₂: Total Liabilities/Total Assets.
- X₃: Working Capital/Total Assets.
- X₄: Short-term liabilities/Total Assets.

- X_5 : Take value 1 [if Total Liabilities > Total Assets], otherwise: 0.
 X_6 : Net Profit/Total assets.
 X_7 : Operating income/Total Liabilities.
 X_8 : Take value 1 [if Net Profit < 0 for the last two years], otherwise: 0.
 X_9 : $(|Net Profit NI(t) - Net Profit NI(t - 1)|) / (|Net Profit NI(t)| + |Net Profit NI(t - 1)|)$.

Specifically, Ohlson built three models: The first reports one year before bankruptcy, the second two years before bankruptcy, and the third between 1 and 2 years before bankruptcy. In some studies, the third model was applied to the third year before bankruptcy, and since the data collected in this study are up to three years earlier, it was deemed appropriate to apply the third model to the third year before bankruptcy here as well. The mathematical forms of the models for the 1st, 2nd, and 3rd years before bankruptcy, respectively, are as follows:

$$\begin{aligned}
 O_1 &= -1.32 - 0.407X_1 + 6.03X_2 - 1.43X_3 + 0.07575X_4 - 2.37X_5 - 1.83X_6 + 0.285X_7 - 1.72X_8 - 0.521X_9 \\
 O_2 &= 1.84 - 0.519X_1 + 4.76X_2 - 1.71X_3 - 0.297X_4 - 2.74X_5 - 2.18X_6 - 0.78X_7 - 1.98X_8 + 0.4218X_9 \\
 O_3 &= 1.13 - 0.478X_1 + 5.29X_2 - 0.99X_3 + 0.062X_4 - 4.62X_5 - 2.25X_6 - 0.521X_7 - 1.91X_8 + 0.212X_9
 \end{aligned} \quad (4)$$

Finally, the probability of default was defined as follows [42] $P = \frac{1}{1+e^{-z}}$, where z is the estimated O-score.

Having calculated the probability of bankruptcy, any rate above 50% indicates a corresponding probability of bankruptcy. After applying the Ohlson O-Score model, the results presented in Table 5 below were obtained. The number of correctly forecasted companies in each category (Type I/Type II error) is indicated and the relative percentages of correct and error predictions are shown. The total number of companies (size n) is also shown in the last column.

Table 5. Ohlson Model forecasting ability.

		Errors	No Correct	% Correct	% Error	Size n
Ohlson Model	1 year before bankruptcy ohlson O(−1)	Type I	9	90%	10%	10
		Type II	5	50%	50%	10
		Total	14	70%	30%	20
	2 years before bankruptcy ohlson O(−2)	Type I	7	70%	30%	10
		Type II	4	40%	60%	10
		Total	11	55%	45%	20
	3 years before bankruptcy ohlson O(−3)	Type I	8	80%	20%	10
		Type II	3	30%	70%	10
		Total	11	55%	45%	20

By observing the results, it can be seen that for the rates for year (−1), i.e., 1 year before bankruptcy, Ohlson's Model has better predictive power (forecasting) than Altman's models. For years −2 and −3 (i.e., 2 and 3 years before bankruptcy, respectively), the rates were low but were above 50%. Finally, the model results for the 2nd year before bankruptcy almost coincided with those for the 2nd year before bankruptcy. The estimated Ohlson O-Scores and their respective probabilities are depicted in Table 6 below.

Table 6. Ohlson Model scores.

		Non-Healthy Companies						Healthy Companies			Healthy Companies			
		O-Scores			Probabilities			O-Scores			Probabilities			
		Year −1	Year −2	Year −3	Year −1	Year −2	Year −3	Year −1	Year −2	Year −3	Year −1	Year −2	Year −3	
Ohlson Model	N1	2.52	2.34	(0.97)	93%	91%	27%	H1	0.38	(0.71)	(0.99)	59%	33%	27%
	N2	2.93	3.21	1.45	95%	96%	81%	H2	(0.73)	(1.36)	0.43	32%	20%	61%
	N3	(1.33)	0.71	1.12	21%	67%	75%	H3	(2.35)	(0.16)	0.79	9%	46%	69%
	N4	2.71	0.68	0.26	94%	66%	57%	H4	2.30	0.54	(1.32)	91%	63%	21%
	N5	0.75	0.88	1.13	68%	71%	76%	H5	(1.91)	0.44	0.59	13%	61%	64%
	N6	5.10	0.20	1.36	99%	55%	80%	H6	(0.08)	0.49	0.63	48%	62%	65%
	N7	1.18	(0.89)	1.38	77%	29%	80%	H7	0.47	0.79	1.43	62%	69%	81%
	N8	3.51	(0.49)	1.68	97%	38%	84%	H8	1.20	1.12	1.04	77%	75%	74%
	N9	0.28	(1.08)	0.67	57%	25%	66%	H9	1.08	(0.39)	(0.51)	75%	40%	38%
	N10	0.63	0.04	(0.35)	65%	51%	41%	H10	(0.19)	1.52	1.87	45%	82%	87%

4.3. Zmijewski Model

The last approach is the model of [13], which is a variant of the Logit model, called Probit (Probability Unit). The main difference from Logit is that the Probit model is based on the assumption that the cumulative probability distribution is normal and not logarithmic [42]. The variables of the model are three and are discussed below as follows:

X_1 = Net Profit/Total Assets.

X_2 = Total Debt/Total Assets.

X_3 = Current Assets/Current Liabilities.

The final function obtained was as follows:

$$X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \quad (5)$$

The higher the score, the higher the chances of bankruptcy. Subsequently, the result of the function (score) must be used to assign the probability of a firm going bankrupt. The probability is derived on the basis of the lower bound relationship [42]:

$$P = F_z = 1/\sqrt{2\pi}e^{-(z^2/2)} \quad \text{όπου: } F_z = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}e^{-(z^2/2)}} dz \quad (6)$$

where z is the estimated score obtained.

The calculations required to compute the model are naturally much more numerous and complex, which makes it difficult to use it widely. [123] ranked the firms in their sample according to the X-Score and also pointed out that there are no critical values for classifying firms into bankrupt and healthy. Firms with a negative X-Score ($X\text{-Score} < 0$) are classified as healthy, while firms with a positive X-Score ($X\text{-Score} \geq 0$) are classified as failing. After applying the Zmijewski X-Score model, the results presented in Table 7 below were obtained. The number of correctly forecasted companies in each category (Type I/Type II error) is indicated and the relative percentages of correct and error predictions are shown. The total number of companies (size n) is also shown in the last column.

Table 7. Zmijewski Model forecasting ability.

		Errors	No Correct	% Correct	% Error	Size n
Zmijewski X	1 year before bankruptcy zmijewski X(−1)	Type I	7	70%	30%	10
		Type II	8	80%	20%	10
		Total	15	75%	25%	20
	2 years before bankruptcy zmijewski X(−2)	Type I	5	50%	50%	10
		Type II	8	80%	20%	10
		Total	13	65%	35%	20
	3 years before bankruptcy zmijewski X(−3)	Type I	3	30%	70%	10
		Type II	8	80%	20%	10
		Total	11	55%	45%	20

While our sample was limited, we extracted results that were closer to reality. In particular, for year −1 (i.e., 1 year before bankruptcy) the results were 75% accurate. For the remaining two years, the results were 65% and 55% accurate, respectively. There also appeared to be a successive decrease of 10% in the three years under consideration, which is a perfectly rational result. Among the models analyzed, the Zmijewski X-Score showed better overall forecasting. The estimated Zmijewski X-Score results are illustrated in Table 8 below.

Table 8. Zmijewski Model scores.

		Non-Healthy Companies			Healthy Companies			
		Year −1	Year −2	Year −3		Year −1	Year −2	Year −3
Zmijewski Model	N1	1.42	3.32	(0.95)	H1	(0.62)	(1.01)	(1.12)
	N2	1.45	0.50	1.11	H2	(0.68)	(0.80)	(1.61)
	N3	(2.09)	(1.29)	(1.19)	H3	(2.49)	(2.56)	(1.86)
	N4	1.33	1.68	(1.70)	H4	3.35	(1.57)	(1.35)
	N5	(0.79)	(1.18)	(1.82)	H5	(2.40)	(2.14)	(2.14)
	N6	3.86	(1.12)	1.69	H6	(1.33)	(2.19)	(1.91)
	N7	0.23	(0.30)	(0.49)	H7	(0.46)	(0.67)	(0.73)
	N8	1.82	0.05	(0.60)	H8	(0.42)	(0.68)	(6.46)
	N9	(0.10)	(0.15)	(1.25)	H9	0.26	0.02	0.17
	N10	0.07	0.16	0.07	H10	(0.30)	0.18	0.18

5. Conclusions

Corporate bankruptcy is of great interest as, although over the last 50 years many analysts have dealt with the issue in Greece and internationally, there has been no convergence of views on both the variables and the method of analysis. The present research has shown that Altman's basic predictive model as well as the revised models have low overall predictability for all three years prior to bankruptcy, compared to the Ohlson and Zmijewski Models. The findings of this research add to the existing literature and should be considered in parallel with similar research, and conclusions are drawn about the predictive ability of corporate bankruptcy prediction models. It should be noted that this is the first effort to compare the three forecasting methods (also allowing for the three alternative Altman score estimates).

Corporate bankruptcy predictions may have important practical implications for financial market structures. Hence, they are extremely important/useful for setting mea-

asures that allow for effective financial regulation, which is of primary importance especially in periods of crisis. Further, they enhance corporate governance efficiency, amplify audit competence, and allow for more effective portfolio management.

Regarding Greece, the present review and comparative application of bankruptcy prediction models contribute to a better assessment of viable companies in the construction sector and will be able to assist in the making of the portfolio, business, financial, risk, and corporate governance decisions of interested stakeholders (as noted by [124]) on the one hand, and of the academic community on the other, paving the way for further research. The study outcomes are especially useful due to the sector's importance to countries' development and growth, particularly due to the consecutive crises the country has faced since 2010 (the economic crisis, the pandemic crisis, the Ukrainian crisis, the energy crisis, etc.).

Further research focused on the construction sector could involve the application of the models examined herein to non-listed companies of approximately the same size for the same period and the critical evaluation of the results obtained, thus overcoming the sample size limitations of the present study. Furthermore, the repetition of the study in a few years would further enhance the results' quality. This is feasible as there are more bankrupt companies due to the continued crisis, thus further addressing the study sample's size limitations. Finally, expanding the application of the models examined in the present study to other sectors of the Greek economy, or to the all the companies listed on the Athens Stock Exchange, and comparing the results obtained could lead to very interesting conclusions for the Greek economy as a whole. Finally, interesting conclusions could be drawn if the same methodology was applied to listed construction companies in the Stock Exchanges of other European countries that signed Memorandums during the economic crisis (i.e., Cyprus, Portugal, Spain, etc.). Finally, the potential extension of this study would involve the comparison of the results to those obtained using other bankruptcy forecasting methods (i.e., machine learning techniques, etc.) as described above.

Author Contributions: Conceptualization, S.A., K.T. and P.B.; methodology, S.A., K.T. and P.B.; validation, S.A., K.T. and P.B.; formal analysis, S.A.; investigation, S.A., K.T. and P.B.; data curation, S.A. and K.T.; writing—original draft preparation, S.A., K.T. and P.B.; writing—review and editing, K.T. and P.B.; visualization, S.A., K.T., and P.B.; supervision, K.T. and P.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

One-way ANOVA.

		Non-Healthy Companies					Healthy Companies					
		SS	DF	MS	F	P	SS	DF	MS	F	P	
Anova	1 year before bankruptcy	Between	2.879	3.000	0.959	4.866	2.866	3.883	4.000	0.971	10.840	0.000
		Within	7.101	36.000	0.197			4.030	45.000	0.089		
	2 years before bankruptcy	Between	2.482	3.000	0.827	9.348	0.000	4.944	4.000	1.236	23.058	0.000
		Within	3.186	36.000	0.885			2.412	45.000	0.053		
	3 years before bankruptcy	Between	2.748	3.000	0.916	16.751	0.000	5.586	4.000	1.397	22.909	0.000
		Within	1.969	36.000	0.055			2.743	45.000	0.061		

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