International Journal of Finance, Insurance and Risk Management
Volume XII, Issue 3, 2022

pp. 23-45

Analyzing Insolvency Prediction Models in the Period Before and After the Financial Crisis: A Case Study on the Example of US Firms

Submitted 02/09/22, 1st revision 23/09/22, 2nd revision 06/10/22, accepted 30/10/22

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Abstract:

Purpose: *The study aims to assess the most accurate bankruptcy prediction model for US firms.*
Design/methodology/approach: *Validating the accuracy of bankruptcy prediction models can provide management with a handy tool as it can decrease potential damage, and carry out corrective actions by intervening and preventing insolvency. The impetus of this paper is not to create a new prediction model but to validate the practical application of 3 widely accepted models to determine accuracy in predicting corporate insolvency for; Altman's, Taffler's and Ohlson's models. The Logit regression framework is employed to estimate the 3 aforementioned models.*
Findings: *The results revealed that: i) Taffler's and Ohlson's models are the most accurate for correctly predicting failed and non-failed firms with an average predictive ability of 75% and 87%, respectively, ii) Altman's model had a rather lower predicting ability of 57%, iii) Altman's model predicts high accuracy for only solvent firms, iv) Taffler's and Ohlson's models can subsequently, assist lenders, auditors, executives, investors and corporations to evaluate bankruptcy risk.*
Practical implications: *An early warning system can protect a firm from running into insolvency. Furthermore, a country with healthy economic conditions can attract national and international investors. In view of that, a robust bankruptcy predictor reduces the probability of large number of insolvencies occurring.*
Originality value: *This study found that failed US firms had low liquidity, low profitability and high gearing. Therefore, these three aspects should be measured as the primary concern when examining a US firm's financial condition.*

Keywords: *Insolvency Prediction Models, Bankruptcy, US firms.*

JEL Classification: *G33.*

Paper type: *Case study.*

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Acknowledgment: *The authors would like to thank the Postgraduate Programme M.Sc. in Finance and Shipping, at the University of West Attica, Greece for funding this paper's expenses.*

1. Introduction

One of the most important threats that businesses are facing today, regardless of their size and nature of operations is insolvency (Charitou *et al.*, 2004). Due to the recent instability of the global economic conditions, the number of corporate bankruptcies has increased (Evans and Borders, 2014). Furthermore, by executive's use of earnings management, which paints an exceedingly optimistic picture of a company's business activities and financial position, it hides the real circumstances, which have made it increasingly difficult to predict corporation's financial distress (Xu *et al.,* 2007).

The issues that lead businesses to failure can differ for individual corporations however, most economists explain the phenomenon due to businesses incurring increased interest rates, recession squeezed profits and severe debt burdens (Charitou *et al.*, 2004). The financially distressed/insolvent company can have negative consequences for its owners, shareholders but also for other interested groups such as bank lenders, investors, employees which can affect the wider economy and society.

The use of insolvency prediction models has been the centre of much interest in the academic and professional research. The need for reliable models that predict corporate failure promptly and accurately is crucial to allow the groups concerned to take preventive or corrective steps (Jackson and Wood, 2013). The main objective of this study is to verify which insolvency prediction model is the most useful for predicting bankruptcy with the help of accounting data provided by the financial statements. Therefore, managers can take the most appropriate actions to avoid future insolvency. Various past studies have developed insolvency models to monitor a business's financial condition.

The main aim of this study is to examine which bankruptcy prediction model is the most accurate as a model for predicting possible corporate insolvency among US companies. Three bankruptcy models are examined: Altman's, Taffler's and Ohlson's models. The aim is not to create a new prediction model, but instead to review the strengths of the existing models that are widely used in practical terms. When a business goes under insolvency there are severe consequences thus, a reliable financial ratio model is crucial for a company.

The last recession in US had a major impact in the US economy as it affected businesses throughout the country. Both large and small corporations felt the pressure during the credit crunch. It led to bankruptcy of many firms, thousands of people made redundant, and slow economic recovery. Due to the large scale of bankruptcy during the economic downturn, it raised the question whether firms' had adequate knowledge of assessing their financial health. Thus, insolvency prediction models are significantly important in order to provide warning signals well in time for management to be able to rectify the problems.

The rest of the paper proceeds as follows. Section 2 reviews the literature on insolvency prediction models. Section 3 describes the methodology and presents the specific models used to predict insolvency. The section also describes how the new coefficients are retrieved and the data sources and data collection process. Section 4 analyses the findings of the paper. Finally, section 5 discusses the research limitations and provides suggestions for future research.

2. Literature Review

It is evident that businesses can share some similarities in the cause which triggered insolvency (Kula, 1998). A common term of financial distress is when a firm *'cannot meet its current obligation'* (Altman and Hotchkiss, 2006, p. 5). This appears when insufficient cash or equivalent to pay a loan leads to legal default which often results in filing for bankruptcy.

A reason for business failure is not having enough short term liquidity (Isachenkova and Weeks, 2009). This is where there is a lack of funds to pay out for short term purposes. To resolve the situation firms often take out short term loans however, most often the temporary lack of liquidity deteriorates with time due to loss in earnings. Hence, the firms become incapable of serving its immediate and long term borrowings/debt obligations, and inevitably runs in to insolvency.

Many failed firms are highly correlated with the county's economic status (e.g., down turn) as well as changes in the interest rates (Samuel *et al.*, 1995). Businesses are more probable to fail under a slow economy compared with a thriving economy. Isachenkova and Weeks (2009) claimed that economic recession would lead to a fall in industrial activities and low profitability for companies. It contributes to a lack of profits and an absence of external financing (IPOS or SEOS).

Vandyck (2006) also suggested that unanticipated economic downturn is a key issue causing business Failure. In the US when the recent recession occurred it was due to economic disruption from aspects such as banks increasing interest rates. There were many businesses that struggled to keep up with their loan payments due to higher interest rates charged and went bankrupt.

In many situations firms become insolvent because they may be influenced by certain characteristics other than financial, some of them qualitative such as poor quality of management, products, equipment (Dimitras *et al.*, 1996). In many businesses poor management has detrimental effects, not knowing what products/service sells better than others and what product/services have a negative response with their targeted audience can be damaging.

Lack of diversification, a firm that is homogeneous can be arguably less productive. Under incompetent management, there may be high levels of gearing, with huge debts and increased expenditure that's out of control. Therefore, weak leadership and incorrect decision making can become a serious concern for firm solvency.

Another important factor which has often lead to insolvency is false and insufficient financial information from invalid data or window dressed figures. This could lead to management making mistakes in financial decision making. For example, if executives display distorted figures in the annual report the company maybe left in a vulnerable state as it may show false positive signs of increased profits however, in reality the operating profit maybe stable or even weaker than what is stated. Window dressing accounts is where a manager purposely hides the actual figures and is an indication for concern regarding the firm's truthful financial performance.

Other important aspects which can affect a firm's solvency is keeping up with fierce competition, advances in technology, and governmental influence (Isachenkova and Weeks, 2009). Poor profitability is an important factor in business failure as it would be difficult to keep up with competitors in the same industry with lower earnings. In many cases the product/ services can become obsolete due to the rapid changes in the market. This means a heavy loss in particular product or services produced as demands have lessened.

Consequently, this results in a weakened company in terms of power and reputation. In some circumstances regulations from government influence a company's failure in a certain way. For example, there are many regulations a firm has to follow, the US government believed that if they had more regulations, imposed more fees and required more licenses that they would be able to "fix" things. However, in reality many firms felt like they were being suffocated and eventually gave up (Synder, 2010).

Altman's (1968) original model has been used in recent research to evaluate financial conditions of firms from diverse industries and periods. It continues to be used in different business situations involving the prediction of bankruptcy and other financial stress conditions. Commercial banks use the model as part of the periodic loan review process, and investment bankers use the model in security and portfolio analysis. The model has been employed as a management decision tool and as an analysis tool by auditors to assess their clients' abilities to continue as going concern (Grice and Ingram, 2001).

Beaver (1966) defined failure as the inability of a firm to pay its financial obligations as they mature. Beaver (1966) was one of the first to develop a univariate model approach. This compared the mean of 30 ratios for 79 non failed and 38 failed firms in the US industry for a five-year period.

The paper was conducted in a manner where Beaver tested the individual ratios predictive abilities in classifying bankrupt and non-bankrupt firms by their asset size. The results indicated that ratios had the capability to separate failing firms from surviving ones. Beaver found that net income to total debt had the highest predictive ability (92% accuracy one year prior to failure). Beaver's (1966) univariate analysis, a number of bankruptcy predictors set the stage for the multivariate attempts which was followed by other authors. There was a need for a combined ratio model, as the univariate study only considered the measurements used for group assignments one at a time.

Differing to the univariate technique, Altman (1968) developed a bankruptcy prediction model by the use of Multivariate Discriminant Analysis (MDA), a statistical technique which is used primarily to classify and/or make predictions in problems where the dependent variable emerges in qualitative form e.g. bankrupt or non-bankrupt.

The purpose of Altman's (1968) paper was to attempt an assessment of the issue on ratio analysis. The paper examined 33 solvent companies and 33 insolvent companies in the US industrial sector. The results demonstrated that firms with a Z score lower than 1.81 were bankrupted and firms with a Z score above 2.99 were financially healthy. Results showed that Altman (1968) paper had high predictive ability one year prior (95%) however, it considerably dropped to 72% for two years before failure, 48% for three years before failure, 29% for fourth year and 36% five years prior failure. This demonstrated that the study formed a high predictive capable model for the first two years before bankruptcy.

Grice and Ingram (2001) carried out a study which evaluated the generalizability of Altman's (1968) Z – score model by using a balanced sample of distressed and non-distressed companies from different time periods, industries and financial conditions other than those used by Altman to develop his model. The findings indicated that the accuracy of Altman's model's declined when applied to the new sample, Altman (1968) reported 83.5% for the overall accuracy for his model using a sample from 1958 to 1961. The new Sample reported an accuracy of 57.8% for the 1988-1991 period in the study. The magnitude and significance of the models coefficients differed from those reported by Altman.

Grice and Ingram (2001) study's findings suggested that Altman's model was not as useful for predicting financial distress in recent periods as it was in the 1960's. It was unlikely that Altman's model would achieve results equally well in all financial periods. A major weakness has been that the Z-score model used samples in prior research that were dated way back to the 1960's and 1970's. Since then, many factors have come in to existence, for example, newer ratios, change in interest rates, the GDP, etc.

The UK is considered as one of the largest economic environments worldwide. The London Stock Exchange has large daily amount of transactions. Researchers argue that it has a financial environment 'ideal' for statistical models that aid the evaluation of company solvency and performance (Taffler, 1983). Kula (1998) asserted that Taffler's (1983) model a UK based discriminant model as the second renowned work in this context. Taffler (1983) investigated insolvency for UK manufacturing and construction firms by developing the MDA statistical technique.

It showed that a firm that had a positive Taffler Z score would not fail, while a negative score could go bankrupt. The research created a discriminant model with an accuracy of 95% for bankrupt companies and 96% for non-bankrupt companies' a year prior bankruptcy. Since Altman's work, enormous amount of literature has evolved using a related approach to identify potential insolvent concerns in diverse industries.

Charitou *et al.* (2004) carried out a study with a data set of fifty-one matching pairs of failed and non-failed UK public industrial firms over a period of 1988-1997. An average classification rate over three years was used for validation for the four methods: 1) Logit: A parsimonious logit model including three financial ratios, a financial leverage, profitability and an operating cash flow. 2) Neural Network (NN), using feed forward neural networks. 3) A second Logit validated by using Lachenbruch Jackknife Technique and 4) Altman's forecast.

Results showed that the NN model and Logit model's results were considered the most reliable for predicting UK corporate failure as it had the highest overall prediction.

One of the most well-known study is Ohlson's (1980) model based on a logit regression analysis. Logit analysis considers the probability that the firm will go bankrupt or not. This is a widely used model in the US for bankruptcy prediction as well as around the world (Tseng and Hu, 2010). This model was tested for generalizability and was deemed to be appropriate for different industrial sectors.

Ohlson (1980) conducted a study of 105 bankrupt firms and 2,058 non bankrupt firms in the industrial sector. Ohlson suggested that the logit regression was better than MDA as it avoided some limitations of the MDA. Ohlson's (1980) 9 factor logistic regression method for US manufacturing companies resulted in a notable accuracy prediction of 96% for both one and two years prior bankruptcy. These were impressive accuracies and since then many authors have used this model for insolvency prediction.

When a model is used in periods different than those used to develop and test the model, researchers sometimes presume the model is steady across economic conditions. However, this is not always true. Menash (1984) evaluated the effect of changing economic factors on the accuracy, magnitude and significance of model coefficients. Menash (1984) developed four models using samples from the 1972-1973, 1974-1975, 1976-1977 and 1978-1980 periods each indicating a different economic environment. He reported that the accuracy and structure of the models changed over the four time periods with changes in regards to inflation, interest rates, and credit availability.

Hence, a firm's performance and survival is influenced by the environment and its changes as well as being influenced by national and international economic conditions (Dimitras *et al.*, 1995).

Prediction time frame is crucial; it is important to consider how far ahead the model is able to accurately predict bankruptcy. Some models were able to predict bankruptcy much sooner than others. Deakin's (1972) model was able to predict bankruptcy with 96% accuracy two years prior to failure. Similarly, Dwyer's (1992) model predicted bankruptcy with 97% accuracy three years prior to failure. El Hennawy and Morris (1983) model accurately predicted bankruptcy 100% up to five years before failure. As a result, a model that is able to accurately predict bankruptcy five years earlier becomes significantly valuable.

The literature on bankruptcy prediction goes back to the 1930's beginning with the initial studies relating the use of ratio analysis to predict future bankruptcy. Research up to the mid 1960's focused on univariate single factor ratio analysis. There was great variety in bankruptcy prediction models, from how many and which factors should be considered to what methods are employed to develop the model. For example, Altman's (1968) model was a 5 factor multivariate discriminant analysis model while Boritz and Kennedy's (1995) model was a 14 factor neural network.

The number of factors ranged from 1 to 57 in the research area of different studies. Appendix A lists the 42 factors that were considered in the vast majority of studies. The most common factor was the ratio of net income to total assets, which was included in 54 studies. The second most common factor was the ratio of current assets to current liabilities, found in 51 studies (Bellovary *et al.*, 2007).

Altman's Z-score model has been a quite accurate model in predicting corporate bankruptcy over the last 30 years. This is more recently confirmed by a number of research studies such as Lugovskaya (2010); Gutzeit and Yozzo (2011a); Li and Rahgozar (2012); Li *et al.* (2013); Bhandari and Iyer (2013); Goswami *et al.* (2014); Mizan and Hossain (2014), among others.

Almamy *et al.* (2016) investigated a modification of Altman's Z-score model, by adding a new variable, in predicting insolvency for UK firms from 2000 to 2013. They used financial ratios (including cash flow ratio) and discriminant analysis. Theirs results suggest that the modification of Altman's Z score model may lead to improved prediction results.

Jones (1987) suggested the need for an appropriate validation technique when creating and testing bankruptcy prediction models and recommended the use of a hold-out sample to test external validity. Many studies have used the Lachenbruch technique (or "Jackknife"). The Lachenbruch technique has been an acceptable and frequently required technique if the sample size is small.

However, a better indication of validity can be obtained through the use of a hold-out sample (a separate set of observations). The model's applied to a new set of observations and is able to obtain a stronger measure of the model's predictive accuracy. However, it appears that many researchers did not use Jones (1987) suggestion for the use of a hold-out sample to obtain external validation of models. Some did but roughly half of the studies continued to use validation techniques other than hold-out testing after the publication of Jones' article (Bellovary *et al.*, 2007).

3. Methodology and Data

3.1 Research Methods

Discriminant analysis was a very popular method for model development of bankruptcy prediction, in the early stages. However, progression and technology made other methods including logit analysis, probit analysis, and neural networks more prominent (Bellovary *et al.*, 2007).

Altman (1968) was one of the first to develop a bankruptcy prediction model using the multivariate discriminant analysis (MDA), this included five financial ratios. The MDA built numerous variables in to one model and the financial ratios were weighted with their power of prediction (Bellovary *et al.*, 2007). To predict a company's failure, the Z score was initiated, for the model to classify observations in to separate groups. The average score of each group was worked out for determining the cut off points.

A sample that had a Z score below the calculated cut off was perceived as a potential bankrupt firm (Leksrisakul and Evans, 2005). The MDA technique has been extensively used as an insolvency prediction model and has immensely been leading amongst other predictive models. An advantage of using this methodology was the high accuracy rate in dichotomously distinguishing solvent and insolvent companies.

MDA considers an entire profile of characteristics common to the relevant firms. The approach has been extensively used in many countries including USA. Bellovary *et al.* (2007) found that 63 studies in different countries had used MDA as the primary methodology. There are certain limitations with the MDA model such as, the measurement of variables as ratios and cut off score in MDA cannot be tailored. As a result, it may not be appropriate in certain conditions.

Logit and Probit models started to appear in the late 1970’s but did not overtake MDA in popularity until the late 1980’s. The Logit model utilizes the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable. In the context of failure prediction, the technique weighs the financial ratios and creates a score for each company in order to be classified as either failed or healthy (Charitou *et al.*, 2004).

Logit analysis and Probit analysis take in to account the probability that the firm will go bankrupt. The main difference between these two methods was that Probit analysis required nonlinear estimation (Dimitras *et al.*, 1996). A benefit is that these models can offer advantages in business decision making (Ohlson, 1980). The drawbacks for these methodologies are that the sample sizes have to be large to provide a more accurate model as the procedure depends on a sufficient number of observations in each of the categories for its clarifying variables.

The paired-sample companies are chosen in this paper to provide a "control" over variables that may have otherwise blurred the association between ratios and failure. By 1923, the ratio literature implied that industry factors must be included in any complete ratio analysis. Beaver (1966) argued that differences appear between industries that prevent the direct comparison of companies from diverse industries.

Another way of presenting this argument would be to say that the same numerical value of a ratio (e.g., a current ratio of 2.00) entails a different probability of failure amongst differing industries. The evidence presented for industry differences is that the ratio distributions differ among industries (Beaver, 1966). Conversely, such evidence is not conclusive, as the failure rate can vary within industries to compensate for the differences in the ratios. No evidence has been provided to specify whether or not the compensating differences do in fact exist.

Even though, little consideration has been given towards the influence of asset size, there are some statistical reasons explaining why the asset size changes the relationship between ratios and failure. Statistical formulae imply that the variability of total return to the firm will increase less than proportionately to the size of the firm. The rate of return of a company will be more stable as asset size rises (Beaver, 1966).

The financial ratios within the three testing models were collected and calculated for three years prior bankruptcy. If the probability is higher than 50% the model predicts solvency and if the probability is lower than 50% the model predicts insolvency. If the models correctly predict the status of each firm it is given a value of 1. On the contrary, if the firm incorrectly predicts a value of 0 is given. The model with the highest predictability percentage is regarded as the best insolvency prediction model.

Altman's Z-score

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

where Z_i denotes the overall index, $x_{1,i}$ is the working capital to total assets, $x_{2,i}$ are the retained earnings to total assets, $x_{3,i}$ are the earnings before interest and tax (EBIT) to total assets, $x_{4,i}$ is the market capitalisation to total liabilities, whereas $x_{5,i}$ denote the sales to total assets. The cut-off score for the original model is 2,675.

However, this paper estimates Altman's model in a logit framework so the Z-score is converted into probability. The probability scores are between 0 and 1. If the probability is higher than 50% the model predicts that this company will survive. If the probability is lower than 50% the model predicts that this company will not survive.

Taffler's Model

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

where Z_i is the overall index, $x_{1,i}$ is the profit before tax to current liabilities, $x_{2,i}$ denote the current assets to total liabilities, $x_{3,i}$ are the current liabilities to current assets, $x_{4,i}$ expresses the no-credit interval in days (liquid current assets / daily cash operating expenses) or (quick assets – current liabilities)/((sales – profit before tax)/365).

In the original model the cut-off score is -1,95. We estimate Taffler's model in logit framework so the Z–score is converted into probability. The probability scores are between 0 and 1. If the probability is lower than 50% the model predicts that this company would not survive. Whereas, if above 50% the company would survive.

Ohlson's Model

$$Z_i = -1.3 - 0.4x_{1,i} + 6x_{2,i} - 1.4x_{3,i} + 0.1x_{4,i} - 2.4x_{5,i} - 1.8x_{6,i} + 0.3x_{7,i} - 1.7x_{8,i} - 0.5x_{9,i} + \varepsilon_i \qquad (3)$$

where Z_i is the overall index, and the explanatory variables follow:$x_{1,i}$:is the log of the ratio total assets to gross national product price level index, $x_{2,i}$ is the total liabilities to total assets, $x_{3,i}$ is the working capital to total assets, $x_{4,i}$ is the current liabilities/ current assets, $x_{5,i}$ is the binary variable that takes the value of 1 if total liabilities are greater than total assets and 0 otherwise, $x_{6,i}$ is the net income/ total assets, $x_{7,i}$ is the funds provided by operation/ total liabilities, $x_{8,i}$ is the binary variable that takes the value of 1if the net income is less than 0 for the last two years and 0 otherwise, and $x_{9,i} = \frac{(NI_t - NI_{t-1})}{|NI_t - NI_{t-1}|}$, where NI_t is net income for the recent year. Initially Ohlson (1980) used 50% cut-off level to distinguish between bankrupt and non-bankrupt firms.

In the present study, only the first 4 variables are used from Ohlson's (1980) model. The probability scores are between 0 and 1. If the probability is lower than 50% the model predicts bankruptcy and if it is above 50% it predicts solvency.

Logit Regression

Running the logit regression within a new sample period meant that, the coefficients of the aforementioned models are re-estimated. The dependent variable is a discriminant variable which takes two results in to account: bankrupt and non-bankrupt. However, instead of a cut -off score the models provides a probability score for each of the observations (Burns and Burns, 2008). The companies are divided in to a basic sample and a hold out sample. The basic sample is used to create the new coefficients for the models. The new coefficients have been estimated with logistic regressions consistent with the method presented in Burns and Burns (2008):

$$P\left(d_t = 1 \setminus x_{j,i}\right) = 1 - \Phi\left(-v_0 - \sum_{j=1}^{N} v_j x_{j,i}\right), \tag{4}$$

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

3.2 Data Sources and Data Collection

The data are collected from Bloomberg database. The figures collected from Bloomberg are from the statement of financial position, income statement and the cash flow statement. The data are collected for the period 2005-2012 for US firms. 50 bankrupt US companies are collected. To check if the models could differentiate between healthy and unhealthy firms, 50 financially healthy US firms are retrieved as well.

Each bankrupt company was matched with each non bankrupt company in regards with industry, asset size. This study paired bankrupt with non-bankrupt companies by their asset size, as the size of a company can have an effect on the likelihood of failure. Firms with similar ratios but different asset size can give confusing results. In addition, a one to one selection i.e. 50 bankrupt and 50 non bankrupt companies is consistent with empirical literature in this field of research.

This includes the three testing models Altman (1986), Taffler (1983) and Ohlson (1980) using same industry/size. When examining the application of bankruptcy prediction models of insolvent firms, the model can better determine when assessing both solvent and insolvent firms, as inaccuracies either way can give the wrong impression to the model users (Fitzpatrick, 1934).

The discussion of the results takes in to account the predictive inaccuracies of each type of error. Only companies with a full data set are included in the sample. The model's predictive accuracy is tested one year, two years and three years, prior to the bankruptcy. Timeframe was an imperative factor of the accuracy of the prediction model as aspects of failed firms commonly deteriorate near the time of bankruptcy.

4. Analysis of Findings

Pongstatat and Lawrence (2004) claimed that Type I and Type II errors differ in their consequences of inaccuracies. Both mistakes can have serious consequences for a firm. Type I error is predicting bankrupt firms as non-bankrupt. Type I error is harmful as it will eventually lead to a company's insolvency with a great surprise due to having a strong belief in the prediction model which suggests that it will not fall in to insolvency.

This leads to management having insufficient time to take preventative actions due to being unaware of the real situation. Type I errors can have a loss of business clients (audit clients) damage to a firm's reputation and possible lawsuit/court costs (Bellovary *et al.*, 2007). Type II is predicting non bankrupt firms as bankrupt. In contrast, Type II errors can mislead a firm to insolvency and have negative impressions with the firm's stakeholders, lenders etc. It can have an adverse effect on the financial decisions made.

Altman Hold out:

	1 Year		***2 Years***		***3 Years***	
	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type I	30%	70%	30%	70%	20%	80%
Type II	90%	10%	80%	20%	100%	0%
Total	60%	40%	55%	45%	60%	80%

***Taffler Hold Out**:*

	1 Year		***2 Years***		***3 Years***	
	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type I	100%	0%	50%	50%	10%	90%
Type II	100%	0%	90%	10%	100%	0%
Total	100%	0%	70%	30%	55%	45%

Ohlson Hold Out:

	1 Year		***2 Years***		***3 Years***	
	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Type I	100%	0%	90%	10%	50%	50%
Type II	100%	0%	100%	0%	80%	20%
Total	100%	100%	95%	5%	65%	35%

Source: *Own study.*

Table 1. *Percentages for Accurate Prediction*

Hold Out For:	***1 Year***	***2 Years***	***3 Years***	**Average**
Altman	60%	55%	60%	**58%**
Taffler	100%	70%	55%	**75%**
Ohlson	100%	95%	65%	**87%**

Source: *Own study.*

First, with regard to the results, it has to be stated that Ohlson's (1980) model comprising of 9 variables was not used. Only the first 4 variables of the model were calculated with new coefficients, due to errors produced when estimating the new coefficients for the last 5 variables. Nonetheless, the four variables that are used under Ohlson's model demonstrated high predictive ability compared to the other two models. The two remaining models, Altman's (1968) model consisting of 5 variables and Taffler's (1983) model comprising of 4 variables, all variables coefficients are included in the original versions and in the re estimated.

It is evident from the results of Table 1 that Taffler (1983) and Ohlson's (1980) model are the most accurate prediction models when applied to US firms. The Ohlson model had an overall correct rate of 65%, 95% and 100% and Taffler's model had accuracy of 55%, 70%, 100% for 3 years, 2 years and 1 year respectively prior bankruptcy.

On the contrary, Altman's (1968) model performed with relatively stable results across the three years, 60% (3 years), 55% (2 years) and 60% (1 year) prior insolvency. Altman's results displayed surprisingly unsuccessful outcomes for measuring failure of US firms. The other two models had 40% higher predictive ability than Altman's (1968) model in year 1. Accordingly, it can be concluded that

Taffler's (1983) model and Ohlson's (1980) 4-factor models are the best predictors of financial distress in terms of practical applications for US companies.

The model's results for insolvent firms alone are promising for the first and second year. Tafller's and Ohslon's model are 15% and 40% higher than Altman's 55% in the second year. This particularly indicates the two models' strengths in high prediction accuracy and weakness in Altman's prediction accuracy.

An examination of Altman's data indicated weaker results because the accuracy rate dropped from first year (60%) to second year (55%) and then came back up to the same percentage 60% in the third year demonstrating its ineffectiveness.

Tables 2, 3 and 4 display for the 3 models, the correct and incorrect predictions for solvent and insolvent predictions over the 3-year period.

Table 2. *Summary of Findings: First Year Before Insolvency*

Group	No. of Firms	Altman		Taffler		Ohlson	
		Correctly Classify	Percentage	Correctly Classify	Percentage	Correctly Classify	Percentage
Insolvent	10	3/10	30%	10/10	100%	10/10	100%
Solvent	10	9/10	90%	10/10	100%	10/10	100%
Overall	20	12	*60%*	20	*100%*	20	*100%*

Source: *Own study.*

Table 3. *Summary of Findings: Second Year Before Insolvency*

Group	No. of Firms	Altman		Taffler		Ohlson	
		Correctly Classify	Percentage	Correctly Classify	Percentage	Correctly Classify	Percentage
Insolvent	10	3/10	30%	5/10	50%	9/10	90%
Solvent	10	8/10	80%	9/10	90%	10/10	100%
Overall	20	11	*55%*	14	*70%*	19	*95%*

Source: *Own study.*

Table 4. *Summary of Findings: Third Year Before Insolvency*

Group	No. of Firms	Altman		Taffler		Ohlson	
		Correctly Classify	Percentage	Correctly Classify	Percentage	Correctly Classify	Percentage
Insolvent	10	2/10	20%	1/10	10%	5/10	50%
Solvent	10	10/10	100%	10/10	100%	8/10	80%
Overall	20	12	*60%*	11	*55%*	13	*65%*

Source: *Own study.*

The ability to correctly classify both insolvent and solvent firms is justified for why Taffler and Ohlson's model are chosen to be the best prediction models for US firms. The discriminants of surviving firms show that Altman's (1968) model is not a better bankruptcy tool in the case of the US firms. A remarkable result from this paper was the low predictive ability of bankrupt firms throughout the three years, 30% in year 1, 30% in year 2, and 20% in year 3.

However, it had a high predicting ability for non-bankrupt firms within the three years. 90% accuracy in year 1, 80% accuracy in year 2 and 100% accuracy in year 3. On the contrary, Taffler's (1983) model demonstrated high accuracy the majority of times for both failed and non-failed firms 100% (Year 1), 50% (Year 2), 10% (Year 3) for solvent firms and 100%, (Year1) 90% (Year 2) and 100% (Year 3) for insolvent firms during the three-year period.

Ohlson's model also indicated high accuracy for both solvent and insolvent firms within the three years.100%, (Year 1), 100% (Year 2) and 80% (Year 3) for solvent firms and 100% (Year 1), 90% (Year 2) and 50% (Year 3) for insolvent firms. These results are evidenced in Table 2, 3 and 4.

4.1 Interpretation and Implications of Results

Comparing the prediction accuracy of the present paper with earlier studies, Taffler's model can be adopted as the better bankruptcy prediction model. Ohlson's (1980) model in the current version constituting 4 variables is also a very good indicator of corporate bankruptcy. The empirical findings in this dissertation reveal that both models had high external validity accuracy than most models in the literature due to providing up to 100% accuracy for one-year prior insolvency.

Thus, it can be suggested that it does not particularly matter if the model is constructed based on firms' observations from one country and tested on a different country's sample. This was demonstrated in the current paper's results. Even though, Altman's (1968) model is constructed based on US firms it still provides weaker results than Taffler's model which is constructed based on the UK firms when examining the predictive ability of the models in US firms.

In the literature of bankruptcy, Grice and Ingram (2001) found that accuracy of Altman's (1968) model declined when applied to a new sample. It had an 83.5% overall accuracy for an earlier 1958-1961 sample and 57.8% for the later 1988-1991 sample. The accuracy had considerably dropped by 25.7%. In consistent with the present paper, Altman's model was also not very useful for predicting insolvency with the new coefficients of a recent sample period. Menash (1984) also reported that accuracy and structure of models changed over different sample periods.

This placed particular emphasis on the fact that Altman's model was created in 1968. The model was ineffective for measuring accuracy with a recent testing period. Altman used sample periods back in the 1960's and 1970's which is a long time ago, since then many new studies have created new more powerful models. For instance, Ohlson (1980) model was developed 12 years after Altman (1968).

Similarly, Taffler's (1983) model was developed 15 years later than Altman's. This means that these and many other new models may have made certain modifications such as including different ratios which are deemed more appropriate for the recent complex corporation's structure.

Taffler (1983) a UK based model has been asserted as a prominent model (Kula, 19998). Large number of papers amongst several countries have progressed while using this approach. In his original study Taffler examined the UK manufacturing and construction industry. His model attained impressive results of 95% accuracy for insolvent companies, and 96% for solvent companies a year prior bankruptcy. In comparison with the current study, Taffler's model produced even higher accuracy prediction accuracy one year prior bankruptcy. This number dropped to 70% in the second year however, still high enough to send warning signals as it was above the 50% benchmark.

Therefore, Taffler (1983) model can be used for high risk bankruptcy firms and thus, it can provide all interested users with warning signals to identify company failure two years before it's occurrence. This does not include the third year before solvency due to a low indication of 55%.

Ohlson's (1980) model has also been extensively used as a prediction model in this field of research. In his original study amongst US firms it included a 9 factor logistic regression. His study produced 96% correct classifications for one and two years prior insolvency. In similarity, the present study included Ohlson's (1980) 4 variable model, which displayed extremely high accuracies. It had 100% accuracy 1 year prior and 95% for 2 years prior bankruptcy.

This validates that Ohlson's model incorporates appropriate ratios for predicting bankruptcy. It's superior accuracy in forecasting bankrupted corporations can contribute to the avoidance of corporate distress for US firms. However, it must be mentioned that we are unaware of how well the model can perform with the full 9 variables incorporated. It may still outperform the other two models or it can even perform worse off. Therefore, this point should be taken in to consideration when assessing the results in the current study for this model.

Many researchers in this line of field have considered the fact that a great number of factors does not essentially raise a model's predictive capability. Beaver (1966) was able to estimate bankruptcy with 92% accuracy with only one ratio. Jo, Han and Lee's (1997) model incorporated 57 factors which had an 86% accuracy rate. "Using too many ratios can actually make a model less useful" (Jones, 1987, p.140). As Jones (1987) suggested it is not necessary that the model with the highest number of factors would achieve the greatest validity.

It depends on what the factors are, and how useful they are in producing high accuracy rates in insolvency prediction. Jones (1987) recommended the use of a hold out sample to test the external validity of the models. This can obtain a more effective measure of the models predictive ability. In the current paper, the predictive accuracy of the models results was based on the holdout sample. The basic sample was only used to provide new coefficients for the hold out sample.

4.2 Results of the two Hypotheses Tested

Hypothesis I: *The Altman's (1968) model is more accurate for predicting bankruptcy than Taffler's (1983) model and Ohlson (1980) model for the US listed companies*. After evaluating the results, this hypothesis is rejected. Altman's (1968) model performed the least well out of the three prediction models. It had an average accuracy rate of 58% whilst Taffler (1983) had an average of 75% and Ohlson (1980) had 87%, Altman's model was 17% and 29% less accurate respectively.

Taffler and Ohlson outperformed Altman in their predictive accuracy and therefore, they are regarded most appropriate in its practical ability to assess high risk bankruptcy firms. When considering only the sample of solvent firms, Altman's (1968) was an effective predictor of solvency with correct classifications of up to 90%, 80% and 100% for year 1, 2 and 3.

This paper concluded that Taffler and Ohlson's model may be more appropriate to be applied to US firms because of its overall superior prediction ability for both failed and non-failed groups. Furthermore, if other group users are interested to assess whether the company has a high solvency rate, they can use any of the three models as they all provided high accuracies for solvency prediction.

Hypothesis II: *Ratio analysis is a useful indicator for predicting insolvency within US firms.* After examining the results, this research hypothesis has been accepted. The majority of the models generated high prediction accuracy. Taffler (1983) suggested that profit before tax to current liabilities is the most vital factor in predicting accuracy within his model. This factor was also used within Altman's model. In Ohlson's (1980) model all 4 variables considered assets.

Hunter and Isachenkova (2001) suggested that low liquidity and profitability was one of the most critical factors contributing to insolvency. As a result, it can be argued that low liquidity and profitability were critical factors that management or other users were primarily concerned in the US insolvency context. In addition, high level of gearing, high debt (liabilities, etc.) is also grounds for firm bankruptcy in many US firms due to excessive liabilities that could not be paid back.

Consequently, low profitability and high liabilities are the most crucial factors that distinguished between solvent and insolvent firms in the current paper (See Appendix B). The high accuracies for the models using ratios revealed the practical ability of financial ratios in predicting financial distress. Overall, it can be proposed that bankruptcy of US firms can be predicted well by the use of financial ratios.

5. Conclusion

After running Logit regressions to estimate the new coefficients of financial ratios variables the Taffler (1983) model and Ohlson (1980) model are able to forecast bankruptcy effectively within the US as they provided impressively accurate results. It can be concluded that Taffler's (1983) model can be employed as the bankruptcy prediction tool for US listed companies.

An examination of the data revealed that the original full version of the Tafflers (1983) model with the new coefficients had the highest predictive ability, whereas Ohlson (1980) had the highest accuracy out of the 3 models including only the first 4 variables out of 9 variables. The average percentage of accuracy for Taffler (1983), Ohlson (1980) and Altman (1968) during the 3-year period before bankruptcy are, 75%, 87%, 58% respectively.

The two models outperformed Altman (1968) with considerably higher precision for 3 years, 2 years and 1 year prior bankruptcy. Taffler's (1983) model had accuracy of 55% (3 years), 70% (2 years) and 100% (1 year) respectively. The Ohlson (1980) model had an overall correct rate of 65%, (3years), 95% (2 years) and 100% (1 year) respectively. Whilst, Altman's (1968) model had relatively stable results across the three years, 60% (3 years), 55% (2 years) and 60% (1 year) before insolvency.

The results of this paper can be useful in predicting bankruptcy for US firms. The recommended models: Taffler (1983) and Ohlson (1980) 4 factor version model can aid model users particularly firm's lenders, auditors, executives, investors and the company as a whole with analysing insolvency risk. During the great depression, there were thousands of bankruptcies which severely damaged the country's financial status.

Thus, it is vital for a firm at potential risk to adopt a sound bankruptcy model. An early warning system can protect a firm from running into bankruptcy. In fact, it can change the situation around to an advantage. For instance, a country with healthy economic conditions not only attracts national investors but potentially international clients as well. In view of that, with an established bankruptcy predictor there is less likelihood of frequent insolvencies.

Furthermore, firstly, companies will be more efficient and thorough in handling their financial performance and secondly, preventative actions can be taken by management if models predict insolvency. The findings suggest that the financial ratios within the models are good predictors of bankruptcy. The paper also proposes that failed firms within the US showed low liquidity, low profitability and high gearing. Subsequently, these factors are of primary concern when examining a US firm's probability of corporate insolvency.

Although the results of the present paper are compelling, there is still a need to address certain limitations. Firstly, with regards to the Ohlson (1980) model, due to errors occurring when estimating the full version of the model only the first 4 variables are used to provide the models new coefficients for this paper. This means that a new version of the Ohlson (1980) model was developed, the 4 factor model. Consequently, the results may have altered if the full 9 variables were used.

Another limitation is that failed firms may have window dressed (alter accounting figures). However, when the failed firms are compared with non-failed firms, their weaker position is evident. Possibly the non-failed firms may have window dressed some data more effectively than the failed firms. In that case, attempts to window dress may have weakened the predictive power of ratios, as it would be covering up some actual accounting data. Thus, hiding the real scenario with regards to some information of the firm's financial performance.

In spite of the differences in the bankruptcy prediction models, the empirical results of the tests for especially of two of the models showed high predictive ability. This suggests that the Taffler (1983) model and Ohlson (1980) model are valuable to the various model users. Moreover, even though a large number of models has been established well within the literature, researchers still persist to look for "new and improved" models to forecast insolvency.

With a large number of well-established models and the visibly restricted use in practice, the question raised is ‘‘Why do we continue to develop new and different models for bankruptcy prediction?’’. Subsequently, the focus of future research should be on the *use* of existing bankruptcy prediction models instead of the production of new models. With over 150 models available, many of which have demonstrated predictive ability. Future research should consider how these models can be applied and, if required, refined. It may also be useful to include a proxy for corporate governance structure in the models in addition to the financial ratios that have been leading in most research until now.

Future researchers may attempt to create a stronger connection between research and practice. Insolvency prediction models can be very useful in practice given they provide the right exposure to managers, auditors, lenders, and analysts. However, an important aspect of insolvency is not yet discussed enough: how firms managed to survive from failure as their problems were detected in time through the use of bankruptcy models? The main focus of this paper is to help firms acknowledging in time that based on current performance they may get insolvent in the future.

Future research may analyse the stages/steps of insolvency avoidance, i.e. how failure may be prevented for a firm that was running in to insolvency. This may help firms to identify important factors which may add to significant information in corporate insolvency context.

Acknowledgments: We would to thank the editor E. Thalassinos and the anonymous referees for providing valuable comments, which have greatly improved the quality of the paper. The views expressed in this paper are those of the authors and not necessarily those of Alpha Bank.

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Appendix A: *Factors included in the vast majority of studies.*

Factor/Consideration	**Number of Studies**
Net income / Total assets	54
Current ratio	51
Working capital/Total assets	45
Retained earnings / Total assets	42
Earnings before interest and taxes / Total assets	35
Sales / Total assets	32
Quick ratio	30
Total debt / Total assets	27
Current assets / Total assets	26
Net income / Net worth	23
Total liabilities / Total assets	19
Cash / Total assets	18
Market value of equity / Book value of total debt	16
Cash flow from operations / Total assets	15
Cash flow from operations / Total liabilities	14
Current liabilities / Total assets	13
Cash flow from operations / Total debt	12
Quick assets / Total assets	11
Current assets / Sales	10
Earnings before interest and taxes / Interest	10
Inventory / Sales	10
Operating income / Total assets	10
Cash flow from operations / Sales	9
Net income / Sales	9
Long-term debt / Total assets	8
Net worth / Total assets	8
Total debt / Net worth	8
Total liabilities / Net worth	8
Cash / Current liabilities	7
Cash flow from operations / Current liabilities	7
Working capital/Sales	7
Capital/Assets	6
Net sales / Total assets	6
Net worth / Total liabilities	6
No-credit interval	6
Total assets (log)	6

Cash flow (using net income) / Debt	5
Cash flow from operations	5
Operating expenses / Operating income	5
Quick assets / Sales	5
Sales / Inventory -	5
Working capital/Net worth	5

Appendix B: *Summary of Financial Ratio Types.*

Type of Ratio	Financial Ratio	Altman	Taffler	Ohlson
Leverage	Retained earnings to total assets	x		
	Market value equity to total debt	x		
Liquidity	Current liabilities to total assets		X	x
	Working capital to total assets	x		x
	No credit Interval		X	
	Current assets to total liabilities		X	x
	Total assets/gross national product price index			x
	Total liabilities to total assets			x
Profitability	Earnings before interest and tax to total assets	x		
	Profit before tax to current liabilities		X	
Turnover	Sales to total assets	x		