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BANKRUPTCY PREDICTION METHODS: A COMPARISON WITH FINNISH DATA

Bachelor's Thesis

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Tallinn 2017

I declare I have written the research paper independently.
All works and major viewpoints of the other authors, data from other sources of literature and elsewhere used for writing this paper have been referenced.

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Abstract

Bankruptcy prediction is one the most studied subject in the areas of accounting and finance. There are countless of articles, books and studies concerning the search for the best method to predict possible future financial distress. This paper studies two of those methods, the main goal to see which works better for Finnish companies, post-financial crises. Altman's (1968) multivariable method, or Z-score, is one of the oldest methods for bankruptcy prediction. Logistic regression was only introduced to the field in the 1980's, but it has a stable position as the most popular method.

The study begins with literature review, going through the two models; multivariable Z-score and logistic regression. The main research questions for this paper are: (1) How do the models perform with modern Finnish data and (2) How do they compare to each other.

The questions are answered in the empirical part of the study, where the two models are first tested using SPSS. In this stage, the evidence clearly shows that the models are not working as hoped with the Finnish data. The models also give very similar results, with both of them having the percentage of correct predictions around 50-60%, with the exception of the training sample of the logistic model, which gives the prediction rate of 72%.

Keywords: Altman, bankruptcy prediction, logistic regression, multivariable method

Introduction

1.1 Background

Bankruptcy prediction is one of the most researched topics in finance and strategic management (Polemis and Gounopoulos, 2012). The amount of methods used for predicting bankruptcy is massive, starting from Beaver's (1966) method of using single-variable ratios and moving to the more recent studies such as logistic regression or hybrid models. For just one model there are countless articles, studies and even books made, for the main purpose of developing them, and nowadays mainly trying to bring the oldest models to the 21st century. Though new methods seem to surface consistently, it seems that the models developed in the mid-end 1900's keep their position in the top most popular.

Bankruptcy models assign firms to one of two groups: a 'good firm' group that is likely to pay any financial obligation; or a 'bad firm' group that has a high likelihood of defaulting on any financial obligation. (Blanco et al., 2012). The literature for bankruptcy prediction dates back to the 1930's beginning with the preliminary studies concerning the use of ratio analysis to predict future bankruptcies (Bellovary et al., 2007). Up until the 1960's the prediction methods were merely focused on single ratio studies and formulas. The most recognizable study for these is Beaver's (1966) original single-variable method. After that the models developed to multivariable methods, out of which the most recognizable is Altman's multivariable "Z-score" (1968). The number of ratios in multivariable formulas vary from two to 57 (Ibid.).

Given the relatively high frequency of bankruptcies filed by both publicly-traded businesses and private firms around the world, and the threat posed to suppliers and other stakeholders that rely on firms' solvency for their own success, a reliable bankruptcy model with consistent predictive power is essential in today's business environment (Hayes et. al., 2010). This accentuates the importance of finding and possibly updating useful bankruptcy prediction methods and models. It is no wonder that bankruptcy prediction is such a highly studied field. Having a working method for predicting bankruptcy is an important mean for a company. If future financial distress is discovered in time, it might help save a company from an otherwise definite bankruptcy. For this reason, it is extremely important for researchers to develop the models to get the most accurate results.

It is not only corporations themselves, though, that use bankruptcy prediction as a source of information on the financial future of a company. Banks and other investors use this data as an informative source when looking for and deciding on new and viable investments. Creditors also get helpful knowledge from this data when considering their investments. As the prediction methods are developing, banks are also benefitting as they are getting more detailed and accurate information of a possible investment and can make more solid investment decisions.

Predicting corporate failure is also important on multiple levels of the economy. For example, having a medium sized company go bankrupt in a small town is a big hit on the economy of the community. The people working inside the company lose their jobs and the unemployment rate goes up. The community is collecting less taxes and therefore most likely taking in more debt. Other parties affected by these bankruptcies might be for example accounting firms, which risk lawsuits in the event that the auditor did not inform the company about possible financial distress in time.

A popular way for creditors and investors to seek knowledge about the financial situation of possible new investments is through credit rating agencies. These ratings tend to be, though, rather reactive than predictive, making it more important for researchers to develop more accurate quantitative models for bankruptcy prediction (Hauser and Booth, 2011).

Bankruptcies are mostly predicted using companies' financial statements. The basic idea behind this is that the differences between healthy and bankrupt companies' closing balances of financial statements and the ratios formed out of these numbers are significant (Laitinen, 1990). There are a small number of studies which use qualitative information in addition to financial statement data. These include, for example, information on company age, defaulted payments, and industry riskiness, which have been found to improve the results of models developed specifically for SMEs (Altman et al., 2017).

1.2 Bankruptcy prediction

Bankruptcy models are of two types: parametric and non-parametric. The most used parametric models are the multivariate discriminant analysis (MDA) and logistic analysis (LA) (Fejér-Király, 2015). MDA classifies the companies into two groups: healthy and distressed. The classification is based on the financial characteristics of the companies, which are calculated with financial ratios. The discriminant score allows the classification of the two groups. Logistic analysis on the other hand takes into account the profitability of failure of the company. The difference between these two is that logistic regression requires logistic distribution (Lo, 1986). The parametric models focus on symptoms of bankruptcy and could be univariate or multivariate whose variables are mainly financial ratios (Andan and Dar, 2006).

In the past decade, a number of researchers have begun to apply neural network approach to the field of bankruptcy prediction, and the results have been promising (Ugurlu and Aksoy, 2006). Neural networks, which were first presented to bankruptcy prediction by Odom and Sharda (2009), are a computing system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state responses to external inputs (Caudill, 1989). An alternative to the previously mentioned methods is Human Information Processing approach (HIP) (Laitinen and Kankaanpää, 1999).

1.3 Bankruptcies in Finland

In Finland, bankruptcy of a limited company can be the consequence of two juridical processes. First, if losses incurred cause the stockholders' equity on the balance sheet to fall below one third of the share capital, the firm goes into liquidation, unless the situation can be fixed in a limited time-period. If the debts of the company exceed the assets, the company is declared bankrupt. In the opposite case, they can continue their operations (Laitinen and Kankaanpää, 1999). Cases like this are sometimes called solidity bankruptcies.

The second case is the so-called liquidity bankruptcy, in which the company cannot pay its debts when they fall due. These failure processes are not mutually exclusive (Ibid.)

The Finnish bankruptcy law defines bankruptcy as "insolvency proceedings as against all the liabilities of the debtor, in which all of the debtor's assets are used to pay claims to creditors" (Finlex Data Bank). Bankruptcy can be declared on any company, natural person, foundation or even an estate. The only exceptions are churches, townships, and a few other public agencies, which cannot be declared bankrupt. For this research, I will only be focusing on limited liability companies.

A bankruptcy becomes legal immediately after the court has declared the company bankrupt. All of the belongings of the bankrupt party are used to pay off creditors. If the property is not enough to cover all of the debts, the debtor is not freed from the debts. After being declared bankrupt the debtor loses all authority to the assets belonging to the company.

Bankruptcy can be petitioned by the creditor or the debtor. The cases in which the petitioner is the debtor are called voluntary bankruptcies. An example of a voluntary bankruptcy could be the bankruptcy of an estate. Figure 1 shows the amount of limited liability companies declared bankrupt in Finland during the years 2009 to 2016 and the number of employees in those companies.

Figure 1: Bankruptcies in Finland 2009-2016

Source: www.stat.fi

We can see from figure 1, that the number of bankruptcies has been slightly above 2000 a year and that they have declined during the last two years. It also seems that most companies are very small, because the average number of employees seems to be about five.

1.4 Objective and research problems

This study is conducted to compare two of the most popular and recognisable methods for financial distress prediction: the multivariable Z-scores formulated by Altman (1968) and the logistic regression model. More precisely, it is meant to analyse and compare the results of two statistical methods for bankruptcy prediction and their prediction ability by using Finnish data. The approach adopted in this study is somewhat similar to that in Bapat and Nagale (2014), who compare the multivariate method, logistic regression model and neural networks in bankruptcy prediction.

2 BANKRUPTCY PREDICTION METHODS

2.1 Multivariable methods

2.1.1 Altman's Z-score

Edward I. Altman (1968) was the first to develop a multivariable formula for bankruptcy prediction. His research was conducted with 66 companies, half of which were bankrupt and half healthy companies. The bankrupt companies were collected from a rather long period of time, as the data was not as easily accessible back then as it is now. Altman only used manufacturing companies for his study, making the original Z-score best applicable for manufacturing companies.

Altman started his research with finding the right ratios. These were the ratios which showed the most changes between healthy and bankrupt companies. He started with 22 original financial ratios. To find the best suitable ratios Altman had two criteria for them:

1. The prevalence of the ratios in field literature
2. The possible significance of the ratios for the research

After conducting this part of the research, Altman ended up with five ratios which he found were the most efficient when trying to calculate the most informative Z-score. The ratios were chosen by their corresponding correlation and how well they worked together on different formulas, instead of their individual performance.

After finding the ratios, Altman drew the linear function, also known as the Z-score. His function consists of the weighted total of the financial ratios. The weights used were estimated by using statistical discriminant analysis.

Formula1. Altman's Z-score

$$Z=0.012\,X1+0.014\,X2+0.0333\,X3+0.006\,X4+0.999\,X5$$

In which,

X1= net working capital / full capital

X2= retained earnings / full capital

X3= earnings before interest / full capital

X4= market value of equity / book value of debt

X5= sales / full capital

Altman also specified, that only the first four ratios are used as percentages, and the last one is to be used as a natural number.

The results are classified into three groups. First the healthy companies, which get values at and above Z=2.99. The second group is the bankrupt companies, or companies with a high risk of facing financial distress, which get values at or less than Z=1.81. The third group is the so-called "grey area". Companies in this grey area get a value for Z which falls between 1.81 and 2.99. These companies, according to Altman, do not have as easily classifiable financial future as the ones falling directly for either healthy or bankrupt values.

All of the five ratios have an area of financial stability that they measure. The first ratio X1 measures liquidity. Altman had all in all three different ratios which he studied for the purpose of measuring liquidity, out of which he found the net working capital / full capital to be the most suitable.

The second ratio X2 measures a company's long-term profitability. For long-term profitability, retained earnings is a good fit, as it is a part of the company's equity that is not divided to the shareholders. The long-term profitability ratio takes into notice the age of the company, which means that it classifies new companies highly sensitive for bankruptcy. This is not necessarily any different from reality, as new companies do tend to have a higher bankruptcy-rate.

The third ratio X3 measures the profitability of a company relative to its total assets. As the main purpose of a company is usually to generate revenue and have high return on capital, excluding non-profit organizations, this ratio is ideal for the purpose.

The fourth ratio X4 measures the financial solidity of a company. Out of all the five ratios, this is the only one which uses the market value of the asset, in this case equity. This makes the original Altman Z-score only applicable for publicly traded companies. Later on, Altman modified the formula to create a version which would be applicable for also private companies. This new Z-score uses book value of equity instead.

The fifth ratio X5 shows how well a company uses its personal capital to generate sales. A low result on this tells that the company has not been able to raise its market share (Narayanan, 2010).

In the 1960's Altman's research was a major leap forward. It was a highly appreciated discovery that bankruptcy prediction could be done using scientific measures. Altman's multivariable formula is able to predict bankruptcy up to two years prior of any visible financial distress.

In his initial testing, Altman found his research to be correct approximately in 72% of the cases. In his testing he found two types of errors that occurred: Type I (false positives) and Type II (false negatives). The percentage of type II errors was only 6%.

The newer version of Altman's Z-score was formulated to suit private companies better than the original one. The original Z-score was altered by removing the market values from the ratios and replacing them with book values (Altman et al. 2017)

The original model was based on market values of the companies, making it only applicable for publicly traded companies. Altman himself emphasized that *ad hoc* adjustments are not scientifically valid and later on made a complete re-estimation of the formula using the book values instead of market values. He used the same data as in the original research and ended up with the following formula:

$$Z=0.717\,X1+0.847\,X2+0.3107\,X3+0.420\,X4+0.998\,X5$$

Because the formula has different values for coefficients for variables X1 through X5, the critical values are also slightly different. When using this formula, the firms are classified healthy if the Z-core is > 2.9 and Bankrupt if Z<1.23.

2.1.2 Laitinen's Z-score

Another big name in multivariable predicting is Erkki K. Laitinen (1990). His approach to the study was very similar to Altman's. He used only small to medium sized companies in his research, as did Altman 30 years prior. Also like Altman, Laitinen used a relatively small amount of companies, having 80 companies in total. These companies consisted of 40 bankrupt companies and a comparative group of 40 healthy companies. Laitinen collected up to seven to eight years, depending on availability of the data, of information on the companies' financial history. To get the most accurate results, Laitinen left out the smallest companies as they have the highest risk of going bankrupt. He also had some other limitations, for example the age of the companies he used had to be at least 10 years. In Laitinen's study, he had a better possibility to do these kinds of deductions and be pickier concerning the data as there was much more data available in the 1990's as there was in the 1960's.

Laitinen's research concluded that the best ratios for the purpose of bankruptcy prediction were financial income percentage, quick ratio, payment of account payables, equity ratio and growth rate of net sales. Finally, he ended up eliminating payment of account payables and growth rate of net sales ending up with an equation as follows:

$$Z = 1.77\,X1 + 14.14\,X2 + 0.54\,X3$$

In which,

X1 = Financial income percentage

X2 = quick ratio

X3 = equity to total assets ratio

The first ratio, X1, describes the company's profitability, emphasizing the internal financing and how it succeeds at helping cover short-time expenses and profit distribution.

The second ratio indicates the company's short-term liquidity. It tells how well the company can perform short-term obligations with their liquid assets. Therefore, when calculating this ratio, one needs to separate inventory from current assets before dividing it with current liabilities.

The third ratio, X3, indicated the ratio of the company's total assets to the portion of assets which is financed by shareholders. This indicates, that the higher the ratio, the better the company endures loss and the better it will be able to make its debt payments.

In his research, Laitinen found an exact critical value, contrary to Altman, which he found to be 18. Companies which scored under 18 are classified as companies under financial distress and companies which scored above it are classified as healthy ones.

Both Laitinen and Altman's formula have been tested and modified over the years to make them more suitable for the current economic environment. They both have developed different formulas which are suitable for a wider range of companies, as both of the original Z-scores are generated for specific industries, and in Altman's case only for US based companies.

2.1.3 Criticism concerning multivariable methods

The Z-scores have both gotten quite a lot of criticism. Especially Altman's Z-score has been questioned in multiple cases. Often the criticism is about the fact that the original data used in the study is very limited, to only one field of business. Altman's study has also been the subject of discrimination for the fact that the data was collected from such a long time-period.

Clark et al. (1997) had an experiment with the classification abilities of Altman's formula. In their research they used seven bankrupt and seven healthy companies. The results showed that most of these companies landed in the so called 'gray area', meaning that the Z-score was not able to classify these companies specifically. Especially the bankrupt companies seemed to be hard for the formula to position.

Grice and Ingram (2001) question in their research whether or not Altman's research is still applicable, all these years later. They found that it does not work as expected when applying it to newer companies. They also mentioned that the Z-scores only take into notice the possible financial struggles of a company. Alas, even if the formula classifies a company healthy, and does not see any financial struggles in the future, a company can still go bankrupt very suddenly. The reason for a bankruptcy is not always primarily financial, for example big law suits can drive any company down. This is one of the reasons why a mathematical formula is not a 100 percent certain in matters like this. Contrary to this, Salimi (2015) finds that Altman's model works fairly well in his sample from 2000-2005 and for companies from multiple industries.

Altman used in his original research only industrial companies, and it seems that this has the effect on the formula that it mostly only works for similar companies. This is one of the difficulties in predicting bankruptcy using scientific methods; it is difficult to create a model that is universally applicable. Especially financial companies are recommended to not to use this formula.

Altman has also received criticism considering his data collecting methods. The financial data he used in his research was gathered from a 20-year period. At the time though it was a necessary act, since getting his hands on the needed information was not an easy task.

2.2 Logistic regression

2.2.1 History

The logit model was first introduced to bankruptcy prediction in the 1980's, but the regression model has been around since late 1800's. In the 19th century the logit model was invented to predict growth of population and the course of autocatalytic chemical reactions (Cramer, 2002). It took almost a hundred years for the model to be applied to the field of bankruptcy prediction.

The father of the idea being applied to the prediction of financial distress is recognized as James A. Ohlson (1980). The biggest advantage the logit model had in bankruptcy prediction, when comparing to the multivariable methods, was that the researchers were able to get rid of the "in-between" companies and "grey areas".

Ohlson (1980) began his original study on the logit model by choosing nine variables, which describe the financial performance of the companies best. The variables were:

1. The logarithmic relationship between capital and GDP
2. Liabilities to assets
3. Working capital to ending balance
4. Short-time liabilities to inventory
5. Dummy value of 1 if liabilities exceed assets, otherwise 0
6. Net profit to total assets
7. Operating income to total debt
8. Dummy value of 1 if net profit has been negative for the last 2 years, otherwise 0
9. Growth

The first four describe financial stability and the last five financial performance. Out of these 9 ratios, he eliminated the ones which did not seem to have statistical significance to the study results and ended up with the following four:

1. Size
2. Indebtedness
3. Financial performance
4. Liquidity

The final four variables all measure the financial stability of the company from different angles. Ohlson's original model classified approximately 96 percent of the companies correctly, the critical point being 0.5 (50%). When looking at this percentage, Altman's model proved to be more efficient, but this can be explained with two arguments. First, Ohlson's study had a much larger amount of data than Altman's. Second, Ohlson's data was not divided in to two same sized groups of bankrupt and healthy companies like in the method of confrontation which was used by for example both Altman and Laitinen.

Logistic regression model is applied into bankruptcy prediction by dividing the sample group of companies into two groups: training sample and testing sample. The training sample is first used to give the companies the values by which the companies are divided into bankrupt and healthy companies. The test sample is then applied to the formula. The test sample is used to see how well the variables which were chosen by the training sample work with other companies.

Ohlson's model is not the only logit model for bankruptcy prediction. Many other researchers have developed their own model, which some vary widely from Ohlson's model when looking at the variables chosen for the study. For example, Laitinen (1999) developed his own similar model for the field of financial distress studies. He used quite a few variables more comparing to Ohlson's, having 15 original variables. Other interesting studies in the field are for example Chesser's (1974), who used the logit model for predicting the neglection of commercial loans, and Martin's (1977) whose research studied the probability of bank failure.

Richard P. Hauser and David Booth developed their own research on the area of logit model bankruptcy prediction in 2011. In their model, they used the same variables as Altman (1968) used in his study. The ratios were Working capital to total assets, Retained earnings to total assets, EBIT to total assets, market value of equity to book value of debt and sales to total assets. The Hauser and Booth study was conducted mainly to compare the ML (maximum likelihood) and BY (Bianco-Yohai) estimators in logistic regression for bankruptcy prediction.

2.2.2 Method

Logistic regression is the most popular method of bankruptcy prediction. It works well with the field as it does not give absolute values on the financial stability of the company, but instead uses a probability of the event of bankruptcy happening. The logit model does not have one simple formula by which it can be defined, but there are some mathematical formulas which can be used to describe the model. A key part of the function form in logistic regression is very similar with the discriminant analysis function. However, the result of this formula is not immediately intuitively interpretable as it results in a logarithmic odds ratio (Laakso, 2016). Below is presented one way to describe the logit formula:

$$ln(P_j/(1 - P_j)) = a + w_1 * X_{1j} + w_2 * X_{2j} + \cdots + w_n * X_{nj}$$

In which

1. P_j = Probability of Company j going bankrupt
2. a = constant
3. w_1 = weight factor of X_i
4. X_{ij} = the value of factor Xi for company j

The right side of the function can be compared to the separation function in linear regression, but the results bear no resemblance to each other.

Figure 2 shows how the logistic model separates the variables on an S-shaped curve. The ability of the logit model to define the bankruptcies can be seen from the curve it presents. If the model has succeeded in the prediction, the variables can be seen in a small area, close to each other. If the prediction has not given a high percentage of correct values, the variables are divided to a wider line. (Hair et al., 2010; Laakso, 2016).

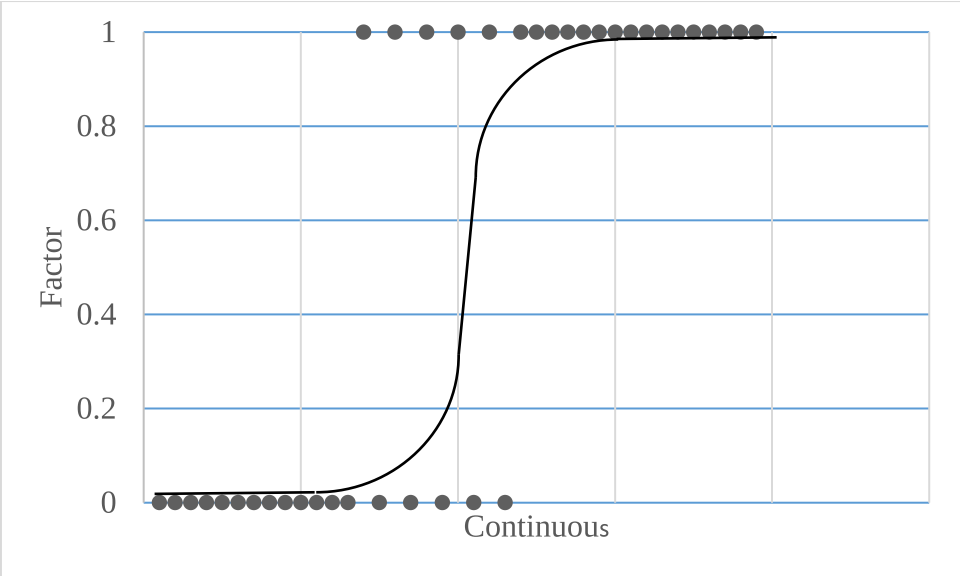

Figure 2. The separation model of logistic regression

3 Empirical study

In this chapter I will be concluding the empirical study and calculations for Altman’s multivariable formula and the logit model, respectively. The initial dataset for both of the studies was selected randomly from a sample of 2000 Finnish companies. The data for this study was obtained from the Amadeus database. The original sample contained two thousand randomly selected Finnish companies and their financial information from years 2014 and 2015. Out of these companies, 137 were bankrupt and the remaining 1863 active. The random selection process did not emphasize bankrupt companies. My starting point for the part of the research project were the 137 companies in the database that went bankrupt. These companies were paired with a randomly selected set of 137 healthy companies. This dataset of 274 companies formed the basis of my analysis.

3.1.1 Data collection

For the purposes of this study at this stage, I selected 30 bankrupt and 30 healthy companies and supplemented the data described above with financial data information for the selected companies so that the final database contains financial information for the years 2011-2015. The selection of companies was based on the availability of information from 2011 onwards. The initial analysis was performed for 60 firms at a general level. For this research, I used the companies’ financial information from a five-year period, starting from 2011 and ending to 2015. To investigate some bankrupt companies in more detail, I randomly selected 10 companies, which are all declared bankrupt. Half of the companies were from different types of manufacturing industries, and half from other industries, such as the travel and advertising industries. Some of the companies chosen had missing financial information for one year but in this case, it should not affect the results.

3.1.2 Data analysis – Altman

Table 1 below illustrates the average values of the ratios in Altman’s Z-score. The values are given for each year of data used, and it is divided for bankrupt and healthy companies. It also provides a statistical F-test which shows if the values of the two groups differ from each other statistically.

The F-test shows us that all of the ratios are statistically significantly different in the two groups, making the use of them in bankruptcy prediction a good fit.

Table 1. Variable means and test of significance (F-test)

Variable	Bankrupt	Healthy	F-test (p-value)
X1	4.36%	18.4%	0.000
X2	-129.80%	-28.20%	0.000
X3	4.36%	3.0%	0.000
X4	16.98%	296%	0.000
X5	4.57	2.68	0.000

Table 2 shows how well Altman's model performed in bankruptcy prediction for the whole sample. The data included was from the last five years before bankruptcy. The table includes the number and percentage of correct predictions for bankrupt companies, i.e. companies with a Z-score lower than 1.23. On the other side the table shows the number and percentage of correct predictions for healthy companies, i.e. companies with a Z-score higher than 2.9. The results of these calculations show, that on the average the formula predicted the bankrupt companies correctly in 39% of cases and the healthy companies correctly in 57% of cases. This tells us that the formula did not work very well for the sample in question, even if it was able to predict 63% of bankruptcies correctly one year before bankruptcy.

The results of this table could be concluded by saying that, even though the ratios are statistically significantly different for bankrupt and healthy companies and the model still does not do correct predictions, the fault could be placed on the weights and critical values of the formula. The model was developed in the United States, and before the financial crises, which could very well be why it is not giving useful results for Finnish based companies. In the next stage I will take a closer look on 10 bankrupt companies and analyse the results a bit deeper to get a better idea of how the Z-score works and a better understanding of the results.

Table 2. Classification into healthy and bankrupt companies

Actual	***Healthy Firms***		***Bankrupt Firms***	
Classified	Correct	%	Correct	%
Year -5	14	47 %	13	43 %
Year -4	18	60 %	6	20 %
Year -3	15	50 %	9	30 %
Year -2	20	67 %	11	37 %
Year -1	18	60 %	19	63 %
Average % correct		57 %		39 %

The next part was calculating the Z-scores for selected 10 bankrupt companies, using Altman's formula and analyzing them in more detail. In this paper, I will use Altman's modified Z-score, meant for private trading companies, as all the companies chosen for the research were small to medium sized private companies. Altman (1983) himself noted that the original Z-score was not applicable for other than publicly traded companies.

Table 3. Classification of Company A using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	-0.23	0.71	0.66	-0.21	-0.16	0.210	Distressed
2012	-0.15	0.65	0.64	-0.45	-0.30	0.133	Distressed
2013	0.08	0.69	0.55	-0.43	-0.29	0.806	Distressed
2014	0.03	0.6	0.95	-0.56	-0.35	0.850	Distressed
2015	0.11	0.58	0.96	-0.58	-0.35	1.077	Distressed

Company A is a household furniture manufacturing company. Company A was a small company, with only approximately 3 people in their personnel. The company was founded in 1996 and was declared bankrupt in 2015.

In Company A's case, Altman's Z-score for private companies worked well, seeing as the formula classified the company as distressed for the whole 5-year period used in this estimation. The sales to total assets and book value of equity to total liabilities ratios were especially low for the whole period of data used. For company A, the Z-score did not have any type I or II errors, as it was successful in predicting the bankruptcy.

Table 4. Classification of Company B using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	-0.11	0.48	3.22	0.81	12.5	9.153	Healthy
2012							
2013	-0.04	0.35	4.43	0	0.15	4.611	Healthy
2014	0.04	0.79	4.39	0	0.12	5.122	Healthy
2015	-0.17	0.55	0.86	-0.24	-0.12	0.472	Distressed

Company B was specialized in manufacturing machinery installation. They had missing financial information for year 2012. The company experienced a major drop in their Z-score in 2015, which is visible from all of the ratios used to calculate the score. Before this the company was maintaining a good position on the healthy side of the Z-score classification. Sudden drops like this can be caused by multiple reasons. For example, the specific market could have been affected by a major incident. Or, as the company was a fairly small one, any type of personnel or owner related issues can affect the company in major ways.

Table 5. Classification of Company C using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	0.10	0.22	2.72	-0.27	-0.12	2.903	Grey
2012	0.06	-0.02	3.15	-0.32	-0.15	2.981	Grey
2013	1.06	0.15	5.42	0.33	1.36	9.653	Healthy
2014	-0.07	0.11	2.71	0.20	0.61	2.992	Grey
2015	0.04	0	2.15	0.23	0.66	2.742	Grey

Company C was a small metal manufacturing company. They were classified in the "grey" zone for most of the period, excluding 2013, for which they were classified as a healthy one. This could be explained by the sudden peak in EBIT to total assets ratio. For most part, the company was at the very limit of being in the healthy area of the graph. For company C, Altman's formula had some difficulties giving a correct classification.

Table 6. Classification of Company D using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	0.12	0	2.04	-1.04	-0.48	1.325	Grey
2012	0.65	0.11	1.73	-0.11	-0.03	3.715	Healthy
2013	0.88	0	2.35	0.48	1.22	5.992	Healthy
2014	0.31	0	1.55	0.59	1.88	3.797	Healthy
2015	0.39	0	1.25	0.72	3.31	4.456	Healthy

Company D is a metal product manufacturing company. Their personnel only includes one person. It was founded in 2006, and was declared bankrupt in 2015. Not including the first year of the period used in this study, the company was classified by the Altman formula as a healthy company. This means, that the original formula did not work as hoped in Company D's case. The fact that the retained earnings to total assets ratio is zero for four out of five years, could have a part in the fact that the company is getting a wrong classification, at least for the year of the bankruptcy.

It is also possible that the company declared bankruptcy on their own, in which case there might not have been any visible signs of it in their financial information.

Table 7. Classification of Company E using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	0.25	0.25	5.25	-0.17	0.09	6.087	Healthy
2012	0.27	0.27	4.47	-0.13	0.07	5.411	Healthy
2013	0.23	0.46	6.54	-0.08	0.18	7.577	Healthy
2014	0.14	0.21	5.57	-0.07	0.17	6.155	Healthy
2015	0.14	0.43	5.71	-0.21	0	6.263	Healthy

Company E was a sporting and athletic goods manufacturing company, which was founded in 1995 and declared bankrupt in 2015. Company E was as well classified as a healthy company for the entire five years in this study. Most of the ratios were quite low, but the EBIT to total assets ratio stayed at a healthy level, which could be why the company classified as a healthy one until the bankruptcy.

Table 8. Classification of Company F using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	-0.22	0	0.16	-0.69	-0.38	-1.266	Distressed
2012	-0.09	0.04	0.23	-0.90	-0.45	-0.972	Distressed
2013	-0.17	-0.03	0.22	-1.30	-0.55	-1.661	Distressed
2014	-0.29	-0.16	0.14	-1.90	-0.64	-2.752	Distressed
2015	-0.35	-0.28	0	-2.85	-0.73	-4.006	Distressed

Company F is also an example where the formula worked well. It was classified as a distressed one for the whole period of five years. Most of the ratios were negative for the whole period, so there is no one ratio which could be incriminated for the low Z-score. The main business for company F was safari ATV rental services and tours. This could well be kept as a so-called luxury item which is not necessarily a flourishing business activity during recession years. It is also a business which can be affected by bad weather and cold summers which Finland has been experiencing recently.

Table 9. Classification of Company G using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011							
2012	-0.10	-0.02	0.62	0.30	0.49	0.754	Distressed
2013	-0.06	-0.12	0.34	0.22	0.34	0.396	Distressed
2014	0.03	0	0.23	0.17	0.24	0.567	Distressed
2015	-0.09	0	0.01	0.09	0.12	-0.142	Distressed

For Company G, the formula classified it as a distressed one for the whole four years it had available financial information. Company G had a very low score on each of the ratios for the whole four year period. The zeros in the second ratio could be explained by some missing information which was needed to calculate the original ratio. None of the variables give an exceptionally low figure, so the results can be explained by all of the variables.

Table 10. Classification of Company H using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	-0.03	0.05	0.58	-0.57	-0.35	-0.108	Distressed
2012	0.06	0	0.7	-0.64	-0.38	0.183	Distressed
2013	0.06	0.03	0.86	-0.64	-0.38	0.364	Distressed
2014	0.15	0	0.76	-0.57	-0.34	0.598	Distressed
2015	-0.04	-0.07	0.06	-0.63	-0.37	-0.803	Distressed

Company H was also classified correctly as a distressed company for the entire five-year period used in this study. As well as company G, neither company H had one specific variable which was exceptionally low to be able to blame the results on just on variable. All of the variables were fairly low, with the negative values in the fourth and fifth variable not helping the situation.

Table 11. Classification of Company I using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	0.07	0.18	1.86	-0.32	-0.2	1.847	Distressed
2012	-0.06	0.23	1.76	-0.53	-0.3	1.160	Distressed
2013	0.11	0.34	1.52	-0.53	-0.3	1.527	Distressed
2014	-0.09	0.25	1.55	-0.71	-0.38	0.686	Distressed
2015	-0.07	0.41	1.43	-0.76	-0.4	0.692	Distressed

Like most of the other service companies, also Company I was correctly classified as a distressed one for the entire five-year period. None of these companies have had just one specific variable which to blame, and all have only been slightly on the distressed side of the scale. Company I follows the pattern as the variables all get figures close to zero but mostly on the positive side.

Table 12. Classification of Company J using Altman's Z-score

	X1	X2	X3	X4	X5	Z-score	Classification
2011	0.36	0	4.44	0.26	0.50	5.977	Healthy
2012	-0.80	0	3.60	0.40	2.33	2.430	Grey
2013	0.85	0	3.70	0.80	19	14.98	Healthy
2014	0.15	0	2.76	0.67	3.13	5.102	Healthy
2015	0	0	5.66	0.63	2.5	7.232	Healthy

For Company J the formula did not work as would be hoped. This could be explained by the second ratio in the formula, retained earnings to total assets, which has a value of zero for the entire period of data shown. None of the other ratios have especially high or low values, so the zero in X2 could have an unwanted effect on the Z-score. The reason for the zero could be for example missing data.

3.1.3 Conclusion

The table 13 below shows how well the Altman Z-score for private companies worked with the sample of 10 companies chosen for this additional analysis. As we can see, the formula only worked for approximately half of the cases and it was clearly a better match for the service companies than for the manufacturing companies. For manufacturing companies the accuracy percentage is 24% and for service companies 76%. The overall accuracy percentage is 50%.

Table 13. Performance of Altman's Z-score in a sample of 10 companies

Year	# of correct predictions	Manufacturing companies	Service companies
1	4 (40%)	1 (20%)	3 (60%)
2	5 (50%)	1 (20%)	4 (80%)
3	5 (50%)	1 (20%)	4 (80%)
4	5 (50)%	1 (20%)	4 (80%)
5	6 (60%)	2 (40%)	4 (80%)

The reason for the small percentage of accuracy for the manufacturing companies could be that as the companies were so small, they are more volatile for a bankruptcy and even a small shift in the market can have unpredictable effects. If the company only has one employee the chances are even higher, as any illness of accident could destroy the company. For this reason, it might be difficult to predict any financial distress in the future as the bankruptcy might be caused by one yearly quarter of slow or nonexistent business. The service companies on the other hand usually have more staff on the hand so an illness of one employee should not affect the companies.

For the service companies in this study the main reason for facing financial distress was bad market conditions and the small recession period Finland has been in for a while now. The service companies in this study were mostly companies which services people tend to keep as somewhat luxury commodities. People are not using the services of companies like these in a recession period as saving becomes more important than spending money on luxuries like travelling.

Based on the combined results in this section it seems clear that Altman's Z-score does not work well within the selected sample for small companies. One reason could be, that the model has been developed for US companies. Another reason could be, that the time period in question was somewhat problematic, because the Finnish economy has been doing quite poorly during the whole research period.

3.2 Logistic regression

3.2.1 Data collection

The data for the logit model part of this research paper was collected from a European database for financial information Amadeus. The original sample consisted of 137 bankrupt companies and 1863 active companies. The sample used in the study consisted of the 137 bankrupt companies in the original sample and a randomly selected batch of 137 active companies. The sample consisted of financial data of Finnish companies, from a two-year period of 2014 and 2015.

The data was divided into two groups; training sample and test sample. The training sample is first used to find the ratios to be used in the logistic regression, and the test model is then applied to the formula created with the training sample to see if it works with other groups as well as with the original. The groups in this study were divided as follows: 60 bankrupt and 60 healthy companies were separated into the training sample and 77 bankrupt and 77 healthy companies to the test sample.

3.2.2 Data analysis

The research started with finding the right ratios that would form the logit model in the end. For this study I used some from Altman's original model (1966) and some from Laitinen's (1990) model.

The first ratio in the research is Current ratio. Current ratio, which is a liquidity ratio, tells us a company's ability to perform its short-term and long-term obligations. The basic formula to measuring current ratio is to compare the company's total assets to its total liabilities.

$$Current\ ratio = \frac{Current\ assets}{Current\ liabilities}$$

The next ratio is LN(Age), natural logarithm of age, which tells the approximate medium ages of bankrupt companies. The third ratio is Growth. The growth ratio shows us the growth in revenues from the previous year.

The fourth on the list is Equity to assets. Equity to assets is a leverage ratio, and it is used to determine the health of a company's balance sheet. This ratio tells us what part of a company's assets are owned by their investors, and therefore not leveraged, and in the case of a bankruptcy could go under the control of debtholders.

$$Equity\ to\ Assets = \frac{Total\ shareholders'\ equity}{Total\ assets}$$

Next is EBIT to assets. This fifth ratio, Earnings before interest and taxes to total assets, shows the proportion between a company's profitability and their assets, meaning that the ratio shows us the profitability of the company's assets.

$$EBIT\ to\ Assets = \frac{EBIT(DA)}{Total\ assets}$$

The sixth ratio is Working capital to assets. This one is also a liquidity ratio, and it shows us the net current assets, or working capital, as a percentage of the total assets of the company. This ratio helps for example stakeholders see the extent of assets tied up in working capital, or, the amount of assets required to run daily operations for the company.

$$Working\ Capital\ to\ Assets = \frac{Net\ working\ capital}{Net\ total\ assets} x100$$

Seventh on the list is Sales to assets. This measures the company's ability to generate sales on as small as possible amount of assets. When this ratio is high, it implies that the company's management is able to get the most out of a small investment in their assets.

$$Sales\ to\ Assets = \frac{Sales}{Total\ assets}$$

Next on the list is Retained earnings to assets, which tells us the company's cumulative profitability over time as a proportion of total assets. It is also a leverage ratio; high scoring companies have financed their assets through retention of profits rather than debt.

$$RE\ to\ Total\ assets = \frac{Retained\ earnings}{Total\ assets}$$

Next is Debt to Equity. This one is also a leverage ratio. IT is calculated by dividing the total liabilities with shareholders' equity. The ratio tells us how much debt a company is using to finance its assets relative to the value that appears in shareholders' equity.

$$Debt\ to\ Equity = \frac{Total\ liabilities}{Total\ shareholders'\ equity}$$

Next is ROE and ROA. ROE is the Return on equity, which is the amount of net income returned as a percentage of shareholders' equity. It is a profitability ratio, measuring this by showing how much profit a company can generate with the money invested by shareholders. ROA is Return on assets. ROA indicates the profitability of a company relative to its total assets. It shows how efficient the management is at using the company's assets to generate earnings. ROA might also be called Return on investment in some cases.

$$ROA = \frac{Net\ income}{Total\ assets}$$

$$ROE = \frac{Net\ income}{Total\ shareholders'\ equity}$$

Liabilities to sales is calculated by dividing liabilities with sales. It tells how many years sales revenue it takes to pay off all of the company's debt.

$$Liabilities\ to\ Sales = \frac{Liabilities}{Sales}$$

Next one, Debt paying ability, is calculated by dividing liabilities at the end of the fiscal year with EBITDA. It measures the company's ability to pay off its debt. The ratio tells us the time that it takes to pay off all debts of the company.

$$Debt\ Paying\ Ability = \frac{Year\ end\ liabilities}{EBITDA}$$

The last ones are EBIT to sales and Cash to assets. EBIT to sales measures a company's profitability by comparing their sales revenue with their earnings, and more precisely the percentage of their earnings remaining after operating expenses. A high value is appreciated in this profitability ratio, as it tells us that the company is able to keep their earnings at a good level using efficient measures to keep some certain expenses low. Cash to assets ratio measures the company's liquidity, or their ability to pay short-term obligations. The ratio is the current value of cash divided by current liabilities, and it compares the currency amount of highly liquid assets, such as cash, for, for example, every one dollar of short-term liabilities.

$$EBIT\ to\ Sales = \frac{EBIT}{Sales}$$

$$Cash\ to\ Assets = \frac{Current\ value\ of\ cash}{Current\ liabilities}$$

Out of the ratios used in this paper, working capital to total assets, retained earnings to total assets, EBIT to assets, equity to assets and sales to assets were taken from Altman's Z-score model.

Out of more than 100 financial ratios, almost 50 per cent were found useful in at least one empirical study (Chen and Shimerda, 1981). In previous studies concerning bankruptcy prediction with logistic regression, it was found that especially leverage ratios seem to work quite well. This is one of the aspects I will be analysing during the study.

Table 14. Distribution of firms by bankrupt and training

		Bankruptcy		Total
		0	1	
Training	.00	77	77	154
	1.00	60	60	120
Total		137	137	274

Table 14 presents distribution of the data into bankrupt and non-bankrupt firms as well as into the training and test samples. The whole data includes 137 bankrupt and 137 healthy companies. The data was further divided into the training sample and test sample. The training sample consist of 60 bankrupt and 60 healthy companies. The companies selected for the training sample were the ones that went bankrupt in 2014 and the rest went bankrupt 2015.

Table 15 presents independent samples' T-tests for all the variables in the analysis by comparing bankrupt and healthy companies. We can see from the results, that not all variables are statistically different in the two groups. However, a number of the variables are highly statistically significantly different in the two groups. These variables include Current ratio, for which the results suggest that bankrupt have lower values. It seems that healthy firms have better liquidity ratios. The next ratio is Ln(Age). For this ratio, the results show that bankrupt companies tend to be younger than healthy companies. Overall, the age of bankrupt companies tends to be quite young, as new companies always have difficulties entering their respective markets in the beginning. Next one is Equity to assets – ratio, which suggests that bankrupt companies are more highly levered than healthy companies. Other highly statistically different variables are Retained earnings to assets, Equity to debt and Cash to assets; Retained earnings to assets shows us that bankrupt companies generate less profits, Equity to debt shows us that the bankrupt companies have relatively less equity than healthy companies and Cash to assets shows that the bankrupt companies have less cash than the healthy ones.

Table 15. Independent sample T-tests

	Mean (st.dev) Bankrupt	Mean (st.dev) Not Bankrupt	t	Sig. (2-tailed)	
Current ratio	0.90 (1.44)	3.34 (5.83)	-4.75	0.000	***
Ln(Age)	2.25 (0.70)	2.59 (0.69)	-3.98	0.000	***
Growth	0.67 (7.23)	0.05 (0.64)	0.98	0.326	
Equity to assets	-1.32 (3.79)	-0.03 (1.99)	-3.53	0.001	***
EBIT to Assets	-0.33 (1.28)	-0.08 (0.65)	-2.08	0.030	**
Working capital to Assets	0.02 (0.66)	0.11 (0.38)	-1.41	0.161	
Sales to assets	4.58 (7.91)	2.72 (3.03)	2.57	0.011	**
Retained earnings to assets	-1.60 (4.08)	-0.36 (2.17)	-3.16	0.002	***
Equity to debt	0.25 (1.03)	2.71 (4.77)	-6.44	0.000	***
ROA	-0.33 (1.28)	-0.08 (0.65)	-2.08	0.039	**
ROE	0.24 (1.51)	0.14 (0.93)	0.67	0.501	
Liabilities to Sales	2.40 (15.40)	-0.15 (11.14)	1.58	0.115	
Debt paying ability	1.00 (16.63)	1.67 (21.63)	-0.28	0.774	
EBIT to Sales	-0.25 (1.53)	0.11 (1.35)	-2.02	0.044	**
CASH to assets	0.11 (0.17)	0.27 (0.29)	-5.62	0.000	***

Overall it seems that bankrupt companies are more highly levered and have lower liquidity than healthy companies. This we can see from the amount of liquidity ratios and capital structure ratios evident in the highly relevant ratios.

Table 16 presents individual one-variable regression models for all the variables selected into the analysis. The purpose of this analysis is to investigate the prediction ability of the individual variables (Lehtinen, 2016).

Table 16. One-variable regression models

	B	Sig.	Percentage Correct
Current ratio	-.353	.000	63.90%
Growth	.041	.496	49.60%
Ln(Age)	-.686	.000	61.30%
Equity to Assets	-.244	.002	61.70%
EBIT to Assets	-.299	.053	57.70%
Working capital to assets	-.344	.173	54.40%
Sales to assets	.079	.019	52.60%
Retained Earnings to assets	-.175	.005	61.30%
Equity to debt	-.621	.000	69.30%
ROA	-.299	.053	57.70%
ROE	.066	.502	60.20%
Liabilities to Sales	.054	.286	56.20%
Debt paying ability	-.002	.774	48.90%
LN(Assets)	.092	.392	51.80%
Cash to assets	-3.091	.000	61.70%

The variables were selected based on previous studies. While most of the variables are statistically significant in the models, some of them are not. For example the variable growth is not statistically significant and only predicts 49.6% of the firms correctly. Other non-significant variables include ROE, Liabilities to turnover, Debt paying ability and

LN(assets). The non-significant variables will be left out from the multivariable analysis in the next stages of this study.

When it comes to the significant variables the ones with the best prediction ability are Current ratio and Equity to debt. This seems to be well in line with also previous studies, which have suggested that liquidity and leverage are important determinants in bankruptcy models.

In the next stage I will be applying Altman's model, or more precisely the ratios Altman used in his 1968 formula development, for bankruptcy prediction with logistic regression

Table 17. Multivariable regression analysis based on Altman's model

	B	Sig.	
Sales to assets	.091	.062	*
Retained Earnings to assets	.058	.300	
Equity to debt	-.486	.000	***
Cash to assets	-2.899	.000	***
EBIT to Assets	-.230	.892	
N	274		
Model prediction ability	71.90%		
Nagelkerke pseudo R^2	0.337		

In Table 17 I present a logistic regression model with variables based on Altman's model for the whole sample N=274. Out of the five variables, only three are statistically significant. First of all, the model predicts that Sales to assets is positively connected with the probability of bankruptcy and this result is statistically significant at the 10% level. The Equity to assets ratio is negatively connected with the probability of bankruptcy and this result is statistically significant at the 1% level. This suggests that a relative increase in equity decreases the likelihood of bankruptcy. The third significant variable, Cash to assets is also negatively connected with the probability of bankruptcy and the result is statistically significant at the 1% level. This result suggests that firms with more cash are less likely to go bankrupt. Surprisingly, two of the variables are not statistically significant. Overall, this model is able to predict correctly in 71.90% of the cases.

In the next stage, I will use logistic regression analysis to build an alternative model. As initial set of variables, I will use all the statistically significant variables from table 16. Table 18 below presents the step-wise analysis with the training sample.

Table 18. Step-wise analysis with the training sample

Variables in the equation	B	Sig.	
Equity to Assets	-1.916	.000	***
Sales to assets	.212	.090	*
Cash to assets	-2.883	.028	**
Constant	.175	.626	
N	120		
Model prediction ability	75.00%		
Nagelkerke pseudo R^2	0.457		

Based on the results above, the step-wise model only selects three variables. The Equity to assets ratio is the most significant variable in this model. It is negatively connected with the probability of bankruptcy and significant at the 1% level. The second most significant variable is Cash to assets. It is also negatively connected with the probability of bankruptcy and is significant at the 5% level. The third, least significant ratio is Sales to assets. This ratio is positively connected with the probability of bankruptcy and is statistically significant at the 10% level. Overall the model predicts the right result at 75% of the cases. The step-wise model shares two significant ratios with the Altman model. Also the equity ratio is present in both models but with a different formula.

In the next table the model developed in Table 18 will be run with the Test sample, which has 77 bankrupt and 77 healthy firms.

Table 19. Step-wise analysis with the test sample

Variables in the equation	B	Sig.	
Equity to Assets	-.002	.978	
Sales to assets	.101	.037	**
Cash to assets	-3.774	.000	***
Constant	.251	.308	
N	144		
Model prediction ability	67.50%		
Nagelkerke pseudo R^2	0.227		

From Table 19 we can see, that the model does not work equally well with the test sample. This we can see from the prediction ability, which goes down to 67.50% from the 75% in the steps-wise analysis and the 71.9% it had with Altman's model. Out of the three variables, Equity to assets is not significant in this model. Both Cash to assets and Sales to assets keep their signs and are statistically significant; Cash to assets at the 1% level and Sales to assets at the 5% level. Overall the analysis suggests that an increase in the level of cash reduces the probability of bankruptcy and an increase in asset turnover increases the probability of bankruptcy. It is important to also apply the model with the test-group, to make sure it is not applicable with just the training group, and that it can be generalized for a boarder spectrum and it is not too specified for the test sample. The ratios in this final part were a rather obvious result, as it is clear that companies with lots of cash and high equity can survive better in the long-term. However, the results also suggest that companies with high asset turnover also bear higher risk in term of bankruptcy probability.

3.2.3 Conclusion

The sample of companies used in this study, N=274, was divided in to two parts, varying with size. The basis of division was the year of facing bankruptcy. The groups to which the companies were divided in were the training sample, which consisted of 120 companies, out of which 60 were bankrupt and 60 were healthy, and in the test sample. The number of bankrupt companies in the training sample was based on the criteria that they had gone bankrupt in 2014. The test sample consisted of 154 companies, out of which 77 were bankrupt and 77 healthy. The testing sample, which consisted of companies that were left after collecting the companies for the testing sample, was formed out of companies which went bankrupt in 2015. In the original sample N=274, the proportion of bankrupt companies only consisted of companies which had gone bankrupt in 2014 or 2015.

In the first stage, Table 15, I performed the independent sample T-tests. In this stage I performed the T-tests for all the variables in the model to find which ones were statistically significant. From Table 15, we can see that there are some variables, which are not statistically different, and for that reason are not significant in this research. The ratios, which were statistically different, and therefore significant for the study, were Current ratio, the natural logarithm of age, Equity to assets, Retained earnings to assets, cash to assets and Equity to debt ratios. Overall, this stage showed us that bankrupt companies tend to be more highly levered with a lower liquidity than healthy companies.

In the next stage, which is shown in Table 16, I preformed the one-variable regression model for each of the variables which were initially chosen for the study. The results of this step were applied to the rest of the study, as the primary reason for this step is to find which of the variables have significance in the case of bankruptcy prediction.

After this I applied the ratios which Altman used in his multivariable research into the logistic regression model. This was done to the whole sample N=274. From Table 17 we can see that only three of Altman’s variables were statistically significant in the logit model.

For the next stage I applied the information gathered previously and built an alternative model with logistic regression. This was first completed with the training sample, as we see in Table 18. For this model, only three variables were chosen. The basis for the three variables was the significance they bring to the results, or their prediction accuracy. It is obvious that companies with high amounts of cash and high equity can survive better in the long term, as they can use their own recourses to keep the business functioning. If the sales to assets ratio is high, it implies that the company is able to generate sales with a very small amount of assets.

The last phase of the study was to complete the test-wise model with the test sample to see how it works with samples that were not used to create the model. This phase is shown in Table 19. From the results, we can see that the test sample did not get as good results as the training sample. For the training sample, the test-wise analysis predicted 75% of the financial distress correctly. For the test sample, this number was only 67.5%. The number of significant variables goes down to two, as Equity to assets does not give the samples any significant results.

The somewhat disappointing results in the testing sample can be the result of many things. For example, it could be, that the samples in this study are two small. It can also be, that the results are not stable because of random sampling. This could be verified by redoing the study with other random samples from the same database, but that is not within the aim of this study.

3.3 Comparison of the study results

The data for both the logistic regression model and the multivariable method was randomly chosen from the same sample of 2000 companies, out of which 137 were declared bankrupt and the rest healthy. This gave the advantage of having similar companies, more precisely private trading companies of approximately the same size.

Neither of the models, the logit model or the multivariate method, gave very good results. In fact, both of them were quite disappointing as the percentages of correct predictions stayed under 70% in each case. Overall, it seems, that the logistic model worked a little better, because within the training sample, it predicted more than 70 % of the cases correctly. The multivariate method was only able to predict at best 63 % of the bankrupt cases correctly. This was one year before bankruptcy. The multivariate was better at predicting healthy companies. However, these results cannot be generalized. This is mainly due to the small number of observations.

The sample sizes were also different. The logistic model was made with N=274, while a wider study on the multivariable method used N=60. A more detailed analysis was the performed on a smaller sample. The main reason for the different sample sizes was data availability.

4 Conclusion

Bankruptcy prediction has received a lot of attention in the accounting and finance literature in recent decades. The main reason for developing new formulas for bankruptcy prediction has usually been to improve the accuracy of these methods. As there is no unified bankruptcy theory, the research has mainly been based on an empirical research for the best predictors or statistical methods (Laitinen and Kankaanpää, 1999).

There are two types of bankruptcy models: parametric and non-parametric. The most used parametric models are the multivariate discriminant analysis and logistic analysis. The aim of this research was to study how these two most common models work and how do the results compare to each other. The empirical analysis was conducted with a sample of Finnish companies and the models chosen were Altman's Z-score model and logistic regression analysis.

In this study, the prediction accuracy for the logit model was 67.5% with the test sample and 75% with the training sample. For the discriminant analysis the percentage of accuracy for the whole sample was only about 50%.

Previous studies suggest that the accuracy of the model may be highly attached to the field in which the company is practicing their business. Altman's original model, and more recently the model for private trading companies, which was used in this project, were originally tested with manufacturing companies. Due to this it would make sense that the model would work best with manufacturing companies. This was not the case, though, in this research. The results from the Altman's Z-score analysis show that the model worked better with the other fields of business in the study. This could be seen as a surprising result, considering that the model should work best with the manufacturing companies.

The logit model also gave somewhat disappointing results with the percentage of correct prediction being only 67.5%. Aziz and Dar (2006) compared in their analysis the accuracy of different prediction methods. In their analysis they had four different methods; discriminant analysis, the logit model, neural networks, and recursive partitioning algorithm. For the purpose of this paper, the discriminant analysis had an accuracy percentage of 85.1% and the logit model 86.7% (Aziz, Dar, 2006). The percentages obtained in this study were somewhat lower.

The results of this study were therefore not quite as good as expected, considering the fact that both of the models used in this study are widely used in the field. The discriminant analysis results were more than 30% less accurate than the average results of the function and the results of the logit model were almost 20% lower than the average results in previous studies. There are many potential reasons for these differences. One possible reason is small sample size, but then again many studies in the field have used much smaller samples. For example, Altman developed his original model with just 66 companies. Another possible reason is that Altman's model was developed with US data, which is not necessarily comparable with Finnish data.

These results have some practical implications. Banks and other stakeholders that use bankruptcy prediction formulas, should modify them to take into account the specific financial market. Models developed in one country during a certain time period, do not necessarily work in other countries and other time periods. Future research should also pay more attention to developing bankruptcy prediction models further to accommodate different environments.

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