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THE APPLICABILITY OF ALTMAN Z-SCORE MODEL: COMPARISON ACROSS EUROPEAN COUNTRIES

Master's thesis

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I hereby declare that I have compiled the thesis independently

and all works, important standpoints and data by other authors

have been properly referenced and the same paper

has not been previously presented for grading.

The document length is 8856 words from the introduction to the end of conclusion.

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Abstract

Predicting bankruptcy is important for banking and finance, as it lets one decide to invest or lend money to the organisation. Altman Z score is a world-renowned model for predicting companies that are heading towards, and thus wording the Altman prediction capabilities in European Union helps us understand if the prediction capabilities of the Altman model hold the same for all countries or is it superior when the analysis is performed country specific.

The thesis aims to develop a uniform model to predict financial distress across a set of countries, these set requires a few of the factors to remain constant among these organisations like entity type, accounting practices, asset size, the field of industry, and economic environment. The sample used to develop the uniform model contains 40 active and 40 inactive companies across this set of countries. The result showed an increase in predictive capabilities of the uniform model when compared to the Altman model (original model) and simultaneously the modified uniform model with fewer independent variables showed a slight increase in the predictive accuracy when compared to the uniform model. Hence, it is possible to build a uniform model which shows a higher accuracy for a set of countries when compared to the original model.

Keywords: Bankruptcy, Multiple Discriminant Analysis, Z-Score, Bankruptcy Models, Multivariate, Univariate

INTRODUCTION

Bankruptcy or financial distress is a state of an organisation where it is unable to pay its financial obligations (Beaver W. H., 1966), which causes large economic and social losses for each stakeholder in the organisation. Due to globalization, an organisation has investors beyond its own nation and during financial distress, it is difficult to allocate the financial capital to international investors. Hence, the prediction of bankruptcy in organisations is important for the stakeholders as it gives time for them to react to crises but also helps managers of the organisation to avoid failure. Bankruptcy prediction also helps external stakeholders like investors to assess the risk associated with the organisation.

Bankruptcy prediction in organisations has been a subject of analysis for researchers since the 19th century, but the first one that was able to predict bankruptcy successfully using financial indicators was Beaver (1966). The prediction using only a few ratios was not very accurate and there was a need for new tools and in 1968 Altman (Altman I. E., 1968) who continued the study of Beaver published a paper that caught the attention of the financial community, as the paper gave access to a bankruptcy model called Altman Z-Score, which uses Multiple Discriminant Analysis to predict bankruptcy of manufacturing companies. This model showed a phenomenal accuracy of 95% one year prior to failure. But the model tends to lose its accuracy when subjected to replication and also the prediction accuracy drops exponentially when data older than 2 years was used.

Discriminant analysis is a statistical method that separates two or more classes or objects by creating a linear combination of features. The initial Altman model created was restricted to listed and manufacturing companies as these organisations behave differently when compared to non-listed companies and thus forcing Altman to modify his model to help financial communities identify the non-listed organisations that are at risk of bankruptcy.

The Altman model which uses discriminant analysis requires modification as soon as the field of industry or the entity type changes, as different industries behave differently as proven by Altman himself. But, this change is not solely restricted to the field of the industry or the entity type but also the geographic location of the companies, as companies situated in different countries behave differently due to culture, legislation, accounting principles, etc. and thus requires a modification of the Altman model to incorporate these change and thus making the model more effective.

The main focus of this thesis is to evaluate the predictive capabilities of the Altman model in the European countries. It is has been proven by Erkki Laitinen (Laitinen, 2013) that the Altman model shows differences in the form and strength across different European countries since this study took in all the companies in the country regardless of the field of industry it functions in. Hence, exploring the predictive capabilities across the European countries in a particular field of industry would be interesting to explore.

This thesis also focuses on creating a uniform model by modifying the existing Altman model for European countries functioning in a particular field of industry, and from previous studies, we can estimate the problems associated when transferring discriminant model from one environment to another and before the thesis proceeds with the analysis it takes into consideration of all the factors which affect the discriminant analysis.

The factors which affect the transferability of Altman model are cultural differences in which the organisation functions, legislation of local governance, the asset size of the organisation, the field of industry in which the organisation function, the accounting practices the organisation uses, the type of entity the organisation is and finally the economic environment in which the organisation functions.

To build a uniform model which can perform well in different environments restricting few of the factors which effect discriminant analysis the most and eliminating the factors which effect the least would make the model perform well in a particular set of enviroment.

The factors which effect the discriminant analysis most are economic environment, accounting practice, asset size, field of industry and entity type, while the ones which effect the least and at the same time are variables which cannot be restricted are cultre and legislation.

Since, the accounting practice, asset size, field of industry, and entity type can be pre-selected in any environment. The main task ahead is to choose an economic environment that contains many countries and the most ideal economic environment for this study is European Union and rest of the factors can be shortlisted accordingly.

To develop the uniform model, the author used the same technique and variables used in the original model to develop a new uniform model for all the countries in Europe. Since there have been many studies that show that the modified Altman model with fewer independent variables showed higher accuracy and to further improve the uniform model with the least effort the uniform model is further modified with fewer variables. This leads us to develop the following research questions.

H1: The Predictive accuracy of the orginal Altman model in the European countries is same as the accuracy shown by Altman in his paper.

H2: The Predictive accuracy of the orginal Altman model in the European countries is same as the accuracy across the European countries.

H3: It is possible to achieve a higher accuracy by modifying the weights of the discriminant coefficients in the original model.

H4: It is possible to achieve the same or higher accuracy with fewer independent variables than contained in the original model.

1. Literature review

1.1. Financial failure

Financial distress is the state in which the organisation fails to pay its financial obligations (Beaver W. H., 1966), which might happen due to a rise in competition, internal conditions, accidents, monetary problems, etc. Hillier (Hillier, 2016) in his book Corporate Finance mentioned that financial distress is a state where the organisations operating cash flows are not sufficient to satisfy the firms operating cash flow is not adequate to satisfy current obligations and the organisation is forced to take remedial measures. But not all orgnisations which face financial distress go bankrupt instead the organisations can choose different ways to exit the market, they can either opt for **voluntary liquidation** where they sell their assets to pay off creditors, or they can opt to **merge** where they sell the who firm to another company or an individual, and finally the organisation can be forced in court by creditors which leads to **bankruptcy** (Balcaen, 2012).

Voluntary liquidation: Liquidation is also most likely for firms with limited growth rates and future prospects, as the Present Value of future cash flows is less than liquidation values. A company might decide to Liquidate Voluntarily when they are facing with the continuity of generating profits, is threatened which can be due to bankruptcy or a takeover attempt, but in the situation of takeover attempt company chooses for voluntary liquidation as the sale of the firm by selling assets is at a higher price when compared to the price offered by a potential acquirer. But it also raises questions regarding the Agency theory which might be arisen due to the Manager's self-interest of not leaning towards the shareholder's willingness to choose other options for companies future, this might occur when the major shareholders in the organisation make their decision on behalf of the manager. Chinmoy Ghosh (Chinmoy, 1991) used discriminant analysis to identify organisational and financial characteristics of firms that choose to voluantary liquidate.

Merger or split: Corporate Merger from the year 1960 took a phenomenal growth, the reason for this merger is due to increase the sale of economics, tax reduction, increase in growth and bankruptcy avoidance, whereas a company can split into many groups and then are sold individually for more value. In 1979 Roland and Donald (Ronald, 1979) mentioned through their research that around 15.2% of the companies which were acquired are near bankruptcy at the time of the accusation. But Since this research date backs to 1979, and from then on there has been an increase in the number of companies that have been merged and so there is a probability of increased number of bankrupt companies prefering to merge to save the face value of the organisation.

Bankruptcy: Is the state where a company has been forced to Liquidate by the creditors, and this situation is very bad for a organisation as here the organisation is not willing to pay there debts in time, might be due to hopes of getting profits in near future, or finding the right value for the assets or a deal with other firms for merging.

Out of all the ways the organisation decides to exit the market, bankruptcy turns out to be the one which causes the most harm to the stakeholders. Since bankruptcy only occurs when the organisation is unable to generate enough cash to meet the claims of all the creditors. Hence it is important for stakeholders to be aware of the best way to deal it, as it can lead to win-win situation for each party.

Onakoya and Olotu (Onakoya, 2017) "provides an overview of bankruptcy thories guiding the procedure of distribution or entitement in bankruptcy among a group of agents", the main bankruptcy theories according to the author are maximisation of social welfare theory, absoulte priority theory, creditor's bargaining theory, risk-sharing theory, value-based thoery, and banruotcy-policy theory.

Maximisation of social welfare theory: According to this theory the social welfare can be maximised when the organisation that shows financial distress is given the opportunity to continue functioning while the ones which show distress beyond finance be liquidated. According to Ghosal and Miller (Ghosal, 2003) when the creditors decide to seize all available assets of an organisation, the organisation tends to go into piecemeal liquidation, where the assets are sold piecewise which tends to be more beneficial when compared to wholesale disposal of firms. Piecemeal liquidation often happens without regulations as creditors takeover the liquidation of assets. Thus, one needs to understand when to liquidate an organisation and when not to so as to maximise the creditors pay off, while simultaneously giving the opportunity to the firms to improve their financial health. (Onakoya, 2017)

Absolute priority rule: According to this theory the bankruptcy laws should ensure that when an organisation is liquidated, the assets are divided equally among all the claimants. In the meantime the law should also respect the priority of claims among different classes of creditors. But there are always exceptions in ways the assets are divided among the claimants, this exception can only be decided by the court as it believes that this theory would not provide fairness at dividing the assets. (Onakoya, 2017)

Creditor's bargaining theory: This theory was first put forward by Jackson (Jackson H. T., 1982) and later expanded by Jackson and Scott (Jackson T. H., 1989) to reflect what distributional bankruptcy law is supposed to be. This theory states that the bankruptcy law should provide exemption when both the parties in bankruptcy are willing to negotiate and come to an agreement, as this would be a strategically better option to optimize the maximum outcome of the liquidation of assets. In case of disagreement between the parties, the creditor must pursue a strategic option to maximize the recollection of debt from the organisation, or the creditor can just go to the couthouse. (Onakoya, 2017)

Risk-sharing theory: This theory was developed over the creditor's bargaining theory and was put forward by Jackson and Scott (Jackson T. H., 1989). The drawback of creditor's bargaining theory are the unequal redistribution of wealth among the claimants. Hence risk-sharing theory aims to maximise the value of assets, by urging all the claimants to partake in the collective risk of the organisation. The risks can be exogenous or endogenous but based on the knowledge of the risk involved and how it can be monitored or controlled, a common risk is equally divided among all claimants to minimize the losses which they can face. (Onakoya, 2017)

Value-based theory: Theis theory was first put forward by Korobkin (Korobkin, 1991) which compares the debtor's assets with human life, just live human life which grows and diminishes at different rates, it is therefore difficult to offer the same panacea for issues arising at different stages of the debtor's assets. (Onakoya, 2017)

Bankruptcy-policy theory: This theory was put forward by Onakoya (Onakoya, 2017) which states that during the of an organisation, there are many creditors who have legal rights to the assets of the organisation, but in case of other stakeholders like employees who are affected by the bankruptcy. The bankruptcy law should consider all the claimants equally, even the ones who have no right to claim the assets of the organisation legally.

1.2. Early bankruptcy prediction studies

The bankruptcy prediction dates to 1930s with the use of univariate ratios to predict future bankruptcy. The Univariate analysis comprised of determining common characteristics of bankrupt firms, which was published as a bulletin in 1930 by Bureau of Business Research with results of a study of ratios of failing industrial companies (Jodi L. Bellovary, 2007) which found eight ratios considered as good indicators of the “growing weakness” of a company which is working capital to total assets, surplus or 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 and cash to total assets, out of which current ratio and working capital to total assets turned out to be the most important financial indicators.

Beaver in 1966 (Beaver W. H., 1966) took this analysis a step forward by testing each available financial ratios individual predictability of bankruptcy and found that Net Income to Total Debt ranked the highest at 92% accurate one year prior to failure, followed by Net Income to Sales at 91% accurate one year prior to business failure. Beaver also suggested the possibility of multivariate analysis of ratios as future research, which paved path towards the multivariate analysis for the first time in history.

The first multivariate analysis in the world of finance was conducted by Altman in 1968, where Altman used the Multiple Discriminant Analysis (MDA) to predict the bankruptcy of companies. MDA is a statistical technique that is used to predict the probability of belonging to a certain class based on multiple predictor variables, which uses linear combinations of predictors to predict the class of a given observation, MDA also reduces the space dimension of the analysis by one, since there are n groups, the space it can be represented is n dimension but using MDA the analysis is transformed into n-1 dimension. MDA which was at that time mainly used by biological and behavioral sciences, caught the attention of Altman, where Altman made two variables or groups bankrupt and non-bankrupt, since there are two groups, the space it can be represented is two dimension but using MDA the analysis is transformed into one dimension that is represented as follows:

$$Z = v_1x_1 + v_2x_2 + v_3x_3 + \cdots + v_nx_n \qquad (1)$$

where

$v_1, v_2, \dots, v_n$ are discriminant coefficients

$x_1, x_2, \dots, x_n$ are independent variables

(Where MDA calculates dicriminant coefficient whereas individual variables are actual values)

Altman selected a total of twenty-two ratios which are then eliminated the ratios which cannot be used in the discriminant analysis by F test and thus was able to winnow down to 5 ratios and the equation for discriminant analysis now is transformed into

$$Z = v_1x_1 + v_2x_2 + v_3x_3 + v_4x_4 + v_5x_5 \qquad (2)$$

where

$v_1, v_2, \dots, v_5$ are discriminant coefficients

x_1 = Working Capital to Total Assets,

x_2 = Retained Earnings to Total Assets

x_4 = Earnings before Interest and Taxes to Total Assets

x_5 = Market Value of Equity to Book Value of Total Debt

The discriminant scores were calculated for each sample using Fisher discriminant method (Fisher, 1936)and then assigned to the respective group based on the score which then gave rise to the final discriminant function as shown in equation 3.

$$Z = 0.012x_1 + 0.014x_2 + 0.033x_3 + 0.006x_4 + 0.999x_5 \qquad (3)$$

After which the discriminant function was used to predict the initial sample which showed a phenomenal accuracy of 95% for one year prior to failure and 93.5% when subjected to secondary data, and the Altman Z score was calculated based on the centroid of the least misclassified group which is 2.67. This led researchers to use MDA analysis for estimating bankruptcy models for various industries of companies, also for SME (Small and Medium Enterprise), private-owned, etc.

Few of the other renowned bankruptcy prediction models which were developed after the Z- Score are as follows:

1) Use of Lawson cash flow to measure bankruptcy (Aziz, 1988)
2) Non-liquid assets ratios are better at predicting financial distress than liquid assets (Beaver W. H., 1968)
3) Are professional standards SAS No. 59 increase the propensity of bankruptcy-related opinion (Joseph V. Carcello, 1995)
4) How managers role in informing and educating staff, vendors, contractors etc. challenges arising from bankruptcy (Camp, 1993)
5) Does the use of discriminant analysis use financial data is sufficient for business failure (Deakin, 1972)
6) MDA analysis for Small Business Failure Prediction (Edmister, 1972)
7) Forecasting bankruptcy more accurately: a simple hazard model (Shumway, 2001)

Altman in July 2000, revised the Altman Z- score (Altman E. I., 2013) which was previously restricted to public markets and manufacturing entities, extending the model to non publicly traded companies and non-manufacturing companies. Since many organisation and communities do invest in non publicly traded companies and having the ability to know the financial health of an organisation helps one decide whether to invest money in it or not and so far with no ground-breaking research done on these organisations, before which the community was dependent on the credit ratings provided by independent investigators.

The new Z- score which was developed was similar to the previous model, and was derived using the same Multiple Discriminant Methods as explained in the previous chapter. Here Altman replaced market value with the book value of equity, since private companies do not have market value they needed a good proxy to the variable, and these organisation functions differently which mean the coefficients for the new models would change and thus required calculation of new coefficients (as shown in the equation in 4) and the cutoff scores, and the sample data for the analysis were manufacturing companies.

$$Z = 0.717x_1 + 0.847x_2 + 3.107x_3 + 0.42x_4 + 0.998x_5 \quad (4)$$

where

x_1 = Working Capital to Total Assets,

x_2 = Retained Earnings to Total Assets

x_3 = Earnings before Interest and Taxes to Total Assets

x_4 = Market Value of Equity to Book Value of Total Debt

x_5 = Sales to Total Assets

Here we can clearly see that the new model is different from the previous model as the coefficients have changed drastically like for X1 the previous model showed it to be 1.2 and for the new model it is 0.717 and this also changed the accuracy of the model. The new model showed 91% accuray for Type 1 accuracy (Type 1 is where the bankrupt companies are predicted as bankrupt) and Type 2 accuracy of 97% (Type 2 is where the non-bankrupt companies are predicted as non-bankrupt). The cutoff for the new model also went down from 1.81 to 1.23 and the cutoff for non-bankrupt came down from 2.99 to 2.90. Since, our study uses the private owned companies rather than public-owned companies, the new model generated by Altman is the one that we would use in the study.

1.3. Application of Altman Z-score

Altman Z Score which was modelled using the United States comapnies, have been applied throughout the world. Like El Khoury (El Khory, 2014) who used Altman Z- score has a barometer for classifying Lebanese manufacturing companies, as small banks cannont affors expensive rating systems for classying their clients (El Khoury has used and proved that Altman Z- score can be used as a valuation tool for classifying different companies, as the result showed high level of accuracy in classifying companies similar to other rating systems). Since, own tailor made models for credit ratings are expensibe and not all non-financial or financial institutions can afford and thus replacing it with Z score proved to be cheaper and works as good as tailor made models.

While Anna Siekelova (Anna Siekelova, 2019) used Altman Z- score to predict the financial stability of Romanian manufacturing companies and Omary J. Ally (Ally, 2019) used Altman Z-score for testing financial distess of manufacturing firms in Tanzania, where the author took 6 production companies and measured the Z- score and then analysed on how the poor Z- score organisations are performing and how managent needs to pay attention towards the financial health of the organisation.

Where as Michal Karas (MICHAL KARAS, 2013) used Altman model application within Czech Republic, here the author first measures the accuracy of the Altman Z- Score in 1619 manufacturing companies operating in Czech Republic and found that Z- Score was only 50.1 % accurate, but if the grey zone of the model was included then the model was 81.8% accurate with 77.1% of the companies likely to be bankrupt. So, author remodelled the existing model so that it can incorporate the different environment which here is Czech Republic. The revised model turned out to be 13.86 % more accurate than the Altman Z – Score.

Maria Reznakova (Reznakova, 2015) showed that Altman bankruptcy model which were created in a different environment and time periods have shown significant fall in accuracy when used in a different environment, and also investigated the ways in which the discriminant capabilities of the model can be increased. The author revaluated the weights of the models coefficients while maintaining the varaibles of the original model and found that the new model was able to accurately identify the bankrupt comapnies except Hungary, the furthur studies to remodel the orginal model by applying statistically significant variables and removing the non-significant ones have shown that in particular environment it is necessary to find its own combination and create a new model. Hence, proving that discriminant analysis used by Altman is a very accurate statistical tool but requires remodelling whenever the model is applied in new environment.

When the researchers realised that the discriminant analysis for bankruptcy model requires a constant changes in either the weights of coefficients or both the coefficients and the independent variables, and thus there is no uniform or global model for bankruptcy. In quest of creating a uniform model Altman again himself in 2017 (Altman I. E.-D., 2017) gave a review on previously developed bankrputcy prediction models and gave a statistical proof that Altman Z- Score developed in 1984 (Altman E. I., 1984) also known as Z” Score model (equation 4) performs well in international context, but Altman himself mentioned that it is possible to extract efficient model for European Countries and Non-European Countries.

$$Z'' = 6.56x_1 + 3.26x_2 + 6.723x_3 + 1.05x_4 + 3.25 \tag{4}$$

Where

x_1 = Working Capital to Total Assets,

x_2 = Retained Earnings to Total Assets

x_3 = Earnings before Interest and Taxes to Total Assets

x_4 = Market Value of Equity to Book Value of Total Debt

Every bankruptcy model developed uses a certain set of samples where they restrict the asset size, field of industry, entity type, etc. Financial communities or researchers would apply prediction models on samples that typically do not fall in the sample restrictions of the bankruptcy models which would lead to biased results. Zmijewski (Zmijewski, 1984) in 1984 used two data sets one which contains the choice-based sample and the second one which contains data that satisfies the model, to identify if the biased results occur only if the data selected is not appropriate with the model or if the bankruptcy model creates biased result even if the data set select is appropriate to the model. The author was able to successfully identify that transferability of the prediction model itself is an issue, it does not matter if the data set used is in accordance with the bankruptcy model but due to change in the location in which the organisation functions the model itself requires a change in its weights of the coefficient to incorporate the changes which organisation functions in.

The studies done by researchers namely (Scott, 1981; Platt, 1990; Dugan, 2001; Wu, 2010; Niemann, 2008) have all applied bankruptcy prediction models in a different environment and all of them have come to the same conclusion that when a bankruptcy prediction model is transferred to a different country it would degrade the prediction accuracy of the model and thus requires the modification in model to incorporate the changes associated with the data set.

There were several studies that try to address the issues associated with the applicability of bankruptcy models and one of the ways to eliminate this issue is by using the Hazard model also called as survival model instead of the bankruptcy model to predict bankruptcy proven by Tyler Shumway (Shumway, 2001). Since the application of the survival model is a tedious task and analysis requires data with a huge time frame and thus cannot be applied to companies that are few years old. Instead, it would be optimal to find a way to build a uniform model by modifying the pre-existing model to incorporate the changes associated with the organisation, as this uniform model can be applied to future companies and thus making it easier for financial communities to use the model at predicting the financial distress of an organisation.

One such application of modifying a pre-existing model to improve its accuracy is published by Laitinen (Laitinen, 2013) tested the International applicability of the Altman model across European countries and tried creating a uniform model for European countries, but since the author took in a big data set which contains all the companies in Europe regardless of the asset size, field of industry, etc. have faced the issue that the Altman model shows a difference in European countries and at the same time concluded that it is possible to develop a uniform generic model which would result in high accuracy in predicting the financial distress model.

2. Data and methodology

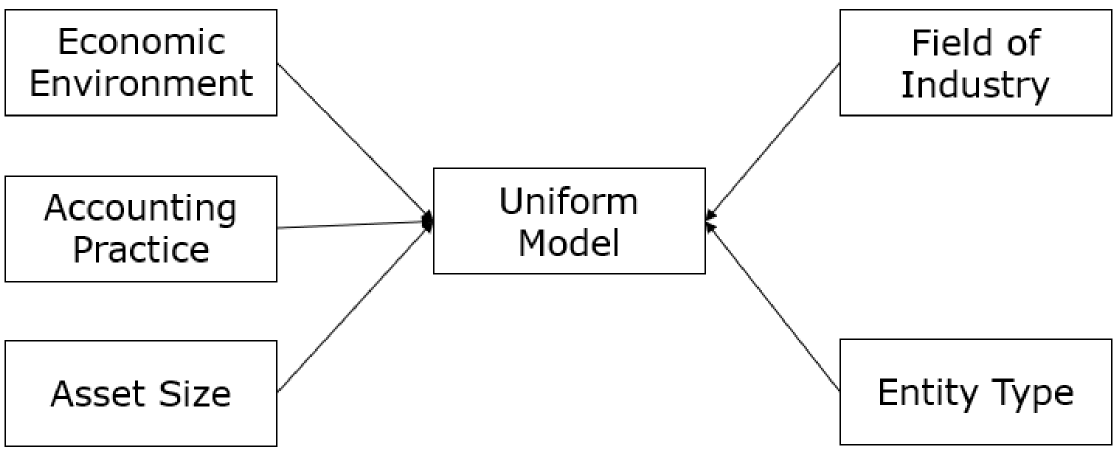
This chapter contains the collection and organisation of the data. Firstly, the research methodology will be made clear method, thereafter we proceed with data collection, cleaning and sample selection and finally the method of data analysis.

2.1. Research design

The study focuses on the application of the Altman model in small companies across Europe and to keep the data set of the study close to the Altman model, selecting manufacturing industries would be most appropriate as the Altman model used manufacturing companies when developing the Z Score. As mentioned in chapter 1 and 2, whenever a bankruptcy prediction model is transferred to a different country it requires a modification in the model to incorporate the changes associated, and simultaneously the study is also tasked with developing a uniform model in Europe, there are several factors like cultural, economic environment, legislation, asset size, the field of industry, entity type, and accounting practices which can affect the discriminant analysis to provide biased results.

Hence to minimize the effects from these factors, the author tried to keep a few of the factors constant which are shown in figure 1, since these particular factors can be applied to the data set, whereas the rest of the factors are volatile and cannot be taken into quantitative analysis.

Figure 1: Selection of factors that effect the discriminant analysis



Source: Autor’s figure

For this study, to keep discriminant equation not be affected much by the changes associated with the countries across Europe the factors which are constant across countries are, the economic environment is European Union, accounting practice is selected as GAAP, asset size is determined according to the data set, the field of industry is selected as manufacturing companies of wearable products (companies which manufacture different products behave differently due to its demand and use in the market), and finally, the entity type is selected as private companies (the study is focused on small companies).

The tools used for the empirical part of the research are Excel, Tableau, and SPSS. Excel is used as the data downloaded from Orbis base is exported in Excel format and the in meantime Excel also helps with cleaning of data. Tableau is used for data visualization, huge data can only be interpreted by visualizing the data. Finally, SPSS is used for discriminant analysis, as any other software requires coding, whereas SPSS makes discriminant analysis easy.

To evaluate the hypothesis, the companies are divided into two groups, Group-I (non-bankrupt), Group-II (bankrupt), and the variables selected for the analysis are carefully taken from the top-performing bankruptcy model (Altman E. I., 2013), since this model has high accuracy and to date viable enough to be used in real-time, the variables are represented in table 1. The research follows with the application of Altman Z' Score (original model) to verify the first hypothesis of the thesis. If the first hypothesis is rejected it is only then the study can proceed with second hypothesis.

Table 1: Variables Selected for Discriminant Analysis

VARIABLES	RATIOS	DESCRIPTION
X1	Working Capital to Total Assets	Determines the short-term Companies Solvency
X2	Owners Equity to Total Assets	Determines how much company relies on debt
X3	Earnings before Interest and Taxes to Total Assets	Determines companies EBIT relative to Total Assets
X4	Owners Equity to Book Value of Total Debt	Determines how the assets decline in value
X5	Sales to Total Assets	Determines how companies are using assets to generate sales

Source: Author's table

In the second part of the hypothesis, the study is tasked with modifying the Altman model while keeping the independent variables constant. This requires the author to perform discriminant analysis in SPSS using the appropriated sample collected from the data set of the study. Once the new weights of the discriminant coefficients is calcualated, the study follows with verification of second hypothesis which is accepted only if the modified model shows higher accuracy than the original model.

Then the thesis proceeds with the final hypothesis, where the Altman model is furthur modified by removing a independent variable which contributes the least towards the discriminant analysis, which is determined by comparing the F-value of the independent variable and its significance. Once the independet variable is removed a new discriminant equation is formed and the weights are calculated by exporting the sample set to SPSS. Then the study follows with verification of the final hypothesis to check if removal of an independent variable shows better accuracy than the modified model developed in second hypothesis.

2.2. Type I and II errors

In the bankruptcy prediction models, the organisations are classified into two classes of groups. An organisation can either show financial distress or it can show healthy financial performance. Whenever the bankruptcy prediction models incorrectly classify the class in which the organisation belongs to it creates an error and to address these incorrectly identified firms, we use type I and type II errors. Type I error typically means that a bankrupt or financially distressed organisation is wrongly classified as a healthy organisation, whereas type II error means that a healthy organisation is incorrectly identified as a financially distress organisation, addressing these errors is important, cause even if a model is unable to identify the financial distress model, it should not wrongly classify them as it may lead to bad investment or actions that can be implemented to avoid the future financial distress.

2.3. Population of study

The population of the study consists of all the privately-owned companies in Europe which are primarily involved in the manufacture of wearable products in Europe. The companies selected are both bankrupt and non-bankrupt companies, in case of bankruptcy the financial data collected was one year prior to bankruptcy, whereas the lastest financial data was collected for non-bankrupt companies, and the financial data collected was limited to the variables which are required for the Altman model.

The study uses Orbis database, which contains data for European Companies, which include industry identifiers, accouting practices, entity type, company status, company income statement, balance sheet, key financial ratios and statement of cash flow for listed companies. Which is ideal for study, as research requires list of bankrupt and non bankrupt for manufacturing companies in Europe. The data is cleaned for those whose financial data was incomplete and then extreme variables were removed using outlier method (Barnett, 1978).

2.4. Data collection

For collecting the data from the Orbis database, we followed the following steps:

Step 1: As per research, we only need the data for the manufacturing companies. So the whole Orbis Database was filtered to manufacturing companies by using the filter NACE Rev. 2 (European Industry-standard classification system) to code 13 – Manufacture of Textile, 14 – Manufacture of wearing apparal, and 15 – Manufacture of leather and related products which include all wearable manufacturing companies, with this the data just shows the list of manufacturing companies of wearable products in Europe.

Step 2: Since Orbis lacks information of bankrupt companies from Publicly listed companies this might because most of the companies in the database consist of privately-owned companies, we are forced to choose privately-owned companies as the entity type thus applying the filter Corporate as Entity type in Orbis Database.

Step 3: Utilizing the benefit of selecting the columns in Orbis, a new filter was added which selected the following columns in Orbis, 1. Company Name, 2. Last Available Year, 3. Current

Liabilities year t to t-2 (where t is the last available year), 4. Non-Current Liabilities year t to t-2, 5. Total Assets year t to t-2, 6. Operating P/L (EBIT) year t to t-2, 7. Net Income for year t to t-2, 8. Profit Margin year t to t-2, and 9. Current Assets year t to t-2. (Note: The Data includes the Companies from whole Europe and due to different currencies in which the Annual report is prepared, we downloaded the value in EUR so as to eliminate the discrepancies that may arise due to it).

Step 4: As there are 2 groups in the research, Group 1 requires the filter where the Status of the company currently is Active, Group 2 required the filter where the status of the company is either Bankrupt or Dissolved due to Bankruptcy.

Step 5: The Orbis data for both IFRS and GAAP was thoroughly checked and since, the data for the companies using GAAP accounting practice was available in style when compared to that of IFRS, and hence we filter the organisation which uses the GAAP as the Accounting Practice.

Step 6: Once the final data is ready it was downloaded from Orbis in the form of Excel.

The Results for the Data Collection after the above steps have been applied in Orbis Database and downloaded as two separate excel sheets namely Bankrupt which contained 11,528 companies and Non-Bankrupt which contained 106,293 companies.

2.5. Data cleaning and outlier method

After cleaning the data for missing and irrelevant data the final result of each group with a number of companies is Group-I (Bankrupt) = 8,079 and Group-II (Non-Bankrupt) = 85,348.

After cleaning the Data, the extreme values which would degrade the study were removed from the sample using the Outlier rule (Barnett, 1978) which was first proposed by Barnett. Outlier is a data point that is more than 1.5 interquartile ranges (IQRs), which are below the first quartile and 1.5 interquartile ranges above the third quartile. The first and the third quartiles of the data are calculated in excel using the quartile function (=QUARTILE (range, quartile)).

Identifying the outlier is a four-step process, first and second steps of the process are identifying the first and third quartile, the third step of the process is identifying the IQRs (Quartile 2 – Quartile 1), finally the lower and upper bound are identified using the formula Quartile 1 - (1.5 * IQRs) and Quartile 1 + (1.5 * IQRs) (ZImmermann, 1995). At the same time, the companies with asset size zeros were removed as zero asset size is unusable in the study. Once the outliers were eliminated the outcome of the groups after cleaning the data are Group-I we have 5,467 and in Group-II we have 46,540.

Since, we have average total assets of both bankrupt and healthy companies were observed using the Frequency distribution in Excel (Pivot table) the most common averages in both the groups which are companies with assets size between 1 – 5 million is the range with most companies available in our data sets. Hence, the final data set consists of 2,037 companies in Group-I where has 8,223 companies in Group-II.

The data was then exported to Tableau for data visualization to help us analyse country wise availability of the data. Since the sample contains only manufacturing companies from wearable products, not all countries have the same number of production plants for this field of industries and thus restricting us to use only countries like Italy, France, Spain, and Belgium as these countries show the minimum number of companies in both bankrupt and active companies to help us for analytical part of the research. The number of companies in each group is shown in table 2.

Table 2: Number of Companies in each group for top 4 countries

COUNTRY	BANKRUPT	NON-BANKRUPT
ITALY	1,350	4,425
FRANCE	236	232
SPAIN	28	934
BELGIUM	23	23
TOTAL	1,637	5,614

Source: Author’s table

From table 2, we can clearly interpret that when it comes to companies which manufacture the wearable products, it is not equally divided in European countries instead Italy has the highest manufacturing companies in this field followed by Spain and France after which there is a significant drop in manufacturing of wearable product companies in the rest of the countries. This also shows that selection of the field of industry plays a huge role in discriminant analysis. For the rest of the thesis, we would be using these four countries and eliminate the rest of the countries.

The final data set for the study has 1,637 companies in Group- I and 5,614 companies in Groups- II. This sample was then exported to new Excel sheet for calculation of independent variables (financial ratios). The descriptive statistics for the independent variables for group 1 (G- 1) and group 2 (G- 2) are shown in table 3.

Table 3: Descriptive statistics of variables in group 1 and 2

	MEAN		MEDIAN		MIN.		MAX.		ST.DEV		VARIANCE	
	G-1	G-2	G-1	G-2	G-1	G-2	G-1	G-2	G-1	G-2	G-1	G-2
X1	-0.132	0.256	-0.020	0.249	-6.385	-2.434	0.977	0.986	0.564	0.279	0.319	0.077
X2	-0.101	0.341	0.023	0.296	-7.611	-4.303	0.995	0.994	0.564	0.274	0.318	0.075
X3	-0.132	0.048	-0.015	0.034	-2.802	-1.219	0.592	1.022	0.299	0.104	0.089	0.011
X4	0.655	1.368	0.023	0.421	-0.884	-0.811	200.2	176.9	8.485	5.832	72.0	34.02
X5	1.135	1.145	0.986	1.072	0	0.000	6.964	10.62	0.742	0.694	0.55	0.482

Source: Author’s table

The descriptive statistics clearly show that the mean and median of X5 are almost similar in both the groups, this also shows that it will be hard to discriminate the groups just using the variable X5, as due to least differences in value between them, whereas the rest of the variables have some difference between the groups which would help the linear discriminant function classify both the groups.

3. EMPIRICAL STUDY

This chapter contains the empirical phase of the research. Firstly, the Altman model is tested on the sample collected, thereafter we proceed with modification of the Altman model followed by the reduction of variable in the Altman model.

3.1. Testing the Altman Z-score model

Since, the data used for the study contains privately owned companies, the Altman model used in this study is the revised Altman model generated in 2000 by Altman, which can be calculated as shown in equation 4.

This modification of the Altman model led to new cut-off for Z-Score where Z value below 1.23 indicates risk of bankruptcy, while values above 2.9 indicates healthy companies and anything that lies in between these ranges are considered as grey zone areas with neutral outcome.

Once the variables for Altman model were calculated, the sample was once again imported to Tableau for Z-score calculation and analysis. The outcome of the result is shown in table 4.

Table 4: Analysis of Altman model to our overall sample.

	BANKRUPT	ACTIVE
SAMPLE	1,634 (100%)	5,614 (100%)
CORRECTLY IDENTIFIES	1,113 (68.12%)	1,354 (24.12%)
GREY ZONE	435 (26.62%)	3,172 (56.5%)
INCORRECTLY IDENTIFIED	89 (5.45%)	1,088 (19.38%)

Source: author’s calculations

The Analysis clearly shows that Altman model was unable to accurately measure the financial distress. The result shows that the Altman model was able to predict bankruptcy with 68.12% and Type I error at 5.45%, but when it comes to predicting the Active companies, the model showed very poor results with 24.12% accuracy and Type II error of 19.38%. The model clearly lacks ability to classify active companies and assigned most of the companies wrongfully in the bankrupt zone.

According to the review published by Altman (Altman I. E.-D., 2017) in 2017, when the Altman model shows accuracy higher than 75% it is only then the model is considered as accurate. But in our sample, the model showed an overall accuracy of 46.12%. Thus, disproving the first hypothesis of the thesis.

The country wise analysis of Altman model is calculated, and the results are shown table 5, which shows that the Altman model shows the different behaviour when compared to the total set of these countries, Italy has shown the highest type I accuracy and low type II accuracy, followed by France which shows high type II accuracy and least type I accuracy, whereas Spain and Belgium have shown low accuracy for both type I and type II accuracy. The type I and type II error was highest for France and the rest of the countries showed similar error rate.

The Altman model showed poor accuracy in predicting the active companies. Thus, this shows that the change in geographic environment does play a significant role in the Altman model and requires remodelling to incorporate the changes and requires us to recalculate the discriminant function.

Table 5: Analysis of Altman model across companies.

	BANKRUPT				ACTIVE			
	IT	FR	ES	BE	IT	FR	ES	BE
SAMPLE	1,350 100%	236 100%	28 100%	23 100%	4,425 100%	232 100%	934 100%	23 100%
CORRECTLY IDENTIFIED	1,000 74.07 %	91 38.56 %	13 46.43 %	9 39.13 %	861 19.46 %	129 55.6%	356 38.12 %	8 34.79 %
GREY ZONE	303 22.44 %	105 44.49 %	14 50%	13 56.52 %	2,595 58.64 %	85 36.64 %	481 51.49 %	11 47.83 %
INCORRECTLY IDENTIFIED	47 3.48%	40 16.9%	1 3.57%	1 4.35%	861 19.46 %	18 77.59 %	97 10.39 %	4 17.39 %

Source: Author’s calculations

The overall accuracy of the Altman model for the individual countries is as follow: Italy = 46.765%, France = 47.08%, Spain = 42.275%, and Belgium = 36.96%. This shows that Belgium shows the least accuracy whereas France and Italy show similar overall accuracy, which further disprove the second hypothesis of the research.

3.2. Remodelling of Altman Z-score model

For remodelling of the Altman Z-score, we simply kept the independent variables the same and just tried to find the new weights for the linear discriminant equation. Altman (Altman I. E.-D., 2017) during his review on discriminant models in various countries has identified that most of the time just changing the weights is enough for the discriminant analysis to work more effectively.

Since the data in our sample for Belgium and Spain are just 23 companies, we cannot perform country-wise discriminant remodelling. Instead, the study seemed viable to perform discriminant remodelling for the set of countries, as we can randomly select 10 companies from each country and thus providing us with 40 bankrupt and 40 active companies for both training and testing the model.

Since, the independent variables are still the same as shown in table 1, we need to find the new discriminant coefficients which makes the linear equation fit the new environment, so the new discriminant equation can be written as equation 2.

Now we can move forward with the identification of discriminant coefficients. The Training Sample was uploaded to SPSS software and with the help of Discriminant Analysis in Correlation, the identification of Coefficients was made much easier.

The new discriminat function is shown in equation 6 and the prediction capabilities for the test sample is shown in table 6. Which shows that the predictive capability of the model is 68.8 % which is better than the orginal model as the orginal was still aunble to predict type II accurately.

$$Z = 0.657x_1 + 1.139x_2 + 1.366x_3 + 0.048x_4 - 0.135x_5 - 0.256 \qquad (6)$$

Table 6: Prediction of training sample without grey zone for new model

	BANKRUPT	ACTIVE
SAMPLE	40 (100%)	40 (100%)
CORRECTLY IDENTIFIES	26 (65%)	29 (72.5%)
INCORRECTLY IDENTIFIED	14 (35%)	11 (27.5%)

Source: Auhtor's Calculations

The centroid for each group mean of discriminant function is -0.415 for bankruptcy and 0.415 for active companies.

The grey zone for the modified model is recognised by using the centroid of the discriminant function, when equation 6 was applied for both training and testing samples, we had 80 companies in each group to shorlist the grey zone. Thus, analyzing the 160 companies the grey zone identified is between -0.48 to 0.09.

Table 7: Prediction of training sample with grey zone for modified model.

	BANKRUPT	ACTIVE
SAMPLE	40 (100%)	40 (100%)
CORRECTLY IDENTIFIES	12 (30%)	17 (42.5%)
GREY ZONE	25 (62.5%)	15 (37.5%)
INCORRECTLY IDENTIFIED	3 (0.75%)	8 (2%)

Source: author's calculations

After applying the grey zone to the modified model, the overall accuracy of the model is 36.5%, but the type I and II errors were drastically reduced when compared to the Altman model.

Discriminant analysis with reduced variables:

Since, Altman model with reduced variable have shown to more accurate when subjected to application of model in different countries. The sample was first tested for ANOVA single factor analysis to check if there is significant difference between the covariance. Thus, the null hypothesis for the ANOVA is H_0.

H_0 : There is no significant difference between the 5 Group Means

The P-value obtained for Anova analysis is less than 0.000 which is less than 0.05 and hence we can reject null hypothesis and conclude there is significant difference between the 5 variables group means.

The sample was further analyzed to test the equality of group means as shown in table 8.

Table 8. Test of equality of group means for our train sample.

	WILK'S λ	F	SIG.
X1	0.912	7.512	0.008
X2	0.872	11.456	0.001
X3	0.905	8.174	0.005
X4	0.950	4.068	0.047
X5	0.981	1.550	0.217

Source: Author's calcualtions

Table 9, clearly shows that out of five variables only X1, X2, X3 and X4 are statistically significant at 5%, as argued by Shumway (Shumway, 2001) that few of the financial indicators included in bankruptcy prediction models are redundant. And thus, due which X5 variable in the model which opt not be important for European environment. Which requires one to choose an alternate way to find the model or change the ratios with the more significant ones.

Thus, eliminating X5 which is Sales over total assets seems most viable and even Altman in 1984 eliminated this variable for Z' model. Sales over total assets ratio shows variation among industries and since the study has taken 3 fields of industry as data set, which explain the low f value for X5. Now the same discriminant analysis was performed in SPSS by removing X5 and result for discriminant coefficient is shown in equation 7.

The Reduced Discriminat Function is shown in equation 7 and the prediction cabalities for the test sample is shown in table 9. Which shows that the predictive capability of the model is 71.3 % which is shows improvement in eliminating type-I errors.

$$Z = 0.586x_1 + 1.258x_2 + 1.372x_3 + 0.05x_4 - 0.456 \quad (6)$$

Table 9: Prediction of training tample without grey zone for reduced model

	BANKRUPT	ACTIVE
SAMPLE	40 (100%)	40 (100%)
CORRECTLY IDENTIFIES	28 (70%)	29 (72.5%)
INCORRECTLY IDENTIFIED	12 (30%)	11 (27.5%)

Source: Author's Table

The centroid for each group mean of discriminant fucntion is -0.413 for Bankruptcy and 0.413 for active companies.

The grey zone for the reduced Altman model is recognised by using the centroid of the discriminant function, when equation 6 was applied for both training and testing samples, we had 80 companies in each group to shorlist the grey zone. Thus, analyzing the 160 companies the grey zone identified is between -0.32 to 0.12.

Table 10: Prediction of training sample with grey zone for reduced model.

	BANKRUPT	ACTIVE
SAMPLE	40 (100%)	40 (100%)
CORRECTLY IDENTIFIES	19 (47.5%)	17 (42.5%)
GREY ZONE	14 (35%)	16 (40%)
INCORRECTLY IDENTIFIED	7 (1.75%)	7 (1.75%)

Source: author's calculations

After applying the grey zone to the reduced model, the overall accuracy of the model is 45%, but the Type II errors were further reduced when compared to the previous model and overall accuracy of the model increased.

3.2. Discussion and results

The Altman model showed poor accuracy in predicting the active companies. Thus, this shows that the change in geographic environment does play a significant role in the Altman model and requires remodelling to incorporate the changes and requires us to recalculate the discriminant function.

The overall accuracy of the Altman model for the individual countries is as follow: Italy = 46.765%, France = 47.08%, Spain = 42.275%, and Belgium = 36.96%. This shows that Belgium shows the least accuracy whereas France and Italy show similar overall accuracy.

When the Altman model was modified by changing the weights of the discriminant coefficients showed a decrease in overall accuracy of the model, but at the meantime the modified model showed a drastic decrease in Type I and Type II errors, but since the model was unable to perform better than the original model we end up rejecting the second hypothesis of the thesis.

The Altman model was further modified by reducing an indeprendent variable, this change showed a drastic increase in accuracy of the model with least errors and can be rivaled to that of the Altman model, but since the model did show a improvement when compared to the modified model, we accept the final hypothesis of the thesis.

The analysis clearly showed a decrease in both type I and II errors in all the developed models, one of the reason for low accuracy throughout the analysis ranging from Altman Z- Score to the developed model in this thesis might because the research in this study utilised the data for the active companies from the most recent data from Orbis database which is the year 2020 and since the recent pandemic (Covid-19) affected the whole world in early 2020 and effected various fields of industries through the year 2020 and this might be the reason for the crowded grey areas in the developed models, in this study as there is no way to consider the pandemic factor into the model, since it has a very different effect on the industry, as there is a significantly positive impact on healthcare product and medicine products while negatively effecting the tourism and leisure businesses the most.

Conclusion

The study first analysed the predictive capabilities of the original Altman model in 4 European countries (Italy, France, Spain, and Belgium) using data from 1,637 bankrupt and 5,614 non-bankrupt companies with an asset size between 1- 5 million euros, while simultaneously checking for predictive capabilities of the model across these 4 countries. The analysis showed that the predictive capability of the Altman model across the four countries is 46.12 % which is like that of Italy, France, and Spain while Belgium showed more decline in predictability at 36.96%. Thus, when the Altman model is transferred to another location the model losses its accuracy, and this also proves that the Altman model behaves differently for each country no matter if the country belongs to the same economic environment.

The third hypothesis of the research was to develop a uniform model to predict financial distress across the four countries using the original variables while finding the new weights for the discriminant coefficients. The uniform model developed in chapter 3.2 showed a decrease in the predictive capabilities when compared to the original model. The developed model did in fact showed an overall decrease in type I and II errors, but since there was an increase in grey zone for the model, the change in weights of the discriminant coefficient proved to further deteriorate the prediction accuracy.

Finally, to further increase the accuracy of the uniform model an independent variable was eliminated which contributed least to the discriminant analysis, to eliminate a variable the test of equality between the variables were analysed and then rejecting the variable with the least f-value which turned out to be sales over total assets. The new reduced uniform model showed an increase in the predictive accuracy of the model. Thus, reduction of independent variable seems to perform better than just modifying the weights of the discriminant analysis. Hence, to modify the Altman model in European countries it is better to reduce the independent variables rather than just changing the weight of the discriminant coefficients.

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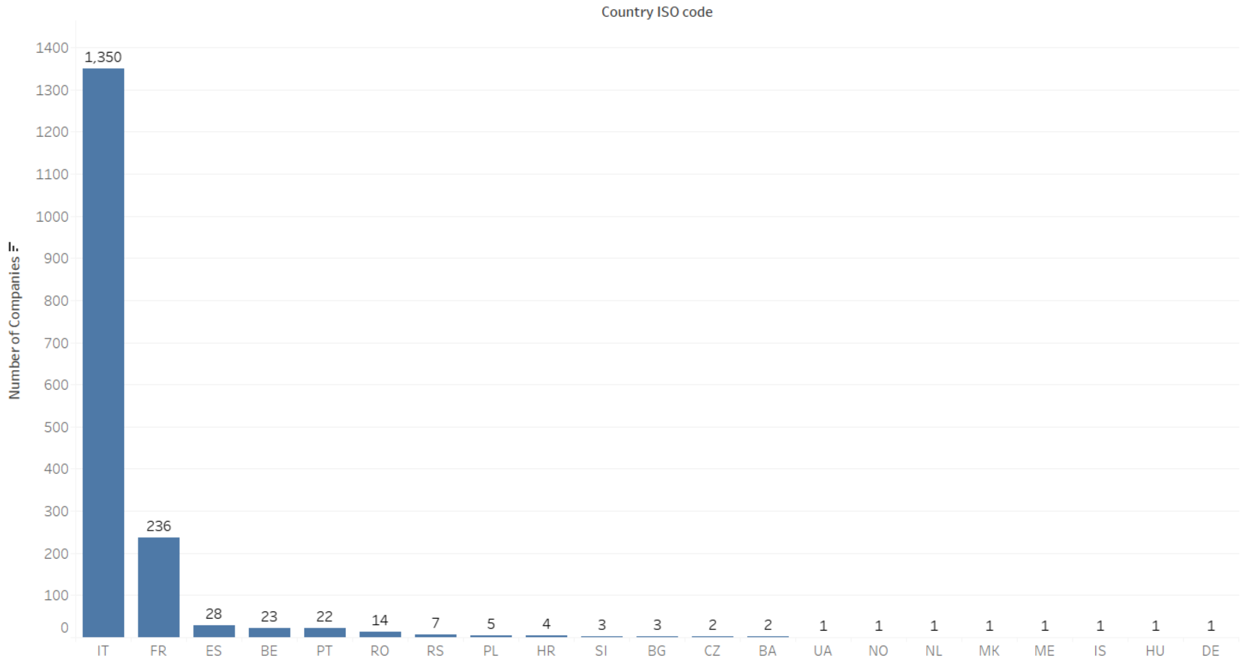
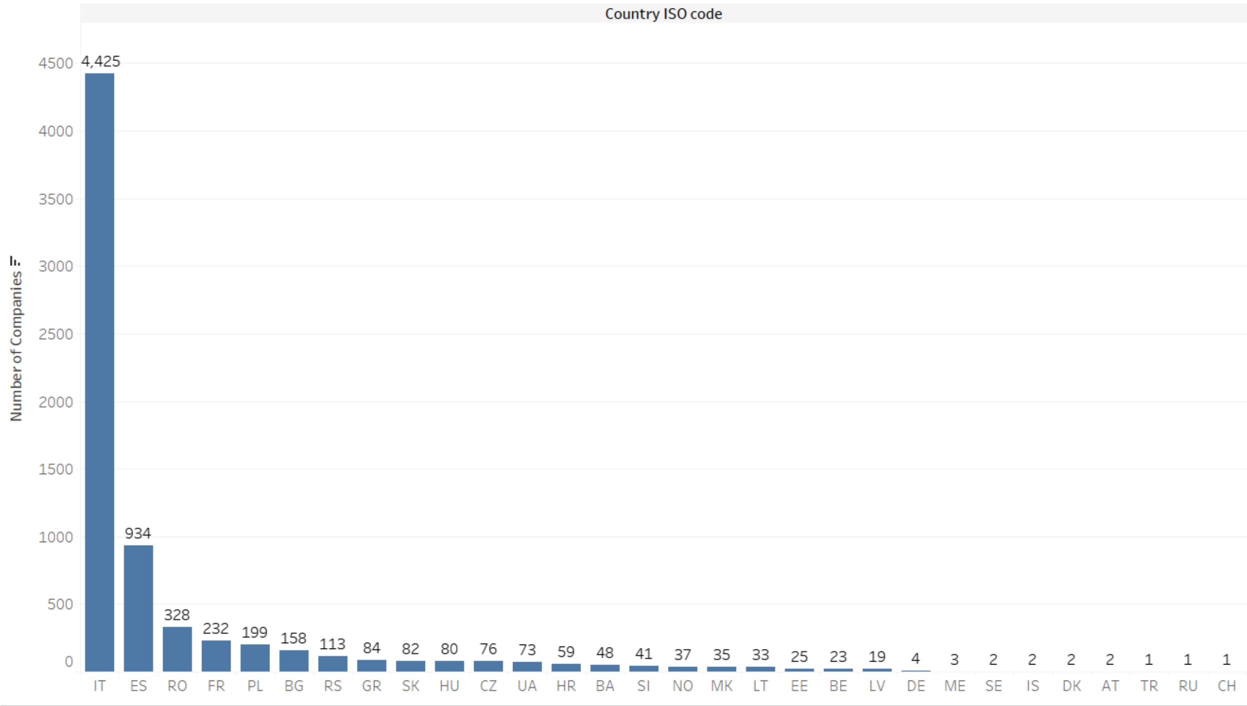
APPENDICES

Appendix 1. Bar chart for all the countries in the bankrupt sample



Source: Author's calculations

Appendix 2. Bar chart for all the countries in the non-bankrupt sample



Source: Author's calculations

Appendix 3. Correlation matrix for bankrupt group

	X1	X2	X3	X4	X5
X1	1				
X2	**0.893**	1			
X3	0.523	0.573	1		
X4	0.153	0.172	0.059	1	
X5	-0.022	-0.08	**-0.245**	-0.001	1

Source: Author's calculations

Appendix 4. Correlation matrix for non-bankrupt group

	X1	X2	X3	X4	X5
X1	1				
X2	**0.598**	1			
X3	0.224	0.263	1		
X4	0.177	0.35	0.013	1	
X5	0.054	**-0.163**	0.264	-0.148	1

Source: Author's Calculations

Appendix 5. ANOVA analysis for sample group

VARIABLES	COUNT	SUM	AVERAGE	VARIANCE
X1	80	12.142	0.152	0.115
X2	80	21.139	0.264	0.158
X3	80	-2.516	-0.031	0.067
X4	80	139.125	1.739	38.008
X5	80	109.562	1.369	0.633

Source: Author's calculations

Appendix 6. Testing sample for discriminant analysis

STATUS	X1	X2	X3	X4	X5
1	-0.45071	-0.55121	-0.40388	-0.35534	2.696584
1	0.377829	0.569552	-0.03307	1.32316	1.585011
1	-0.1105	-0.20545	-0.55099	-0.17044	1.533576
1	0.240677	0.356867	0.013001	0.554888	1.728106
1	0.448852	0.594243	0.005544	1.46453	1.498457
1	0.198055	0.204524	-0.16641	0.257109	2.446692
1	0.051431	0.652592	0.004942	1.87846	2.368091
1	0.39012	0.133351	-0.02222	0.153869	0.95532
1	0.205416	0.210499	0.010416	0.266622	3.794886
1	0.243427	0.255995	0.062801	0.344077	1.903807
1	0.088926	0.053802	0.037732	0.056861	0.52342
1	0.342357	0.869591	0.004315	6.66817	0.004931
1	0.199196	0.226588	0.034679	0.292972	1.786897
1	0.385932	0.629236	0.007027	1.697132	0.332574
1	0.311556	0.454231	0.041842	0.832277	0.89009
1	0.240607	0.662538	0.165952	1.963294	1.228987
1	0.583144	0.77168	0.049974	3.379824	0.717479
1	0.812368	0.754063	0.03942	3.06608	0.776761
1	0.456285	0.623124	0.093243	1.653393	1.124839
1	0.786685	0.31307	0.001027	0.455753	0.810925
1	-0.08851	0.262464	-0.06076	0.355867	2.180493
1	0.211715	0.289163	-0.14426	0.406792	2.556499
1	0.46129	0.483071	0.020734	0.934503	1.202176
1	-0.27899	-0.04113	-0.05332	-0.0395	1.126975
1	0.471102	0.011742	0.008964	0.011881	1.975628
1	0.735744	0.795693	0.107163	3.894595	1.169584
1	0.448264	0.66661	0.030902	1.999494	1.277017
1	0.512709	0.395992	0.007467	0.655608	3.020816
1	0.036534	0.350856	0.022993	0.54049	1.418846
1	0.552179	0.482462	0.285089	0.932226	1.770153
1	0.179755	0.240754	0.020765	0.317095	1.488872
1	0.027077	0.072475	0.085877	0.078138	1.702052
1	-0.6082	0.189278	0.00233	0.233468	0.049856
1	-0.36754	0.070988	0.009532	0.076412	0.425542
1	0.13701	0.137499	0.01284	0.159419	1.355822
1	0.275064	0.17519	0.034365	0.2124	1.59199
1	-0.07595	0.213812	-0.18207	0.271961	1.263051
1	-0.0181	0.011398	-0.03062	0.011529	0.375873
1	0.16549	0.19345	0.03111	0.239849	0.781742
1	-0.14228	0.307839	0.014709	0.444751	0.283323
0	0.511198	0.346642	0.22642	0.530556	1.157804
0	0.724533	0.747773	0.074008	2.964687	3.475647
0	-0.68841	-0.54605	0.003913	-0.35319	0.104911

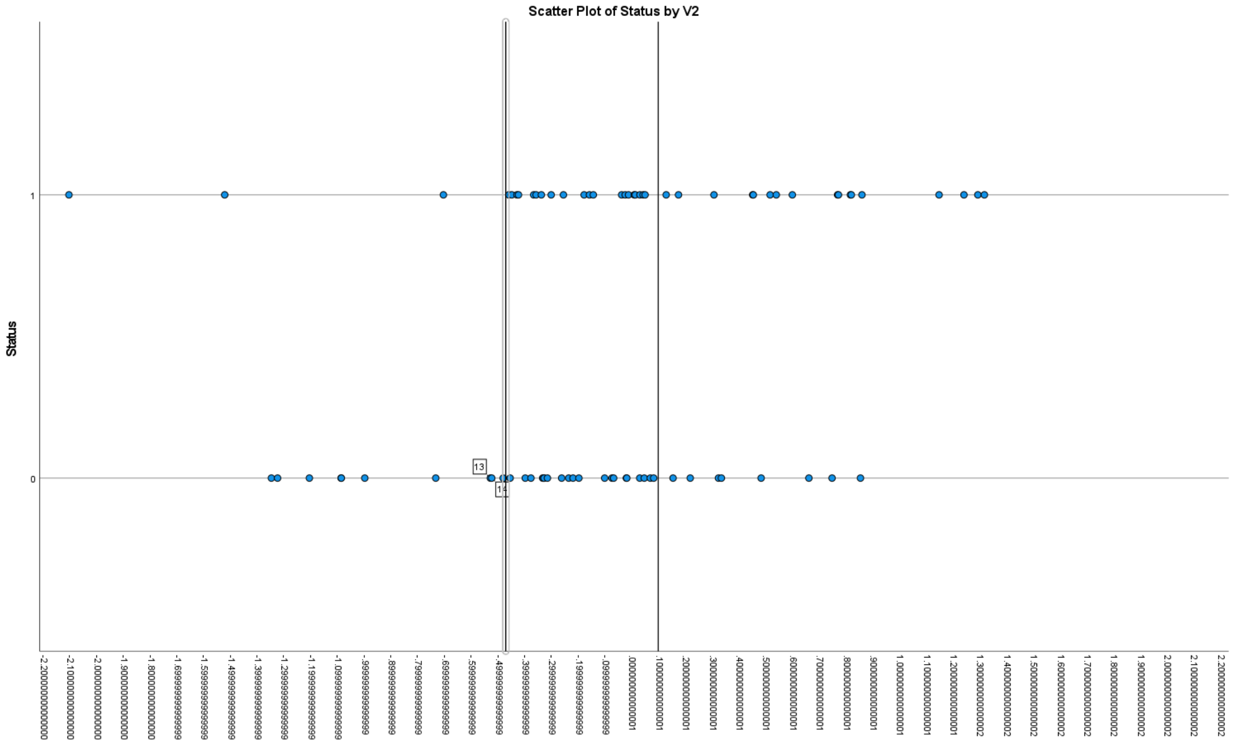
Appendix 6. (Continuing)

0	-0.09454	-0.2751	-0.36573	-0.21575	1.418407
0	-0.62562	-0.21639	-0.18995	-0.1779	0.240341
0	-1.1408	-1.00309	-0.79737	-0.50077	1.375773
0	-0.00209	0.263574	0.048956	0.35791	0.492523
0	0.031403	0.035771	-0.00727	0.037098	0.505666
0	0.1531	0.085347	0.050541	0.093311	1.644353
0	0.226466	0.009949	0.026154	0.010049	0.17149
0	0.082073	0.105832	-0.15026	0.118357	1.544585
0	0.295328	0.432446	0.018193	0.761946	2.091564
0	-1.80054	-1.83046	-0.38622	-0.6467	2.421578
0	0.497453	0.187606	-0.11969	0.23093	3.993209
0	-0.23213	0.062571	0.034692	0.066748	1.310867
0	-0.36723	-0.01579	-0.2537	-0.01555	1.725568
0	0.533111	0.584143	0.097205	1.404675	1.630012
0	0.078906	0.14513	0.014792	0.169769	0.738606
0	0.178077	-0.565	-0.02269	-0.36102	1.304231
0	0.433135	-0.00109	-0.15605	-0.00109	1.481045
0	0.226215	0.158267	0.069361	0.188025	0.768181
0	0.264416	0.214087	0.262541	0.272405	1.534615
0	-0.00331	0.023423	-0.00823	0.023985	0.023545
0	-0.42434	0.00599	-0.36317	0.006026	0.524777
0	0.336654	0.193374	0.080516	0.239733	1.196478
0	-0.09092	0.229705	-0.12994	0.298203	0.792159
0	0.243985	0.123444	-0.12506	0.140829	1.651175
0	0.111631	0.013575	-0.3068	0.013762	1.155664
0	0.434658	0.311369	0.071511	0.452156	1.39632
0	0.022679	0.06867	0.059095	0.073734	1.110388
0	0.165395	0.038654	0.001343	0.040208	1.76256
0	0.068443	-0.0031	-0.18613	-0.00309	0.469998
0	0.517817	0.43476	-0.03459	0.769159	0.699252
0	0.082828	0.278829	-0.0432	0.386634	0.764013
0	-0.15376	0.064973	-0.14325	0.069488	0.461299
0	0.037855	0.297933	-0.00327	0.424365	1.135942
0	-0.0896	0.155594	-0.03016	0.184265	1.235577
0	0.032895	0.264912	0.093421	0.360382	1.417982
0	0.343387	0.163518	0.019055	0.195483	1.137022
0	0.203076	0.152603	0.029574	0.180084	1.310726

Source: Author’s calculation

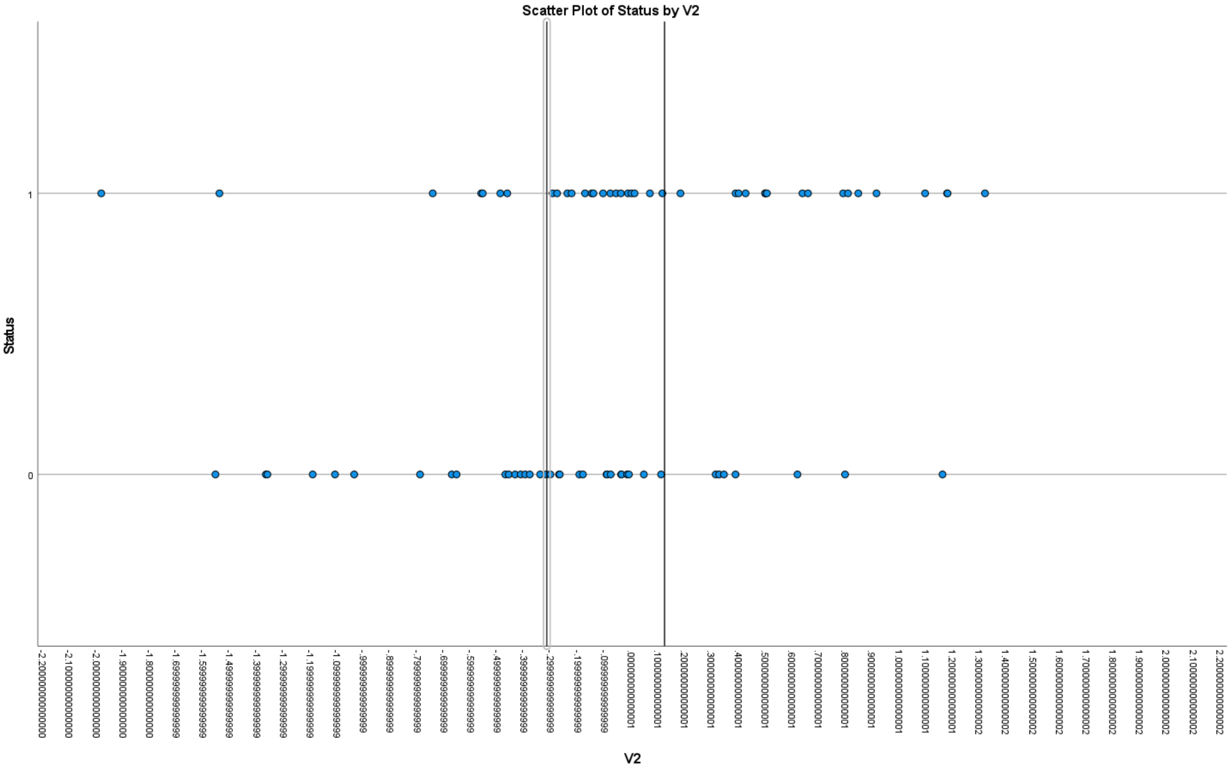
Where, Status = 1 means active and Status = 0 means bankrupt

Appendix 7. Scatter plot for grey area in the modified Altman model



Source: Author’s calculations

Appendix 7. Scatter plot for grey area in the reduced Altman model



Source: Author’s calculations

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