Financial Distress Prediction in the Netherlands:

An Application of Multiple Discriminant Analysis, Logistic Regression and Neural Network.

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Preface

The principle of financial distress prediction always interested me. The first time I came in touch with the subject was at the higher general secondary education, where the equation of Altman was explained. It immediately came to my attention that this is a fascinating subject with great potential. A few years later the subject was again introduced at the Saxion university of applied science, where I followed my bachelor's in business administration. The third-time financial distress prediction was introduced to me, was on the University of Twente, where it was briefly explained and what the potential implications are.

The one thing these introductions had in common was that I was triggered to investigate the further possibilities of financial distress prediction. This resulted in my interests in this subject to further explore this in my master thesis for Business Administration at the University of Twente.

The period of thesis writing was with ups and downs. There is an abundance of literature available on the subject of financial distress prediction. At first, I almost drowned in the amount of literature available and the many ways of predicting financial distress, only to find the right path after a few talks with the supervising professor.

My word of thank goes out the first supervisor professor dr. M.R. Kabir who's feedback helped me to strive for the best results. Next, I would like to thank second supervisor Dr. H.C. van Beusichem for his feedback and insights on the subject. Third I would like to thank the University of Twente for facilitating the means to conduct research and especially the library of the University of Twente for the availability of fast stream of scientific literature.

Summary

Predicting financial distress is for scholars an interesting topic for more than 50 years. Altman (1968) developed the Z-score for predicting financial distress using the Multiple Discriminant analysis method (MDA) and was able to correctly predict bankruptcies with an accuracy of 95%.

The performance of prediction methods and models differ substantially throughout literature. The lowest reported accuracy of a model is 58% and the highest 97%. Altman et al. (2017) tested the performance of the model of Altman (1984) on a large sample of different European countries and achieved on average an accuracy of 75%, but they argue that the accuracy could be increased well over 80% with the aid of country specific variables. The aim of this study is to adjust existing prediction models to achieve an accuracy higher than 80% in an exclusively Dutch setting.

Scholars in the 1980s focused more on the development of new prediction models like the Logistic Regression (Logit) model, to overcome the statistical assumptions of the MDA model. with the increased computing capabilities in the 1990s, different methods of predicting financial distress originated. One of these new models is the Neural Network model (NN). These three methods are the most used methods in financial distress prediction literature.

Financial distress prediction literature of Europe, America and Asia is compared on the performance of the prediction method and the use of different ratios. Over 400 different ratios are identified in this approach, out of which 27 are selected for the use in the Netherlands. In addition, other factors are investigated which might influence financial distress prediction in the Netherlands. These factors are the cultural influences on bankruptcies and the large percentage of SME companies in the Netherlands.

Financial data is collected from the Reach database. Financial data is collected for a total of 125 matched pairs of bankrupt and non-bankrupt companies.

The results indicate that in a Dutch context, the Z-score model of Altman (1968) is decent in predicting non-bankruptcies, but not able to predict bankruptcies in the Netherlands. Re-estimating the model of Altman results in a slightly better performing model, although it cannot be generalized because of the model assumptions. Estimation with the use of the Logit method results in a similar performing model. This study presents evidence that the ratios used by Altman (1968; 1984) are not the optimal ratios for predicting financial distress in the Netherlands.

Additional ratios are investigated to further increase the performance of prediction models. Four additional sets of ratios are identified using the t-test for differences in ratio means, stepwise regression and correlation matrices. All additional sets of ratios are used to create prediction models for the MDA, the Logit and the NN methods. The results indicate that these models perform better than the models based on the model of Altman (1984).

The results indicate that it is possible to predict financial distress with an accuracy percentage of higher than 80%.

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List of Abbreviations

AR	Accuracy Ratio
AUC	Area Under Curve
B-LSSVM	Bayesian Least Squares Support Vector Machine
BVD	Bureau van Dijk
CCM	Contingent Claims Model
CY	Current year
DT	Decision trees
EBIT	Earnings before interest and taxes
FN	False Negative
FP	False Positive
FTE	Full time employee
GP	Genetic programming
Hazzard	Hazzard Models
HIPA	Human Information Processing Approach
Hybrid	Hybrid models
LDA	Linear Discriminant Analysis
Logit	Logistic Regression Analysis
MDA	Multiple Discriminant Analysis
MFD	Markov for Discrimination model
NN	Neural Networks
PLS	Partial least squares
PY	Previous year
ROC	Receiver Operating Characteristic
RP	Recursive Partitioning
SA	Survival Analysis
SME	Small and Medium Enterprises
SVM	Support Vector machines
TA	Total Assets
TL	Total Liabilities
TN	True Negative
TP	True Positive
VIF	Variance Inflation Factor

1. Introduction

The grounding of predictions in scientific theory is one of the main goals of science, but how predictive success contributes to the probability of the theory being (approximately) correct is a complex challenge. The question is why we legitimate think a theory which makes good predictions is more probably right than a theory which makes less good predictions, even when both theories do not make bad predictions. In particular, surprising predictions tend to make us confident on the validity of the theory that has been able of making them. The history of science is full of examples of surprising predictions working in pushing the scientific community to accept a theory towards which strong doubts existed before.

An example is the model of Altman (1968) for predicting financial distress of companies. The Multiple Discriminant Analysis (MDA) model of Altman (1968) was accurate in predicting bankruptcy in the initial sample of 95% and in the control samples of 96% correctly predicted companies. In the beginning, the model was an approach to bridge the gap between the decreasing importance of traditional ratio analysis and the more rigorous statistical techniques. When Altman (1968) published the research using the MDA method instead of the univariate ratio analysis, academics where pushing toward elimination of ratio analysis for assessing the performance of businesses.

A lot has changed since the introduction of financial distress prediction almost 50 years ago. Altman (1968) stated his method had to be optimized for the use without computer support because managers, executives and bankers had limited access to sophisticated computers and programs. A statement we no longer have to mention with all the advancements in computers and statistical education.

The foundation of financial distress prediction was built with the work of Beaver (1966). Since then may scholars have improved prediction method or discovered new approaches of predicting financial distress. Altman (1968) used the MDA analysis technique to predict financial distress, where after the following years many scholars (Blum, 1974; Deakin, 1972; Edmister, 1972; Taffler, 1982) assessed and added literature to the stream of prediction theories. Scholars in the 1980s focused more on the development of new methods for predicting financial distress, to overcome the statistical assumptions of the MDA model. One of the more popular models in that time was the Logistic Regression Analysis (Logit) model. Multiple scholars focused on this method to increase the accuracy of predictability of this method (Hamer, 1983; Ohlson, 1980; Zmijewski, 1984). Most prediction methods until 1990 were statistical models. Here after the artificially intelligent models became more popular. Scholars could adopt a wider range of methods previously unavailable because of the lack of computing capabilities. In that period, many new models were developed. One of these new methods is Neural Networks (NN), which is the third most used method in prediction literature next to MDA and Logit methods (Jackson and Wood, 2013).

Altman (1968) stated that his research could have a significant impact on business loans evaluation and his method would be a fast and efficient manner for detecting unfavourable credit risk and avoid potentially disastrous decisions. Financial distress prediction research would benefit bankers, credit managers, executives and investors significantly (Altman, 1968). This target audience is still relevant. Additionally, other stakeholders could also benefit from financial distress research, for example employees of companies, or governments in areas where the society is dependent on a few companies. Palepu, Healy and Peek (2013) argue for the importance of financial distress prediction as a screening tool for summarising financial statement data of many firms prior to an in-depth analysis of corporate strategy. Financial distress prediction could be a proxy for bankruptcy risk in exploring activities as mergers and investments. Financial distress prediction could also be a powerful ally in signalling a company for adjusting their corporate heading. Jackson and Wood (2013) state in their research about applying financial distress prediction in the UK that a future increase in corporate insolvencies are likely to affect others as insolvency practitioners estimate that around 27% of corporate insolvencies are triggered by another company's insolvency, the "domino effect". Financial distress prediction could be an early warning signal to adverse the effects of this domino effect.

Altman, Iwanicza-Drozdowska, Laitinen and Suvas (2017) stated that the MDA model underperformed compared to market-based models, but the model preforms well for short-term distress prediction. Therefore, the MDA model will be used as a benchmark in this study and as suggested by Altman et al. (2017) with the aid of country specific variables, improved for the use in the Netherlands. Altman et al. (2017) indicated that the MDA model preforms well, but results are difficult to generalize. The authors assessed the model in an international context and concluded that the model preforms reasonably well for most countries. The accuracy is approximately 75%, but could be improved above 80% by using country-specific variables incorporated in the model. Because of the mixed opinion of scholars regarding the most accurate model for predicting financial distress, the Logit and Neural Network model will also be used to predict financial distress in the Netherlands.

The aim of this master thesis is to predict financial distress with an accuracy percentage of 80%[1]. This leads to the following research question:

- Is it possible to adjust existing prediction models to achieve an accuracy of 80% or higher?

The main question is assisted with three sub questions. These questions need to be answered for constructing a model which could predict financial distress in the Netherlands:

- Which models are used to predict financial distress?
- How is financial distress predicted in other countries?
- Which other factors could influence financial distress prediction?

[1] 0,9 is the AUC value Altman et al. (2017) anticipated to be able to achieve. An AUC of 0,9 translates to an accuracy ratio of 80%.

The main scientific contribution of this thesis is the assessment of financial distress prediction in an exclusively Dutch context with a recent dataset. No literature was found applying financial distress prediction with a recent dataset in the Netherlands. The most recent literature is from Altman et al. (2017) which used a sample up to 2010 for different European countries, including the Netherlands. This research aim is to apply the MDA, Logit and Neural Network method on a recent sample of Dutch companies.

The remainder of this thesis will be as follows. Section II presents the theoretical framework, where a scientific background on the sub questions is given, leading to the development of hypotheses. Section III presents the research design. Section IV describes the data collection and sample selection. The results of the hypothesis testing are discussed in section V. Finally, the main conclusion and limitations are discussed in section VI.

2. Literature Review

The theoretical framework of this study is discussed in this chapter. First the definition of financial distress is addressed. Thereafter the different models for predicting financial distress are explored. Followed by an analysis how financial distress is predicted in different economic regions (countries). Finally, other factors that could influence financial distress prediction are investigated. Hypotheses are composed out of the used literature, after the theoretical framework is discussed,.

2.1. What is financial distress?

2.1.1. Definition of financial distress

The term “Financial Distress” is frequently used in literature. In the beginning the term “predicting bankruptcy” (Altman, 1968; Ohlson, 1980) or “business failure identification” (Altman 1984) was used. Begley, Ming and Watts (1996) used the designation “bankruptcy prediction” as indicators of financial distress. Zhang, Altman and Yen (2010) gave many examples of different definitions used for financial distress throughout literature, although choose for the discrimination between bankrupt and non-bankrupt companies. Balcean and Ooghe (2006) argue for the importance of using a well divined meaning of financial distress because the definition of failure or financial distress may have consequences for the prediction model when using it in situations outside of theory.

The definition of financial distress in this research is also a discrimination between bankrupt and non-bankrupt companies. Donker, Santen and Zahir (2009), who also researched financial distress in the Netherlands chose the definition of financial distress which also will be used in this research: “A company is in financial distress when it suffers insolvency, declares bankrupt, undergoes suspension of quotation by the stock exchange or is liquidated”.

2.1.2. History of financial distress prediction

Altman (1968) developed the Z-score theory for prediction of financial distress. In the beginning, it was a theory to bridge the gap between the decreasingly importance of traditional ratio analysis and the more rigorous statistical techniques. When Altman published the research of the Z-score, using the multiple discriminant analysis (MDA) instead of the univariate ratio analysis, the academics where pushing toward elimination of ratio analysis for assessing the performance of businesses. The model was accurate in predicting bankruptcy in the initial sample (95% correctly classified) and in his control samples (96% correctly classified) and could predict bankruptcy up to two years prior to bankruptcy. Altman (1968) stated that his research could have a significant impact on business loans evaluations and his method would be a fast and efficient manner for detecting unfavourable credit risk and avoid potentially disastrous decisions.

Altman (1968) deviated from the usual univariate methods of analysing company performance and made use of the MDA method, which attempts to derive a linear combination of characteristics which best discriminates between groups (bankrupt and non-bankrupt companies). These characteristics (financial ratios) where selected out of a list of 22 ratios based on the popularity in literature and the relevance of the research. In terms of type I and type II error, the model is very accurate. The major limitation of the model is that all companies in the sample are publicly held American manufacturing corporations. Another limitation is the small sample size of 91 companies (original sample of 66 and control sample of 25 companies).

A lot has changed since the introduction of Altman's Z-score almost 50 years ago. Altman (1968) stated that his original model had to be optimized for the use without computer support because managers, executives and bankers had limited access to sophisticated computers and programs for calculating the Z-score. A statement we now no longer have mention with the advancements in computers and statistical education.

Over time Altman re-estimated the model multiple times. The original purpose was to assess whether an American manufacturing company had a change of becoming financially distressed. The model was not applicable for private held companies because of ratio X4 (market value of equity / book value of total liabilities), which includes the variables Market value of equity. Altman, Casey and Bibeault (1984) re-estimated the Z-score into Z'-score and replaced the "market value of equity" for "book value of equity". Altman et al. (1984) analysed the accuracy of a four-variable model excluding the ratio sales / total asset variable to increase the applicability of the model to non-manufacturing companies. They re-estimated the coefficients and revised the model into the Z"-score. Though Altman adjusted his model to be more suitable for non-manufacturing companies, the model remains primarily based on North American business failures. Thus, generalizing the model for markets other than the North American manufacturers is difficult.

Preceding Altman, Beaver (1968) discussed many of the variables Altman (1968) applied in his research. Beaver (1968) illustrated methods for empirically evaluating alternative accounting measures and the ability to predict financial distress using univariate methods. Substantial literature was added to the stream of prediction theories after the introduction of the Z-score. Deakin (1972) suggested to improve the theory of Altman to increase the long range predictive accuracy and had proven that discriminant analysis could predict up to 3 years prior to bankruptcy. Edmister (1972) recalculated different financial ratios for the MDA model to predict the possibility of failure for small and medium enterprises. The disadvantage of his research is that for the method to be accurate he needed three consecutive financial statements. Lau (1987) improved the existing literature by not only recalculating the variables in the Z-score, but also adding means for classifying the severity of a company's financial distress (0 to 4) and thus predicting the probability of a company being classified as: financial healthy, reducing dividend, difficulties on loan payment, protection under the bankruptcy act and bankrupt. Zmijewski (1984) voiced concerns of financial distress researcher oversampling distressed firms and the non-randomicity of samples. This research demonstrates the existence of choice-based samples and oversampling. In contrary to the research, oversampling and choice-based samples do not affect the statistical inference or the classification rates. Dimitras, Zanakis, and

Zopounidis (1996) show in their research of 158 published articles that before 1980 the MDA method for predicting bankruptcy was the most popular method in scientific literature. After 1980 many other mathematic models appeared to overcome the limitations of the MDA method, of which the Logistic regression analysis method was most popular. The O-score for financial distress, using the Logit method of Ohlson (1980), was widespread used next to the model of Altman (1968). Ohlson (1980) states that the comparison of his research with other notable research is difficult because of the use of data from different time periods. According to Begley, Ming and Watts (1996) Ohlson's O-score outperforms Altman's Z-score in terms of misclassification. Begley et al. (1996) re-estimated both models to the same timeframe and presented evidence for both models underperforming compared with the original model in the original timeframe. This implies that the performance of the models decreases when they are generalised to other samples in other timeframes.

In a recent review of Altman's Z-score, Altman et al. (2017) stated that the Z-score model underperformed compared to market-based models, but the model preforms well for short-term distress prediction. They also assessed the performance of the Z-score model for firms from 31 European and 3 non-European countries. Altman et al. (2017) established a set of 4 criteria in selecting data: companies must be industrial (manufacturing) companies, owners of companies must have limited liability, companies must have a minimum size exceeding € 100,000 in total assets and lastly, a minumum of 60 companies per country have to be present in the sample to be included in the results.

The results indicate that the Z-score preforms well, but results are difficult to generalize. The authors tested the model in an international context and concluded that the model preforms reasonably well for most countries. The accuracy is approximately 50% (AUC of 0.75 is AR of 50%), but could be improved above 80% (AUC of 0.9 is AR of 80%) by using country-specific variables incorporated in the Z-score.

Altman et al. (2017) also used data from the Netherlands. A total of 15845 non-bankrupt and 147 bankrupt Dutch companies are used in testing the Z-score. The timeframe spanning between 2000 and 2010 and the highest achieved accuracy for the Nederland's in 57.4% (AUC of 0.787 is AR of 57.4%) in model 7 of their research.

Manny scholars make the claim that their model could predict financial distress accurately for their dataset. The major problem with financial distress prediction is the disagreement of scholars over the optimal method of financial distress prediction (see chapter 2.3 How is financial distress predicted) and the generalisation of the model to other time periods than the estimation period and generalisation to other economic regions. almost all articles investigated for this study report a high accuracy percentage of the used prediction model, ranging from 58% accurate prediction in articles where models were tested outside their estimation period (Grice and Ingram, 2001) to a highest of 97% accurate for testing a new method (Chen, 2011). No articles were found with an accuracy percentage of 100%. Many articles test different methods against each other. Sometimes a scholar may report that the method he tested is superior to another method and another scholar might report vice versa.

2.2. Which methods are used for predicting financial distress?

Financial distress is predicted in many ways. Altman (1968) used different ratios to analyse the probability of bankruptcy and came up with the Z-score. Since then may scholars have tried to improve this prediction method or discovered new manners of predicting financial distress. These different methods have one thing in common, they all employ the use of financial ratios and non-financial ratios in prediction financial distress.

The value of accurately predicting financial distress has led to a growing interest in prediction models since the 1960s. Aziz and Dar (2006) stated that overviews of financial distress prediction models were either outdated, too narrowly focused or did not gave a complete comparison of different approaches. Therefore, they made an overview of 16 different methods divided in three categories (Statistical methods, artificially intelligent methods and theoretical methods). Jackson and Wood (2013) Evaluate several different methods which have been popularly employed in prior literature to assess corporate bankruptcy. They identified 25 different methods, of which the MDA, the Logit and the Neural Networks are the most used methods. The authors state that more methods could be identified if variation within methods would be accounted for (Jackson and Wood, 2013). The authors surveyed a total of over 350 articles and separated them in the three categories of Aziz and Dar (2006).

A larger overview of the different models has been added in appendix I. this overview is based upon the studies of Aziz and Dar (2006), Baclean and Ooghe (2006), Chen, Ribeiro and Chen (2016) and Jackson and Wood (2013). The models identified by these scholars has been grouped into the categories of Aziz and Dar (2006). The second part of this chapter discusses the different categories of financial distress prediction models (Limited to the most popular methods in literature), and highlights the MDA, the Logit and the NN method.

2.2.1. Statistical models

The statistical models include both univariate and multivariate analysis, of which multivariate analysis is most used. The most used statistical models are the MDA model and the Logit model. The multiple discriminant analysis method creates for each company a score which indicates whether a company is healthy or bankrupt. Altman (1984) used the following classification of Z-scores: a score below 1,1 means a company is in the distress zone, a score between 1.1 and 2.6 is the grey zone (the company is stuck in the middle, but could become healthy or bankrupt) and a higher than 2,6 suggests the company is financial healthy.

The multiple discriminant analysis method has four major assumptions which must be met when using this method. The data used in the model should be normally distributed, there should be equal variance matrices across the failing and non-failing group, there should be a specified prior probability of failure and misclassification costs and the data must be absent of multicollinearity. According to

Balcean and Oohge (2006) Most MDA failure prediction studies do not check whether the data satisfy the assumptions, resulting in a non-generalizable model.

Scholars opinions are divided whether the MDA method or the Logit method is the best method to use for predicting financial distress. Altman et al. (2017) used the Logit model in their research and concluded that the Logit and MDA method are comparable in terms of accuracy. Charitou et al. (2004) also compared the MDA and Logit method. They report in the results that the Logit method (80.95%) has a lower accuracy percentage than the MDA method (82.5%).

Aziz and Dar (2006) report in their overview of 89 financial distress research studies that in 30% of the financial prediction studies use the MDA method and 21% use the Logit method, making these methods the most popular in financial distress prediction literature. The average predictive accuracy over these studies is 85% for MDA and 87% for Logit method. The predictive accuracy is slightly higher when using Logit. Laitinen and Kankaanpaa (1999) compared the predictive accuracy of the MDA, Logit and other methods and concluded that the Logit method was the most accurate model in predicting financial distress one-year prior bankruptcy. The accuracy of the Logit model was 89.5% versus 86.8% for MDA method. Wu, Gaunt and Grey (2010) report that the MDA model preforms poorly relative to other models and the Logit method preforms adequately.

Because of the limitations of the MDA method, Ohlson (1980) employed the Logit method for predicting financial distress. The data in the MDA method must be normally distributed in the independent variables, must have equal variance matrices, must have specified prior probability of failure and misclassification costs and must be absence of multicollinearity. Whereas the Logit method only must meet the requirement of the dependant variable being dichotomous. Also, must be noted that the Logit model is extremely sensitive to multicollinearity, outliers and missing values (Balcean and Oohge, 2006). The Logit model has the advantages of being easily interpreted in terms of odd ratios, providing the class membership probability for one of the set of the two categories (distressed or non-distressed).

2.2.2. Artificially intelligent models

Most models until 1990 were statistical models. Here after the artificially intelligent models became more popular with the developments in computer technology in the 1990s. Scholars could adopt a wider range of methods previously unavailable because of the lack of computing capabilities. Many new methods were developed in that time period. A new class of classification models are artificially intelligent systems.

The artificially intelligent methods identified by Jackson and Wood (2013) are Recursive partitioning, Case-based reasoning, Neural Networks, Genetic algorithms, Support vector machines and Rough sets. Jackson and Wood (2013) present evidence for Neural Networks (NN) being the most popular method of the artificially intelligent methods. Besides being the most popular in this category, Neural Networks are the third most popular prediction method used, next to MDA and Logit methods.

As is with statistical models, artificially intelligent models also mainly focus on symptoms of failure, draw information mainly from company accounts and are heavily dependent on computer technology (Aziz and Dar, 2006). Artificially intelligent methods often have training sets and testing sets of data. A major advantage of artificially intelligent methods is that many variables or ratios can be used as input at the same time, whereas by statistical methods it is uncommon to have more than five ratios as input for a model.

A Neural Network is an artificial intelligence that mimics the biological neural network of the human nervous system. Recent studies in Neural Networks have revealed a wide variety of applications of Neural Networks. Neural Networks consider an interrelated group of artificial neurons and process information associated with them using a so-called connectionist approach, where network units are connected by a flow of information. The structure of Neural Networks changes based on external and internal information that flows through the network during the learning process, and it uses nonlinear function approximation tools to test the relationship between independent variables (Ciampi and Gordini, 2013). The structure of a Neural Network has an input layer, a hidden layer, and an output layer. This is generally sufficient to model any complex system with any desired accuracy when dealing with classification problems. Each upper layer receives inputs from units at a lower level and transmits output to units at a higher level. A major advantage of the Neural Networks model is that no assumptions have to be made about the functional form of the relationship between independent variables and default probability, or about the distributions of the variables (Kumar and Ravi, 2012; Ciampi and Gordini, 2013).

A disadvantage of the NN method is that calculating the model is complex. The NN model equation is presented in section 3.1.3 of this study, but the calculation and interpretation is difficult. Ratios and variables are presented as input in the computing software, where after the software takes over and presents the results. The results of the NN model cannot be translated to a specific equation for that model, which makes generalisation and reproduction of the specific model almost impossible.

2.3. How is financial distress predicted in different countries/regions?

This part of the literature review is dedicated to the literature of the prediction of financial distress with a data sample of a specific country or region, to assess whether there are differences in specific literature for different countries. Specific ratios are selected out of this literature which could increase the accuracy of the prediction model for the Netherlands.

Laitinen, Lukason and Suvas (2014) compared how financial distress differs through countries. Based on the behaviour of financial ratios it was found that the behaviour of financial ratios before failure can vary through countries. This makes it difficult to select the best ratios for predicting financial distress in the Netherlands, because almost all ratios in failure prediction studies are selected based upon popularity in previous studies. Despite possible differences in ratios for different counties, this study will investigate how financial distress is predicted in different countries. The possibility exists that a ratio that has predictive value in another country could also have predictive value in the Netherlands. The information of the research of others needed for this study are the variables and ratios used in predicting financial distress, the assessment whether a model could be generalized and the highest reported accuracy. The ratios most popular[2] in literature are reported in appendix II, these ratios will be used to create financial distress prediction models for the Netherlands.

The next section of this chapter discusses these points for different countries all over the world. A summary of the literature investigated can be seen in Table 1:. Thereafter the literature is briefly discussed.

Table 1: Overview of highest reported accuracy of prediction and used models

#	Author	Accuracy	Models used	Origin of sample
1	Chen 2011	97%	DT and Logit	Taiwan
2	Abdullah et al. 2008	95%	Hazzard, MDA and Logit	Malaysia
3	Abdullah et al. 2016	94%	Logit	Malaysia
4	Hua et al. 2007	92%	SVM and Logit	China
5	Alfaro et al. 2008	91%	NN	Spain
6	Laitinen and Kankaanpaa 1999	91%	LDA, Logit, RP, SA, NN and HIPA	Finland
7	Hayes et al. 2010	90%	MDA	United States
8	Altman and Sabato 2007	90%	Logit	United States
9	Bauer and Agarwal 2014	90%	Hazzard	United Kingdom
10	Van Gestel et al. 2006	89%	SVM	Netherlands/ Belgium
11	Mselmi et al. 2017	89%	Logit, NN, SVM, PLS and Hybrid	France
12	Lin 2009	88%	MDA, Logit, Probit and NN	Taiwan
13	Hu and Sathye 2015	86%	Logit	Hong Kong
14	Xie et al. 2011	85%	SVM and MDA	China
15	Tian and Yu 2017	85%	Hazzard	Japan
16	Jackson and Wood 2013	83%	MDA, Logit, NN, CCM,	United Kingdom
17	Almamy et al. 2016	83%	MDA	United Kingdom
18	Charalambakis 2015	82%	Hazzard	Greece
19	Chen and Du 2009	82%	NN	Taiwan
20	Lensberg et al. 2006	81%	GP	Norway
21	Agarwal and Taffler 2008	79%	MDA	United Kingdom
22	Charitou et al. 2004	78%	Logit and NN	United Kingdom
23	Volkov and Van den Poel 2012	75%	MFD	Belgium
24	Altman et al. 2016	75%	MDA	Europe
25	Charitou et al. 2013	74%	Logit and NN	United States
26	Ciampi and Gordini 2013	68%	NN	Italy
27	Leksrisakul and Evans 2005	59%	MDA	Thailand
28	Grice and Ingram 2001	58%	MDA	United States
29	Donker et al. 2009	not reported	Alternative method	Netherlands
30	Manzaneque et al. 2016	not reported	Logit	Spain
31	Hillegeist et al. 2004	not reported	MDA and Logit	United States

2.3.1. Europe

Van Gestel et al. (2006) used the Bayesian Least Squares Support Vector Machine (B-LSSVM) method for financial distress prediction in the Netherlands and Belgium. They used a dataset of 74 bankrupt and 348 non-bankrupt companies with firm data between 1991 and 1997. They present evidence that

[2] It is common practice to select ratios for input in financial distress prediction models based on popularity in literature. See also section 3.3.5.

the B-LSSVM method yields better performance in accuracy (AUC 0.893) than the logit (AUC 0.831) and MDA (AUC 0.833) method for Dutch and Belgian mid cap companies.

Donker et al. (2009) propose an alternative prediction model based on ownership structure for identifying financial distress. They assessed the impact of ownership structure on the likelihood of financial distress of Dutch companies listed at the Amsterdam Stock Exchange from 1992 to 2002.The data sample contains 144 active and 33 inactive firms. The authors used a Logit model. The results propose high management shareholding reduces the likelihood of financial distress. Large outside shareholders reduce the probability of financial distress. Almost all the variables used in the research of Donker et al. (2009) cannot be applied for this research because a large part of the companies are privately held companies, thus ownership data is not relevant for this study.

Volkov and Van den Poel (2012) propose a method of information extraction from financial data and investigate the usefulness in bankruptcy prediction. They used 1,090 bankrupt and 13,662 non-bankrupt companies in a period between 2002 and 2006 using the Markov for Discrimination method (MFD). The results indicate that MFD is able to predict bankruptcy, nevertheless other models are probably better suited for dealing with the complexity of the financial distress problem according to Volkov and Van den Poel (2012)

Tinoco and Wilson (2013) assessed the use of accounting, market and macroeconomic ratios in predicting financial distress in the United Kingdom. A dataset of 2,641 non-failed and 379 failed companies was used to test ten accounting, market and macroeconomic variables between 1980 and 2011. The purpose was to create a model with predictive accuracy, practical value and macro dependant dynamics relevant for stress testing. They concluded that market variables add information that is not contained in financial statements and thus complement accounting ratios. Models tested with only macroeconomic variables only contribute marginally to the overall classification accuracy. Agarwal and Taffler (2008) argue that neither the market based-model nor the accounting-based model is a sufficient statistic for failure prediction and both contain unique information about the failure of the company.

Agarwal and Taffler (2007) Evaluated the original MDA model of Taffler (1982) for the United Kingdom and presented evidence for the predictive value of the model. The authors state that it could be dangerous to apply a model which was not estimated for a population. They argue that the Z-score of Altman (1968) could not be applied to the situations in the UK and therefore the UK-based Z-score is a better alternative. Agarwal and Taffler (2008) also compared the UK based Z-score model proposed by Taffler (1982) against market-based models. The data sample contains companies from non-finance industry of UK listed firms at the London Stock Exchange between 1985 and 2001. A total of 2,006 non-bankrupt and 103 bankrupt firms were used in this research. Later Bauer and Agarwal (2014) compared Hazzard Models against The Taffler Z-score model where they present evidence for the superiority of hazard models to other alternatives.

Charitou, Neophytou and Charalambous (2004) examined the incremental information content of operating cash flows in predicting financial distress and thus develop reliable failure prediction models for UK public industrial firms. They used a paired dataset of 51 matched pair of failed and non-failed publicly held industrial firm between 1988 and 1997. The results indicate that a relatively easy model that includes three financial ratios, a cash flow, a profitability and a financial leverage ratio, yielded an overall correct classification accuracy of 83% one year prior to the failure. Other methods have been used as a benchmark. The Neural network model has an accuracy of 78% and logit model had an average of 76% in the research of Charitou et al. (2004). Both models can be viable alternatives for bankruptcy prediction. Altman's Z-score was also tested bud did not perform that well compared with the other models.

Jackson and Wood (2013) compared different models and tested the efficacy of the models with ROC curves. They report that the efficacy of the tested models is lower than reported in prior literature. In their study, the contingency claims model was the most accurate.

Ciampi and Gordini (2013) assessed whether prediction models using Neural Networks could predict financial distress for SMEs in Italy. They used a large dataset from 2001 to 2005. As is required with NN models, a training set and a testing set was constructed. The authors used for the training set 500 matched pairs of failed and non-failed firms. The testing set contained 3,063 failed and 3,050 non-failed firms. The datasets were also assessed for regional differences in Italy. The results indicate that the Neural Network model could predict financial distress accurately, with the highest accuracy in central Italy.

Mselmi, Lahiani and Hamza (2017) analysed financial distress for small and medium size firms in France using a variety of models. The models used: Logit model, Artificial Neural Networks, Support Vector Machine techniques, Partial Least Squares, and a hybrid model integrating Support Vector Machine with Partial Least Squares. For testing the data, the authors used a total of 106 matched pairs of failed and non-failed firms. Of these 106 pairs, 71 pairs were used for training of the models and 35 pairs were used for testing the models.

The results indicate that for one year prior to financial distress, Support Vector Machine is the best classifier with an overall accuracy of 88.57%. Meanwhile, in the case of two years prior to financial distress, the hybrid model outperforms Support Vector Machine, Logit model, Partial Least Squares, and Artificial Neural Networks with an overall accuracy of 94.28%.

Charalambakis (2015) evaluated the impact of accounting and market-driven information on the prediction of bankruptcy. The dataset contained Greek listed firms at the Athens Stock Exchange with a total of 303 companies over a period between 2002 and 2010. A total of 76 bankrupt and 227 non-bankrupt were selected. The results indicate that three accounting ratio components of the Z-score and three market driven ratios is the most appropriate model for predicting financial distress in Greece. This model outperforms models which only use financial components and outperform models which only use market-driven components. Charalambakis (2015) also argue that the bankruptcy rate, the government bond spread, GDP and GDP growth have no impact on the probability of financial distress in Greece.

Alfaro et al. (2008) argue to show an alternative method to corporate failure prediction using the Neural Networks and AdaBoost method, with the MDA method as benchmark. A sample of 590 paired bankrupt and non-bankrupt Spanish firms were analysed in a period between 2000 and 2003. The results indicate the improvement in accuracy that Adaboost (92.3% correct) achieves against Neural Networks (89.2% accurate) and the MDA method (79.3% accurate).

Manzaneque, Priego and Merino (2016) assessed the impact of ownership and board characteristics on the impact of financial distress for Spanish listed companies between 2007 and 2012 using 308 matched pairs of companies. The results show that Spanish companies' ownership distribution and corporate governance system characteristics are more likely raise the agency problems and, therefore, they could contribute to worsening situations of financial distress.

Manzaneque et al. (2016) argues for the importance of ownership structure in financial distress prediction literature, the same as Donker et al. (2009) does. For this reason, the variables cannot be applied for this research because a large part of the companies are privately held companies, thus ownership data is not relevant for this study.

Lesnberg, Eilifsen and McKee (2006) analysed 28 potential bankruptcy ratios found significant in prior research. The aim was to improve the understanding of bankruptcy through research convergence and improved insights into the pattern of bankruptcy classification factors. A total of 211 matched firms (total of 422 companies) bankrupt and non-bankrupt firms were analysed between 1993 and 1998. Evidence was provided for a higher accuracy with genetic programming (81%) than the Logit model (77%). The most significant ratio in the model was the prior audit opinion, implying the relevancy of the auditor's report.

Laitinen and Kankaanpaa (1999) assessed whether one of the methods: linear discriminant analysis, logit analysis, recursive partitioning, survival analysis, neural networks and the human information processing empirically differ in results from each other. Data for testing was gathered between 1986 and 1989 from 38 bankrupt and 38 non-bankrupt firms. The variables tested were for every method the same. The authors stated "the aim is not to increase failure accuracy but to compare the prediction ability of alternative methods. The results indicate that no superior method has been found.

2.3.2. United States

The financial distress prediction literature analysed for the US primarily used the models of Altman as a basis to test whether it can be generalized to another timeframe or sample.

Grice and Ingram (2001) analysed the original model of Altman (1968) in another timeframe. They argue that the z-score model is not as accurate in testing sample (1988-1991). Therefore, they re-estimated the coefficients using data of failed companies between 1985 and 1987. Grice and Ingram (2001) argue for always re-estimating the model of Altman for the country and timeframe of which it needs to predict.

Altman and Sabato (2007) analysed a set of financial ratios to assess which ratios have the most predictive power. The model they created was tested on data of a total of 2010 US SME companies of which 120 were financially distressed between 1994 and 2002. They did not pair the failed and non-failed firms in this study, but tried to maintain the natural default percentage of companies in the US. Their research presented evidence for the model for SMEs having a higher accuracy than the generic MDA model of Altman (1983).

Hayes, Hodge and Hughes (2010) tested the model of Altman on a small sample of firms during the financial crisis. They argue for the model being a useful managers tool to detect financial distress in times of turmoil. The model could correctly classify most of the companies and classified two companies as bankrupt despite not being correct at that time, the two miss classified companies filed for bankruptcy short after the data collection period.

Hillegeist, Keating, Cram and Lundstedt (2004) compared the model of Altman (1968) to the model of Ohlson (1980) and Black-Scholes-Merton (1974) (BSM model). The authors present evidence for the superiority of the BSM model over the other two, even when the models are updated for the same sample (data between 1980 and 2000).

2.3.3. Asia

Financial distress prediction is somewhat different in china then in the rest of the world. When a company defaults in China, it is not registered as bankrupt, but is registered as “special treatment”. Therefore, financial distress research in China investigate “special treatment companies.

Xie, Luo and Yu (2011) examined the performance of the MDA and the SVM model for 130 matched paired of failed and non-failed companies in the years 2005,2006 and 2007. The authors present evidence for the superiority of the SVM model and state that additional governance and external market variables have predictive power for Chinese companies.

Hua, Wang, Zhang and Liang (2007) developed a new model for the Chinese market based upon the SVM model. They added an integrated binary discriminant rule in the SVM model, which leads to a lower misclassification. The authors compared this new model against the normal SVM model and the Logit model and concluded that their model is superior.

Lin (2009) examined the most common used model in Taiwan (MDA, Logit, Probit and NN). The results indicate that the Probit method has the highest accuracy, but when the statistical assumptions are not met, the NN achieve a higher accuracy.

Chen and Du (2009) assessed the use of Neural Networks and datamining techniques for financial distress prediction in Taiwan. Financial and non-financial data was used in constructing this model and factor analysis was used in assessing which ratios to use in the model. Results indicate that when factor analysis is more used than needed the accuracy of prediction declines. Also, if factor analysis is used, more companies that are in destress are classified as non-distressed. Finally, the results indicate that Neural Networks are more accurate than Data Mining techniques.

Chen (2011) did a similar study as of Chen (2009) but compared Data Mining with Logit Regression and used also financial and non-financial ratios in combination with principal component analysis. The results for principal component analysis are similar to factor analysis. The more they are used the less the accuracy becomes and when principal components analysis is used the error of classification also increases. The results also indicate the Data Mining has a higher accuracy than Logit.

Hu and Sathye (2015) used the Logit and Jackknife model to predict financial distress for a sample of companies out of Hong Kong between 2000 and 2010. The study finds that a model that includes firm-specific financial variables, firm-specific non-financial variables and a macro-economic variable is a better predictor of financial distress than is a model that includes only the first set of variables or a model that includes the latter two sets of variables. It also finds that a model that includes the latter two sets of variables is a better predictor of financial distress than is a model that includes only the first set of variables.

Abdullah, Halim, Ahmad and Rus (2008) compared three different methods for financial distress prediction in Malaysia. they concluded that the Hazzard model was the most accurate model and Logit was the least accurate. The results also indicate that the variable net income growth has more predictive power for the MDA method than other methods and the ROA has more predictive power for the Logit model.

Abdullah, Ma'aji and Khaw (2016) developed a distress prediction models combining financial, non-financial and governance particularly ownership and board structures, on the likelihood of financial distress by using the logit model. The results indicate that young SMEs seems to be more likely to fail as compared to longer existence SMEs due to experience and growth development. In addition, debt ratio is positively related to failure among SMEs.

Tian and Yu (2017) compared bankruptcy prediction in Japan, UK, Germany and France. They constructed different models optimized for each country and compared these models with the data of the others. The results indicate that using a model with three ratios demonstrates strong predictive ability and has superior prediction power over the model of Altman.

Xu and Zhang (2009) present evidence for the possibility of model generalisation to the Japanese market. The authors compared the models of Altman (1968) and Ohlson (1980), which have predictive power in Japan.

Leksrisakul and Evans (2005) applied the model of Altman (1968) to the market of Thailand. Therefore, they used firms listed at the Thai stock exchange between 1997 and 2002. A total of 53 failed and 106 non-failed were used in their sample. The authors concluded that the Z-score could be used to predict financial distress in Thailand.

2.4. Which other factors could influence financial distress prediction?

2.4.1. Cultural influences on the prediction of bankruptcy.

Cultural influences are a significant moderator for many financial predictors in the prediction of financial distress, according to Laitinen and Suvas (2016). They analysed the influence of Hofstede's cultural dimension on the prediction of financial distress and measured this using 22,594 failed and 1,255,768 non-failed European companies between 2002 and 2010. The variables used in this research are Return on assets, Quick ratio, Equity ratio, Standard deviation of ROA, Natural logarithm of TA and Long-term growth rate of total assets. The cultural dimensions tested are Power distance, Individualism versus Collectivism, Masculinity versus Femininity and uncertainty avoidance

Power Distance measures the extent to which the less powerful members of institutions and organisations within a country expect and accept that the power is distributed unequally. The Netherlands scores low on power distance, which means that Dutch people accept less than others that power is distributed unequally (Hofstede, 2017). Laitinen and Suvas (2016) present evidence for when the power distance is low, the long-term growth rate of total assets and standard deviation of ROA have strong positive effects on the probability of financial distress, meaning that the standard deviation of ROA and long-term growth of total assets increase the probability of financial distress. The Logarithm of Total assets has a strong negative effect on the probability of financial distress, meaning this ratio decreases the probability of financial distress.

Individualism measures the degree of independence a society maintains among its members. The Netherlands scores high on independence, which means that individuals are expected to take care for themselves (Hofstede, 2017). Individualism strongly moderates the total effect of the natural logarithm of TA on risk failure. When the individualism rate is high, the effect on business failure is negative, suggesting companies with a larger size in individualistic societies have less chance of becoming financial distressed (Laitinen and Suvas, 2016).

Masculinity versus Femininity measures what motivates people, wanting to be the best (Masculinity) or liking what you do (Femininity). This means for the Netherlands that it is a feminine society in which the work live relation should be in balance (Hofstede, 2017). Masculinity strongly moderates the natural logarithm of TA in the same manner as Individualism, hinting on multicollinearity in the dimensions masculinity versus femininity and Individualism versus collectivism Laitinen and Suvas, 2016).

Uncertainty avoidance measures the extent to which the members of a culture feel threatened by unknown situations and have created beliefs and institutions that try to avoid these. The Netherlands scores in the middle of this dimension and slightly prefers the avoidance of uncertainty. (Hofstede, 2017). Laitinen and Suvas (2016) suggest that in countries with a high uncertainty avoidance it would be difficult to find companies in financial distress, where as in low more financial dimensions affect the decision making. The Netherlands is in the middle, making the results of this dimension not significant.

The research of Laitinen and Suvas (2016) implies for the Netherlands that Long-term growth rate of total assets and the standard deviation of ROA increase the probability of financial distress, whereas the natural logarithm of total assets decreases the probability of financial distress. These variables could increase the accuracy for predicting financial distress in The Netherlands when used.

2.4.2. Small and Medium Enterprises (SMEs)

When Altman (1968) proposed the Z-score model, the initial sample was restricted for companies with a size measured in total assets between 1 million and 25 million. Altman and Sabato (2007) hypothesize that applying a default prediction model developed on large corporate data to SMEs will result in lower prediction power and likely a poorer performance of the entire corporate portfolio than with separate models for SMEs and large corporates. This was confirmed in the results of their study. Altman et al. (2017) also set minimum requirement for the size of companies, because “financial ratios of small companies are too unstable for a failure prediction model”. They set the minimum size of total assets to be at least 100,000 Euro. For this thesis, the SME definition in the Netherlands will be used. Therefore, every company with annual sales of less than €10 million will be accounted for as a company that can be categorised as SME.

Carter and van Auken (2006) argue that most serious problems of bankrupt firms can be condensed into three categories: lack of knowledge, inaccessibility to debt, and economic climate. Bankrupt firms also appear to be older, more likely to be in the retail industry, and organized as proprietorship or partnership than nonbankrupt firms. They are also less likely to use the Internet in their business operations than the nonbankrupt firms.

Altman and Sabato (2007) compared the predictive power of the Logit model and the MDA model for a sample containing 2010 U.S. SMEs with an sales less than 65 million dollar over the period 1994-2002 and found that the Logit model was more accurate (78%) than the MDA model (62%).

Ciampi and Gordini (2013) assessed whether prediction models using Neural Networks could predict financial distress for SMEs in Italy. They concluded that using a Neural Network model (68.4%) was more accurate in predicting financial distress than a Logit model (67.2%) or a MDA model (65.9%).

The Netherlands is a small country, as are most of his companies. According to the “MKB Desk” (Information source for SME sector) 99% of the Dutch companies are SME companies (250 full time employees or less, or total annual sales of less than €50 million). According to the Dutch Chamber of Commerce there were 1,832,812 active companies and 453,130 part-time companies (companies operating 15 hours or less a week) registered in the Netherlands in 2016. 48% of the Dutch companies are freelance companies with only one employee. Only 1% of the Dutch companies is a large company with more than 250 FTE or more than €50 million in revenue (MKB Desk, 2017).

2.5. Hypothesis development

The aim of this master thesis is to assess whether existing financial distress prediction methods could be used to accurately predict whether a company will be bankrupt or non-bankrupt. A model will be deemed accurate when it can correctly classify a company of being (non)bankrupt with an accuracy ratio of 80% (80% is the accuracy percentage Altman et al. (2017) anticipated to be able to achieve).

2.5.1. Hypothesis 1: the MDA model of Altman

Altman (1968) was able to predict financial distress with an accuracy of 95% in the initial sample and 96% in the control sample. This sample consists of only manufacturing countries listed in the United States. The MDA model of Altman (1968) has been re-estimated multiple times to be generalized to non-listed companies and non-manufacturing companies. The most recent version is the model of Altman (1984). It is is also used by Altman et al. (2017) who tried to generalise their model for 34 countries and achieved an accuracy of approximately AUC 0.75 (AR of 50%) for the total sample. The Dutch sample in the study of Altman et al. (2017) has an AUC of 0.787 (AR of 57.4%) which is notably less than the accuracy of Altman (1968). Grice and Ingram (2001) warns scholars for the use of Altman's model because the ability of the model to accurately classify companies financially distressed might differ considerably from that assumed by those employing the model, as is shown in their results.

The MDA model was promising in the early years of financial distress prediction, with high accuracy ratios. The highest reported accuracy found in recent literature was of Hayes et al. (2010) with an accuracy ratio of 90%. The MDA method has an average accuracy of 85% based on 89 scientific articles assessed by Aziz and Dar (2006). Grice and Ingram (2001) argues for a model performing worse in other samples than the sample they are estimated on. Therefore, I argue for the MDA model performing worse in an exclusively Dutch setting than the model average of Aziz and Dar (2006) (mean accuracy ratio of 85%) and worse than in international setting of Altman et al. (2017) (accuracy ratio of approximately 50%). Therefore the anticipated accuracy would be lower than 50%. Besides testing whether the model is able to correct classify Dutch companies, it also service as a benchmark for the other models to assess if the accuracy could be improved in a Dutch setting.

H1 The MDA model of Altman (1984) preforms worse in the Dutch setting than in the international setting of Altman et al. (2017) (AUC of 0.75 or AR of 50%).

2.5.2. Hypothesis 2: re-estimating the coefficients of the MDA model

Grice and Ingram (2001) argue for the use of re-estimation of the original model developed by Altman. They state, "those who employ Altman's Z-score model should re-estimate the model's coefficients rather than relying on those reported by Altman". Grice and Ingram (2001) used the original model from 1968 and achieved only a correctly classified percentage of 56.1% when applying the model to the dataset. Re-estimation of the model is also supported by Altman et al. (2017). They argue that the original data is almost seventy years old and recommend using data as close as possible to the present. They also re-estimated the coefficients (using only the MDA method) and state that re-estimation marginally improves the classification accuracy.

Re-estimating the coefficients could improve the accuracy of classification of financially distressed companies for the Netherlands. Grice and Ingram (2001) argue for always re-estimating the coefficients, Altman et al. (2017) also support re-estimating, but do not find evidence for a significantly higher accuracy of predicting.

Re-estimating the coefficients in a Dutch setting could have a different impact on the accuracy of classification of financially distressed companies, because the model is, after re-estimation, specified for only the Dutch companies instead of the model of Altman. Besides, the accuracy of the model can only be truly compared with the model of hypothesis 1 when it is re-estimated in the same timeframe.

H2 Re-estimating the MDA model yields a better performance in a Dutch setting, than the original model.

2.5.3. Hypothesis 3: the Logit method

Because of de divided opinion of scholars which model is superior, a second prediction model will be used. The second most popular model in financial distress prediction is the Logistic regression method (Aziz and Dar, 2006; Jackson and Wood, 2013). This method shares similarities with the MDA method, but does not share the statistical assumptions of multi-normality, homoscedasticity and linearity (Altman et al., 2017). Altman et al. (2017) state that the MDA method might be more useful for smaller samples (sample of Altman (1968) was 66 companies, and therefore the MDA model is more suited) and the Logit model could be more accurate in a larger sample. The Logit model is on average only slightly more accurate (87%) than the MDA model (85%) (Aziz and Dar, 2006).The Logit model could be a good alternative for the prediction of financial distress in the Netherlands because of the on average higher accuracy and not having the limitations of the MDA model. The same ratios will be used in for this model as used in the previous hypothesis, to compare the accuracy of the model, instead of the ratios used.

H3 The model using Logistic regression yields a better performance in a Dutch setting.

2.5.4. Hypothesis 4: The NN method

The Neural Network model achieves on average a higher accuracy (87%) than the MDA model (85%), but has on average the same accuracy of the Logit model (87%) (Aziz and Dar, 2006). Barboza et al. (2017) compared the Neural Network, MDA and Logit model and concluded that the Neural Network was most accurate in the training sample (NN 84.86%; Logit 82.74%; MDA 64.81%), but was the second most accurate in the testing sample (Logit 76.29%; NN 72.98%; MDA 52.18%). Mselmi et al. (2017) used Neural Networks on a France sample and compared the results with the results of Altman et al. (2017). They concluded that the Neural Network model (88.57%) was more accurate in predicting financial distress for a French sample than the MDA was (AUC of 0.845 is AR of 69%).

As is with the comparison with the MDA and Logit method, the opinion of scholars is also divided for the Neural Network. As is in the case of France I expect for the Neural Network model to be more accurate than the MDA model and the Logit model reported in other studies. But it could be that the Neural Network is as accurate as the Logit model of hypothesis 3, because of the similar on average accuracy ratios in other studies. Therefore, I think the Neural Network will be as accurate or better as the Logit model. Therefore, the following hypothesis can be drawn:

H4 The Neural Network model yields a better performance in a Dutch setting, than the MDA and Logit model.

2.5.5. Hypothesis 5: adding additional ratios and variables to the models

The base of literature contains many scientific studies from countries in Europe, America and Asia. These publications were assessed for their use in this study. These studies contained a total of 446 ratios out of which the ratios and variables were chosen which have predictive power in that study. Most of the studies use the same ratios or a slightly different variant. Some literature reports certain ratio having predictive power and other literature contradict this statement. The ratios with predictive value were striped of double ratios and slightly different variants, thus reducing the number of variables. The remaining ratios could increase predictive accuracy for the Netherlands and will therefore be tested for the Dutch dataset to assess whether one or more ratio has predictive value. It might be possible for a set of ratios to have more predictive power than the ratios used in the previous hypothesis.

H5 The performance of models is better when other or additional ratios are used in the model.

3. Methods

This chapter discusses the research design of this study. The subjects are the financial distress prediction methods and assumptions, the measurement of performance of models and how the hypothesis are tested.

3.1. Financial distress prediction methods

3.1.1. MDA method

The multiple discriminant analysis method creates for each company a score which indicates whether a company is bankrupt or non-bankrupt. The score is computed with the following formula:

Eq.1: MDA model equation

$$Z = a + b_1x_1 + \cdots + b_nx_n$$

Where a is the constant, b are the coefficient and x stands for the independent variable. The value Z is used to determine in which group a company is discriminated. Usually the Z-score model is accompanied with a guiding table to interpret the Z-score. This score indicates wheter a company will be bankrupt. The model of Altman (1984) has three outcome categories, which indicate the financial status of the companie. A companie belongs to one of the categories when the Z-score is in the range of the outcome categorie.

The multiple discriminant analysis method has several assumptions which must be met when using this method. The data used in the model must be normally distributed independent variables, there must be equal variance and covariance matrices across the failing and non-failing group, there must be a specified prior probability of failure and misclassification costs and the data must be absent of multicollinearity. According to Balcean and Oohge (2006) do most MDA failure prediction studies fail to comply with the model assumptions, resulting in a non-generalizable model.

3.1.2. Logit method

The Logit method creates a score for each company by weighting the independent variables. The score is then used to determine the probability of membership in a specific group (bankrupt or non-bankrupt). The probability is computed using the following formula:

Eq.2: Logit model equation

$$P(Z) = \frac{\exp(a + b_1x_1 + \cdots + b_nx_n)}{1 + \exp(a + b_1x_1 + \cdots + b_nx_n)}$$

Where a is the constant, b are the coefficient and x stands for the independent variable, exp stands for the exponential function of the expression between brackets and the result P(Z) is the probability of membership to a pre specified group. The value of P(Z) is always between 0 and 1. When a company has a score between 0 and 0.5 it is classified as non-bankrupt and a score higher than 0.5 to 1 is classified as bankrupt. The logit model resemblance in a certain way the MDA model, the Z in the MDA model and the (-Z) in the Logit model are both a set of the weighted sum of independent variables. A major advantage of the Logit model is the ease of interpreted the outcome of the model, compared to the difficult to interpret MDA model.

Because of the limitations of the MDA method, Ohlson (1980) employed the Logit method for predicting financial distress. The data in the MDA method must be normally distributed in the independent variables, must have equal (co)variance matrices, must have specified prior probability of failure and misclassification costs and must be absence of multicollinearity. Whereas the Logit method only must meet the requirement of the dependant variable being dichotomous. Also, must be noted that the Logit model is extremely sensitive to multicollinearity, outliers and missing values (Balcean and Oohge, 2006).

3.1.3. Neural Networks method

Artificial neural networks are among the most popular artificial intelligence techniques and have inspired other computational classification models. This method establishes an analogy with human neural processing. Many non-linear relationships can be analysed using NN methods (Barboza, Kimura and Altman, 2017).

The Neural Network model makes minimal demands on model structure and assumptions, which implies that a NN can be used without speculation over which variables are related to each other. A NN utilizes a learning process, which can determine of a linear relationship between the dependant and independent variables is appropriate. If a non-linear relationship is more appropriate, the NN will automatically correct the model structure (IBM SPSS Manual). The Neural Network can be expressed by equation 3:

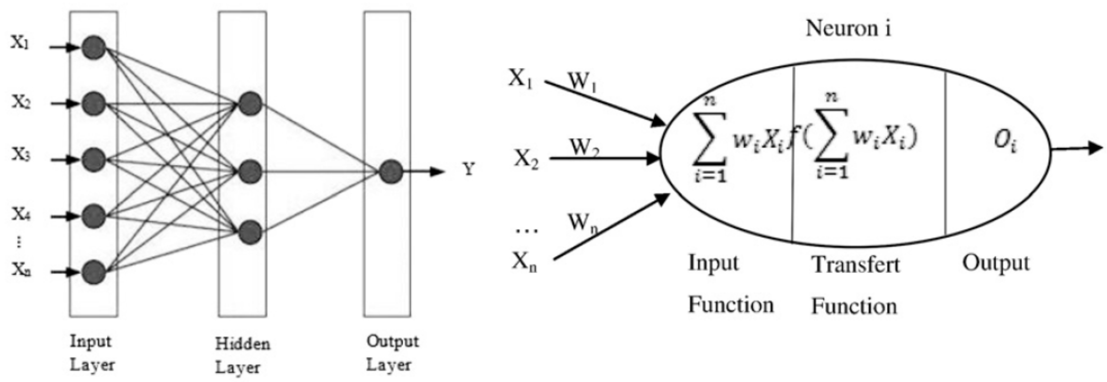
Eq.3: Neural Networks model equation

$$o_i = \sum_{i=1}^{n} W_i X_i f\left(\sum_{i=1}^{n} W_i\, X_i\right) + \varepsilon_i$$

Where *n* is the total number of hidden units (neurons) in the hidden layer between inputs and outputs, W are weights from the economic–financial ratio inputs to the hidden layer, and the X_i parameters are weights from the hidden layer to the output layer

Barboza et al. (2017) discuss three major disadvantages of the Neural networks. The performance for unbalanced data is poor because it tends to classify more observations in classes with more data and, reducing the test set’s forecasting performance. The model accuracy improves as the training set becomes larger, but the validation is insufficient to provide a satisfactory error rate. Selecting the hidden layers is difficult, given the relationship between computing time (i.e. more time is required for more layers) and higher predictability.

Figure 1: Graphical representation of the input, hidden and output layer of a Neural Network.



Source: Mselmi et al. (2017)

3.2. Measuring the performance of a model

The performance of a model is assessed by different methods. Altman (1968) used the method of dividing all correctly classified companies by the total sample size. Altman et al. (2017) compare the AUC value of each individual model and also briefly discuss the link between the AUC and the accuracy ratio, but do not use the accuracy ratio. Laitinen and Suvas (2016) actively use both the AUC and the accuracy ratio for comparing the different models in their study. Mselmi et al. (2017) uses the same method as Altman (1968), dividing the total correct classified companies by the total sample size.

A notable issue is that Altman et al. (2017), Laitinen and Suvas (2016) and Mselmi et al. (2017) do not report the type I and type II error in their study. In contrary to Altman (1968) and Barboza et al. (2017). Type I and II error is an important measurement to assess whether the accuracy is high because the model is good at classifying bankrupt or non-bankrupt or either.

Because different methods are used in scientific literature to assess the performance of a model, will all method be used to assess the performance of the financial distress prediction models in this study.

3.2.1. Area Under Curve of the Receiver Operating Characteristic

The accuracy of the model may be calculated using the AUC statistic, extracted from the ROC curve. The ROC curve is a line plotted, based on the sensitivity and 1- specificity of a model. The Area Under Curve (AUC) is literally the total area covered under the curve and can be measured as a number between 0 and 1, but an area under 0.5 is not common.

This method is used to measure the performance of the models. If AUC equals 1, the accuracy of the model is perfect, while AUC equals 0.5 refers to a random model without any classification ability.

Eq.4: Accuracy Ratio

$$Accuracy\ Ratio = 2(AUC - 0{,}5)$$

Results are also reported based on the Accuracy Ratio (AR) (eq. 4). An accuracy ratio of a perfect model equals 100%, whereas for a random model it equals 0%. A model needs to have at least an AR of 50% or higher[3] to be acceptable (Altman et al., 2016; Barboza et al., 2017; Laitinen and Suvas, 2016).

3.2.2. Sensitivity and Specificity Ratio

The Sensitivity Ratio and Specificity Ratio of a model are derivatives of the type I and type II error. Altman (1968) calculated the accuracy of a as the number of accurate classifications divided by the total number of elements in the validation set. The sensitivity and specificity Ratio are equivalent to those proposed by Altman (1968) (Barboza et al., 2017). The Sensitivity Ratio is expressed by equation 5 and Specificity Ratio is expressed by equation 6. Both can also be presented as a percentage of observed companies being bankrupt classified as bankrupt (eq. 5) or percentage of observed non-bankrupt companies being classified as non-bankrupt (eq. 6).

Eq.5: Sensitivity Ratio

$$Sensitivity = 1 - Type\ I\ error = \frac{TP}{TP + FN}$$

Eq.6: Specificity Ratio

$$Specificity = 1 - Type\ II\ error = \frac{TN}{TN + FP}$$

Where TP is True Positive, Bankrupt companies are correctly classified as bankrupt. TN is True Negative, where non-bankrupt companies are correctly classified by the model. False Negative (FN) indicates that the model classifies as non-bankrupt, but the company is actually bankrupt and False Positive (FP) indicates a classification as bankrupt when the company is non-bankrupt (summary in table 2). The Sensitivity Ratio has a value close to 1 when the type I error is low. When the specificity ratio is close to 1, the type II error is low.

Table 2: Type I and type II error.

	Company is non-bankrupt	Company is bankrupt
Model indicates bankruptcy	False Positive (FP). Type II error.	True Positive (TP). Correctly classified as bankrupt.
Model indicates non-bankruptcy	True Negative (TN). Correctly classified as non-bankrupt.	False Negative (FN). Type I error.

3.2.3. Percentage of correctly predicted companies

The final method of assessing the performance of a model is the same method as Altman (1968) used for assessing the predictive accuracy of the MDA model. The method used as dividing the hits (correctly classified companies) by the sum of the hits and misses (not correctly classified companies). This

[3] All three sources do not mention who the threshold of 50% AR established or why is was chosen but use it anyway.

method could also be used for this study in the manner of dividing all correctly classified companies by the total sample.

The classification model of Altman (1968) has three outcome options: bankrupt, non-bankrupt and the grey area, where a company could become financial healthy or financially distressed. The notable issue with assessing the accuracy of a model using the statistical method is that the accuracy is usually measured in the total hits and misses, but the grey zone is excluded. This is also the case of Altman (1968) where the grey zone is excluded from the mathematics of assessing performance, resulting in a higher accuracy score than when the grey zone is included. In this study, the accuracy is measured including and excluding the grey zone.

3.3. Testing hypotheses

3.3.1. Hypothesis 1

The first hypothesis predicts that the Z-score of Altman (1963) is not able to predict financial distress accurately for the Dutch sample, but has an accuracy of lower than 75%. In order to test this hypothesis, the financial data of the Dutch companies must be inserted in the equation of the Z-score of Altman. Altman's Z-score is expressed by equation 7.

Altman (1984) used for the most recent version of the Z-score the following classification of Z-scores: a score below 1.1 means a company is in the distress zone, a score between 1.1 and 2.6 is the grey zone (the company is stuck in the middle, but could become healthy or bankrupt) and a higher than 2,6 suggests the company is financial healthy.

The Z-score is computed and gives a value when all financial data is available for that company. When one or more ratios are missing, in computing the Z-score, a missing value will be given to the company. This is preferred over giving the company a value based on three or less ratios out of four, because the Z-score would not be interpretable when it is not based on all four ratios.

Eq.7: Altman's Z-score

$$Z'' = 3.25 + 6.56x_1 + 3.26x_2 + 6.72x_3 + 1.05x_4$$

$$x_1 = \frac{Working\ Capital}{Total\ Assets} \qquad x_3 = \frac{EBIT}{Total\ Assets}$$

$$x_2 = \frac{Retained\ Earnings}{Total\ Assets} \qquad x_4 = \frac{Book\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities}$$

3.3.2. Hypothesis 2

The second hypothesis predicts that with the use of re-estimated coefficients for the MDA model[4], the accuracy of prediction is higher than the original model. This hypothesis uses the same four ratios as

[4] The MDA model will be re-estimated in SPSS under the tabs "Analyse", "Classify", "Discriminant"

the original model, but will make use of re-estimated coefficients and a re-estimated explanation of the classifying score.

To re-estimate the coefficients, the bankrupt companies must be paired with a non-bankrupt company. The multiple discriminant analysis method has four major assumptions which must be met when using this method, besides the pairing of failed and non-failed companies. The data used in the model must be normally distributed independent variables, there must be equal variance and covariance matrices across the failing and non-failing group, there must be a specified prior probability of failure and misclassification costs and the data must be absent of multicollinearity. According to Balcean and Oohge (2006) Most MDA failure prediction studies do not check whether the data satisfy the assumptions, resulting in a non-generalizable model.

The method is re-estimated using a training sample and a validation sample. The results of the model after re-estimating can be compared based on the AUC, the AR, the percentage of correctly classified companies, sensitivity and specificity for a complete evaluation which model is superior.

3.3.3. Hypothesis 3

The third hypothesis predicts that with the use of Logistic regression instead of Multiple Discriminant Analysis, the performance of the model would higher than the accuracy of hypothesis 1.

The same ratios will be used for this hypothesis, but because there are no coefficients known. Altman et al. (2017) also applied the Logit method to the variables in the Z-score and used these as a benchmark for the following hypothesis. This is also the intention of this study, as well as with the model of the first hypothesis.

Logistic Regression[5] is used to understand whether an outcome (dependant variable) can be predicted based on one or more independent variables. In order to calculate a binary logistic regression, four assumptions must be met. First the dependant variable must be dichotomous. Second there must be one or more independent variables, which must be continuous or categorical. Third, there should be independence of observations. Finally, there needs to be a linear relationship between any continuous independent variable and the logit transformation of the dependant variable.

The performance of the logit model is assessed by comparing the AUC, the AR, the percentage of correctly classified companies, sensitivity and specificity with the results of hypothesis 1 and 2.

3.3.4. Hypothesis 4

The fourth hypothesis predicts that the Neural Network method is more accurate in predicting financial distress for the Netherlands than the MDA and Logit models of the previous hypothesis.

[5] Binary Regression is the SPSS equivalent of the Logistic Regression analysis. Binary analysis is conducted in SPSS under the tab “Analyse”, “Regression”, “Binary Logistics”.

A Neural Network model[6] has an on average higher accuracy than the Logit and MDA models (Aziz and Dar, 2006). Mselmi et al. (2017) used Neural Networks on a France sample and compared the results with the results of Altman et al. (2017). They concluded that the Neural Network model was more accurate in predicting financial distress for a French sample than the MDA was. This hypothesis explores whether the Neural Network is more accurate in predicting financial distress for the Netherlands than the re-estimated MDA and Logit model.

3.3.5. Hypothesis 5

The fifth hypothesis predicts when additional or other ratios and variables are used than the four ratios used in the previous hypotheses, the performance of the MDA, the Logit and the NN method could be higher.

Beaver (1968) argued for the prediction of financial distress using 14 ratios'. the individual ratios could correctly classify a company in financial distress with an error percentage of 44. This is slightly higher than the error expected from random prediction. Although the error rate was high, Beaver also suggested the financial statement relationship with prediction of financial distress, paving the road for Altman to use ratios combined with the MDA technique in predicting financial distress. Altman (1968) compiled a list of 22 ratios out of many significant indicators for financial distress, selected based on the popularity in literature and relevance for his research. According to Mclaney and Atrill (2014) there is no underlying theory of financial failure to help guide researchers in their selection of appropriate ratios. As stated by Altman (1968) the ratios used where selected based on popularity in recent literature and relevance of the research.

In failure prediction studies, financial ratios are usually selected based on three criteria: they should be commonly used in failure prediction literature, the information needed to calculate these ratios should be available, and finally, the researchers' own decisions based on their experience in previous studies or based on the preliminary trials (Alfaro, Garcia, Gamez and Elizondo, 2008).

Tsai (2009) indicate that redundant ratios inputted in predictive models would lead to a much more time-consuming model and could reduce the accuracy of the model. Tsai argues for ratio selection as a pre-processing step to select the most valuable information out of the massive stream of related literature. He also states that "many studies focus on developing more effective prediction models per se which provide better predictive capabilities, some even without considering ratio selection before constructing their models" (Tsai, 2009). He argues for using the T-test over other methods of selecting ratios (Correlation matrix, stepwise regression, principal component analysis and factor analysis) for constructing the optimal model. Using the T-test to choose the ratios leads to more representative ratios and a higher performance of prediction. Chen and Du (2009) used factor analysis for selecting

[6] A Neural Network can be calculated in SPSS using the "analyse tab", "Neural Network" and then "Multilayer Perceptron" option.

the ratios in the model. They present evidence for when factor analysis is used the predictive accuracy declines. Chen (2011) used principal component analysis and came to the same conclusion as Chen and Du (2009).

The ratios and variables in this study are selected based on popularity in literature and predictive value in literature. Over 400 different ratios are identified in financial distress prediction literature, out of which the most popular ratios are selected. thereafter factor analysis and T-test is used to assess the difference in mean statistics of the variables and ratios between the failed and non-failed companies. Also, correlation matrices and multicollinearity diagnostic need to be computed.

4. Data collection and sample selection

The Reach database of Bureau Van Dijk (BVD) is used to collect financial data. This database is a Dutch database of privately held companies. Reach contains a wide-ranging selection of company data (financial, activities, structure, ownership, etc.). the entire database contains approximately 3.6 million company record, of which 0.8 million annual reports and approximately 60,000 records of bankruptcy.

The most recent dataset found in literature of the Netherlands was the research of Altman et al. (2017), which used a dataset from 2007 until 2010. This study makes use of a data set from 2011 to 2017.

4.1. Sample

Initial screening of the Reach database resulted in a total of 900 records of bankrupt companies and more than 30,000 records of non-bankrupt companies. Financial data of bankrupt and non-bankrupt companies is collected for the time period between 2010 and 2017. A substantial part of the sample had only data available from 2010 until 2015. Many records were deleted because only the company name was mentioned and had no financial data available. After further examination of the Reach data only 125 bankrupt and 125 non-bankrupt companies remain in the sample.

The 125 bankrupt companies are paired with a non-bankrupt company these companies are paired based on company size. The sample is further divided into two sub samples, an estimation sample (which is used to estimate the model) and a holdout sample (which is a separate sample and is not used to estimate the model). This is for multiple reasons, first because the models are estimated in the 2010-2017 timeframe. One can have confidence in the predictive abilities of a model when it is tested on data subsequent to its development and the efficiency needs to be tested on a new sample other than the development sample (Balcean and Ooghe, 2006).

The companies in the sample have a total assets ranging between €0 and €1,047,113,000 for bankrupt companies and between €31,000 and 1,516,384,000 for non-bankrupt companies. The EBIT of the non-bankrupt companies is between -€47,243,000 and €41,104,000. The non-bankrupt companies have an EBIT between -€25,902,000 and €142,000,000. The total of employees is between one and 6324 for bankrupt companies and between 2 and 86750 for non-bankrupt companies. The youngest company in the sample, exists for only one year and the oldest company is in corporation for 137 years. See appendix III for the descriptive statistics of the sample, ratios used and the list of companies in the sample.

Table 3: Sample size

		Non-bankrupt Count	Percentage	Bankrupt Count	Percentage
Estimation sample	Small-company	33	16.7%	33	16.7%
	Medium-company	33	16.7%	33	16.7%
	Large-company	33	16.7%	33	16.7%
Total estimation sample		99	50.0%	99	50.0%
Test sample	Small-company	9	17.3%	9	17.3%
	Medium-company	8	15.4%	8	15.4%
	Large-company	9	17.3%	9	17.3%
Total test sample		26	50.0%	26	50.0%

4.2. Ratios and variables

27 ratios are selected out of the over 400 ratios present in the literature used in chapter 2. The ratios are selected based on popularity in literature, as is common in financial distress prediction. The ratios are presented in table 5 with the designation R#. The columns on the right of table 5 report all variables which are used to compute the ratios. The ratios and their reference in literature are presented in appendix III. the descriptive statistics of the ratios is presented in appendix IV.

The financial statement data of the companies are collected up to 6 years before bankruptcy, of which the year prior to bankruptcy is designated with time t-1 and time t-6 is six years before bankruptcy. Most financial distress studies only focus on one or two years before bankruptcy (Altman et al., 2017). Financial data of the periods before t-6 are mostly not available for the bankrupt companies and are therefore not collected.

A couple of control variables are added to make a detailed analysis of the companies in the sample. The control variables are shown in table 5 with the designation C#. First, a dummy variable for bankruptcy is taken into the sample. This dummy variable is a dichotomous variable with a 0 for non-bankrupt companies and a 1 for bankrupt companies. Second, a control variable for the company size is added. The companies are given a number between 1 and 3. 1 represents the category small companies, which is a combination of the micro and small classification of the Dutch SME categories. A company is categorised as a small company when it has less than 50 full time employees and an annual turnover of less than €10,000,000. 2 represents the middle companies. Companies classified as middle have less than 250 full time employees and an annual turnover of less than €50,000,000. 3 represents the large companies. Companies classified as large have more than 250 full time employees and more than €50,000,000 in annual turnover (MKB Servicedesk, 2017).

Finally, the date of bankruptcy (when the company is bankrupt, otherwise 0) and the date of last record available are added. These dates are collected to be certain which records belong to the year of bankruptcy or the year before bankruptcy.

The Reach database reports a detailed balance sheet on every company in their database, but only the major labels on a balance sheet are filled in (fixed assets, current assets, etc.). Smaller and individual labels are frequently reported as N.A. (not available). Therefore, the data required for testing the hypothesis is limited to the availability in Reach. An example is that many records did not contain the equity of a company. Therefore, the total assets reduced by total liabilities is used as a proxy for equity. An issue might occur when not all financial information is available for the bankrupt companies. In that situation, SPSS includes the companies which have information available and excludes companies which do not have information available, reducing the amount of bankrupt companies (see appendix IV red coloured items represent ratios of which less than 50 observations are available). This might lead to test whether that particular ratio has predictive value based on a small number of bankrupt companies against a large number of non-bankrupt observations. A result could be that the model is accurate in predicting non-bankruptcy but not in predicting bankruptcies.

Table 4: Variables and ratios

Control variables		Variable
C1	Dummy for bankruptcy	Bankruptcy (current status)
C2	Dummy for company size	Cash and cash equivalents
C3	Date of bankruptcy	Cash flow
C4	Date of last record available	Current assets
Liquidity		Current liabilities
R1	Current ratio = Current assets / Current liabilities	Date of bankruptcy
R2	Cash Ratio = Liquid assets / Current liabilities	Date of last record available
R3	Debt Equity ratio = Total Liabilities / Equity	EBIT
R4	Cash flow / Current liabilities	Equity (Total assets - Total liabilities)
R5	Cash flow / Total liabilities	Net income
R6	Current liabilities / Total assets	Non-current liabilities
Profitability		Number of employees
R7	EBIT / Total Assets	Retained earnings
R8	Sales / Total Assets	Sales
R9	ROA = Income after taxes / Total assets	Total assets
R10	ROE = Income after taxes / Equity	Total liabilities
R11	Gross profit = Net income / Sales	Working capital
Liability		Years of corporation
R12	Equity / Total Liabilities	
R13	Solvency Ratio = Income after taxes / Total Liabilities	
R14	Total Liabilities / Total Assets	
Growth		
R15	Growth rate of net income (CY-PY)/PY	
R16	Growth rate of EBIT (CY-PY)/PY	
R17	Growth rate of equity (CY-PY)/PY	
Size		
R18	Logarithm of total assets	
R19	Logarithm of equity	
Structure		
R20	Retained earnings / Total assets	
R21	Equity / Total assets	
R22	Working Capital / Total assets	
R23	Cash and cash equivalents / Total assets	
R24	Current assets / Total assets	
Other		
R25	Years of corporation	
R26	Total assets / Number of employees	
R27	Standard deviation of ROA	

4.3. Ratio selection

Intensify analysing large sums of information of different companies is likely to take much time and human resources, especially when the information is overabundance. Therefore, how to filter the large amount of data is important to predict financial distress. Redundant information inputted into a model could cost more time and even reduce the degree of accuracy of the model (Tsai, 2009).

Ratio selection is required for hypothesis five. In this hypothesis the MDA, the Logit and the Neural Network methods are used to test the most prominent ratios. The techniques utilised for ratio selection are; t-test, stepwise regression and correlation matrices.

The t-test method is used to determine whether there is a significant difference between two group's means. It helps to answer the underlying question: do the two groups come from the same population, and only appear differently because of chance errors, or is there a significant difference between these two groups (Tsai, 2009). The null hypothesis of the T-test assumes the equality of means between the bankrupt and the non-bankrupt group. The means of the bankrupt and non-bankrupt groups are significantly different when the null hypothesis is rejected ($P<0.05$).

In order to select the optimal set of predictors and improve the performance of the models, ratio selection is also undertaken by using stepwise regression. When using regressions to build models, one common technique to find the best combination of predictor variables is stepwise regression. Although there are many variations, the most basic procedure is to find the single best predictor variable set and add variables that meet specified criterion. The result is a combination of predictor variables, all of which have significant coefficients. (Tsai, 2009). In stepwise regression method, the ratios enter after each other into the model, depending on the significance value of the ratios together. A ratio is inserted in the model with a significance value of 0.05 and excluded from the model with a significance value of 0.1.

A correlation matrix is used to confer the correlation of two quantitative groups, as well as to analyse whether one group affects the other one. A correlation coefficient is the result of a mathematical comparison of how closely related two variables are. The relationship between two variables is said to be highly correlated if a movement in one variable results or takes place at the same time as a similar movement in another variable. To select appropriate variables affecting much more parts of the result by this technique could obtain related advantages. The correlation matrix is used combined with the Cronbachs alpha to determine whether the selected ratios measure the same construct. Reliability analysis is used in SPSS to determine the Cronbachs alpha for the ratios with a significant difference in means. The Cronbachs alpha is developed to measures the internal consistency of a test. The internal consistency measures the extent to which all items measure the same concept. The Cronbachs alpha ranges between 0 and 1, where a score of below 0.5 is poor and a score above 0.8 is good.

Overall four additional sets of ratios have been selected to be used in the MDA, the Logit and the Neural Networks model (see appendix IV for the ratio selection process). Set 1 is the ratio set of Altman, which were used in H1 to H4. The ratio sets 2, 3, 4 and 5 are selected using ratio selection methods and used in the financial distress prediction models of H5.

- Ratio set 1 R7, R12, R20 and R22

- Ratio set 2 R4, R5, R7, R13 and R21
- Ratio set 3 R5, R9 and R13
- Ratio set 4 R1, R10, R12, R21 and R22
- Ratio set 5 R5, R9, R11, R21 and R22

4.4. Assumptions of models

Three assumptions need to be considered for the prediction methods to function properly. The assumptions are checked for the ratio sets identified during the ratio selection process.
The multiple discriminant analysis method has four major assumptions which must be met when using this method. The data used in the model must be normally distributed independent variables, there must be equal variance and covariance matrices across the failing and non-failing group, there must be a specified prior probability of failure and misclassification costs and the data must be absent of multicollinearity. According to Balcean and Oohge (2006) most MDA failure prediction studies do not check whether the data satisfy the assumptions, resulting in a non-generalizable model.

Because of the limitations of the MDA method, Ohlson (1980) employed the Logit method for predicting financial distress. The Logit method must only meet the requirement of the dependant variable being dichotomous. Also, must be noted that the Logit model is extremely sensitive to multicollinearity, outliers and missing values (Balcean and Oohge, 2006).

Neural Networks can analyse complex patterns with high accuracy. A major advantage of the Neural Networks is that they are not subjected to the statistical assumptions of the MDA and Logit method. In particular the assumption of normal distribution (Balcean and Ooghe, 2004).

4.4.1.1. Normal distribution of data

The Shapiro-Wilks test is used for testing the normal distribution of data between groups. The null hypothesis of the Shapiro-Wilks test assumes normally distributed data. The assumption can be made for the data being non-normal distributed when the null hypothesis is rejected ($P<0.05$). The Shapiro-Wilks statistic has been calculated for all ratios (see appendix V).

Only ratio R21 t-2, R22 t-2 and R22 t-3 have normally distributed data over both bankrupt and non-bankrupt groups. For all other ratios only the bankrupt or non-bankrupt or neither of those are significant for normality of data distribution. The assumption of normal distribution of data cannot be made and therefore the MDA method can only be re-estimated for this sample and not be generalized outside of this sample.

4.4.1.2. Equality of variance

The second assumption for the MDA method is the equality of variance between groups. Equality of variance is usually tested with the “Levene’s test” for normally distributed data and the “Non-parametric Levene’s test” for non-normally distributed data. The null hypothesis of the Levene’s test assumes equality of variance (P>0.05). The assumption can be made that there is no equality of variance when the null hypothesis is rejected (P<0.05).

The statistics are asses for the five ratio sets, where after the conclusion can be made that there is no equality of variance among the bankrupt and non-bankrupt groups for the different ratio sets. Appendix V shows which ratios have an equality of variance in a certain period.

4.4.2. Multicollinearity

The ratio sets as input for the MDA and Logit model must be absent of multicollinearity. Therefore, the multicollinearity is tested for each set of ratios in terms of the VIF statistic (appendix V). The rule of thumb for assessing multicollinearity is that there is no multicollinearity when the VIF statistic is between 0 and 3. Multicollinearity issues might arise when the VIF is between 3 and 10 and there are multicollinearity issues when the VIF is above 10.

Ratio set 1 has no multicollinearity issues. The VIF statistics are not higher than 1.283. Ratio set 2 has some multicollinearity issues. Almost all VIF values are higher than 3, with R13 having a value of 10.219. Ratio set 3 might also have multicollinearity issues. All VIF statistics are between 3 and 10. Ratio set 4 might have issues with R12 (VIF 5.156) and R22 (VIF 5.543) but is within the acceptable range. Ratio set 5 has only R9 with possible multicollinearity issues (VIF 4.247) but is within the acceptable range.

5. Results

The results of prediction models are presented in this section. Reporting is limited to the results up to two years prior to bankruptcy, because performance of models appears to be random form 3 years before bankruptcy and earlier.

5.1. Performance of prediction models one year before bankruptcy

5.1.1. Performance of models in estimation and holdout sample

The performance of the different models is assessed by comparing the Area Under Curve (AUC), the Accuracy Ratio (AR), the percentage of correctly classified companies, sensitivity and specificity (as discussed in section 3.2). First the performance, one year before bankruptcy will be compared with each other. Table 5 presents the results of the models one year before bankruptcy.

Table 5: Performance of prediction models one year before bankruptcy

Model	Sample[1]	N[2]	AUC[3]	Sensitivity[4]	Specificity[5]	AR[6]	Percentage correctly predicted[7]
H1 MDA	Estimation	93	0.866	0.353	0.947	73.2%	83.9%
	Holdout	24	0.594	0.000	0.857	18.8%	75.0%
H2 MDA	Estimation	97	0.727	0.462	0.738	45.4%	70.1%
	Holdout	27	0.906	0.500	0.696	81.2%	66.7%
H5 MDA set 2	Estimation	63	0.896	1.000	0.816	79.2%	85.7%
	Holdout	14	0.833	1.000	0.667	66.6%	71.4%
H3 Logit	Estimation	97	0.764	0.231	0.444	52.8%	72.2%
	Holdout	27	0.906	0.250	0.410	81.2%	63.0%
H5 Logit set 2	Estimation	63	0.979	0.357	0.959	95.8%	82.5%
	Holdout	14	0.750	0.500	1.000	50.0%	92.9%
H5 Logit set 5	Estimation	64	0.896	1.000	0.820	79.2%	85.9%
	Holdout	14	0.875	1.000	0.750	75.0%	78.6%
H4 NN	Estimation	97	0.500	0.000	1.000	0.0%	87.3%
	Holdout	45	0.500	0.000	1.000	0.0%	84.4%
H5 NN set 2	Estimation	49	1.000	0.909	1.000	100.0%	98.0%
	Holdout	28	1.000	0.800	0.957	100.0%	92.9%
H5 NN set 5	Estimation	51	0.800	0.538	0.947	60.0%	84.3%
	Holdout	27	0.750	0.667	0.958	50.0%	92.6%

[1] The estimation sample is used to estimate the model. the holdout sample is a different sample, not used to estimate the model.
[2] The total amount of bankrupt and non-bankrupt observations, which the results are based on.
[3] The AUC value of the prediction model. An AUC ≤ 0.5 represents a model without predictive capabilities. A decent prediction model has an AUC ≥ 0.75.
[4] The sensitivity indicates the ability of the model to predict bankruptcies (value between 0 and 1). The sensitivity is interpreted as the rate at which bankrupt companies are predicted to be bankrupt. A model with a low sensitivity value is not able to predict bankruptcies.
[5] The specificity indicates the ability of a model to predict non-bankruptcies (value between 0 and 1), the specificity is interpreted as the rate at which non-bankrupt companies are predicted to be non-bankrupt. A model with a low specificity is not able to predict non-bankruptcies.
[6] The AR is a derivative of the AUC. The AR is used to give an accuracy value in percent to the AUC.
[7] The percentage of correctly predicted companies is used since Altman (1968) and is computed by dividing all true positive and true negative results by the total amount of observations. Note that in the case of the model of Altman (1984), the model used in H1, the grey area is excluded from the calculation. This is to compare the results in the same way as Altman (1968,1984) did.

The model of Altman (1984) (model of H1) seems to be a decent prediction model, based on the results in table 5. The rule of thumb of the AUC, implies that a model has predictive power when the AUC is 0.75 or higher. This applies to the model in the estimation sample (AUC of 0.866), but not in the holdout sample (AUC of 0.594). The AUC in the holdout sample is closer to 0.5. An AUC close to 0.5 resembles a model without any predictive capabilities. The AUC one year before bankruptcy is higher than the highest AUC (AUC of 0.787 AR of 57.4%) for the Netherlands in the study of Altman et al. (2017).

The sensitivity results of the model is very low in both samples (0.353 in estimation and 0.0 in holdout). This implies that the models performs poor at predicting bankruptcies. The specificity is in both samples high or almost perfect (0.947 in estimation sample and 0.857 in the holdout sample). This implies that the model is good at predicting non-bankruptcies.

The model of Altman has three outcome categories, the bankrupt zone, the non—bankrupt zone and the grey zone, in which the company could become bankrupt or non-bankrupt. The percentage of correctly classified companies is on average lower when the grey zone is included in calculating the percentage (amount of correctly predicted results divided by the total observations). The accuracy percentage is between 5% and 10% higher when the grey area is excluded from the calculation. Altman (1968) did not include the grey zone in calculating the accuracy, and therefore the grey zone will also be excluded in this study.

The model of Altman (1984) seems to be a model which is not good at predicting bankruptcies, but good at predicting non-bankruptcies, based on the results in table 5. The model might achieve decent results in a sample true to the total population, because there much more non-bankrupt companies in the true population than in the matched pairs sample of this study. It was hypothesised that this model would not achieve an accuracy percentage higher than 50%. The results of the estimation sample show the opposite, but the holdout sample confirms the hypothesis. Based on the results in table 5, hypothesis one cannot be confirmed or rejected at one year before bankruptcy.

Some improvements can be observed in the re-estimated MDA model (table 5, model H2 MDA). The sensitivity of the re-estimated model is higher (0.462>0.353 and 0.5>0.0) and reproduce comparable results in the holdout sample. This implies that this model is better in predicting bankruptcies than the previous model. The AUC (0.727) and related AR (45.4%) is lower in the estimation sample, but considerably higher in the holdout sample (0.906 and 81.2%) The specificity of the model is lower than the previous model in both the estimation (0.816<0.947) and holdout sample (0.667<0.857). The percentage of correctly classified companies is lower than that of the model of H1. Note that the model of H1 has three outcome categories out of which two are used to calculate the percentage, whereas the model of H2 only has two outcome categories, which are both used to calculate the percentage. The re-estimated model seems to be a better in predicting bankruptcies but is not considerably better than the original. Some evidence can be presented in favour of accepting hypothesis 2, but the evidence is not overwhelming. A final note on the assumptions of the model is that the re-estimated MDA model of H2 does not comply with the model assumptions and it therefore cannot be generalized outside of this study.

The Logit model combined with the ratios of Altman (1984) results in a model with comparable performance in terms of accuracy percentage and percentage of correctly predicted as the re-estimated MDA model of H2. The only difference is that the sensitivity and specificity are lower in the estimation and holdout sample than that of the model in H2. It was hypothesised that the Logit method would perform better than the MDA method. This is not the case at one year before bankruptcy and with the ratios used by Altman.

A difference can be observed when comparing the coefficients of the model of Altman (1984) (H1) with the coefficients of the re-estimated MDA model (H2) and the Logit model (H3). The influence of R7 (working capital / total assets) on the outcome is in both the re-estimated model as the Logit model increased. R20 (retained earnings / total assets) has almost no influence in the re-estimated MDA model and a much lower influence in the Logit model. R22 (equity / total liabilities) influence is decreased in both models. A last notable difference in the models is that the coefficient of the beta is negative in the re-estimated MDA model and the Logit model, whereas in the original model the beta is positive

The NN method combined with the ratios of Altman (1984) is not a good predictive model in terms of AUC and related AR. The AUC (0.5) has the lowest value of the four models in table 5. The sensitively of the model is terrible (0.0) and the specificity is perfect (1.0). This implies that the model cannot correctly predict bankruptcies and does not make mistakes in identifying non-bankrupt companies. the high performance in terms of percentage of correctly classified companies cannot be explained. It was hypothesised that the NN method would perform better than the re-estimated MDA model and the Logit model. Based on the results in table 5, the NN model performs worse than these models, presenting evidence for rejecting H4 at one year before bankruptcy.

The models of hypothesis 5 (lower half of table 5) perform considerably better than the models of hypothesis 1 to 4 (upper halve of table 5). The NN model based on ratio set 5 has the lowest performance in terms of AUC of the models of H5. Despite having the lowest AUC, this model is still a decent performing model in the estimation and holdout sample. The NN model based on ratio set 2 has a perfect AUC of 1. Two models have a perfect score on sensitivity, which indicates that the models are extremely good at predicting bankruptcies. Only the Logit model based on ratio set 2 does not perform well in terms of sensitivity, which is comparable with the performance of the models based on ratio set 1. Overall it can be noted that the models of H5 outperform the models of H1 until H4, with the NN model based on set 2 outperforming all models at one year before bankruptcy, and thus presenting evidence for accepting H5 at one year before bankruptcy.

5.2. Performance of prediction models two years before bankruptcy

5.2.1. Performance of models in estimation and holdout sample

The performance of models, two years before bankruptcy, is measured at the same manner as one year before bankruptcy. The same models are used to produce the results in table 6 as are used to produce the results in table 5, with the only difference being the time before bankruptcy. The performance, reported in table 6, is also split u in the same estimation sample and holdout sample.

The performance of prediction models at two years before bankruptcy is different from the models at one year before bankruptcy. On average, in terms of AUC, the models at two years before bankruptcy perform slightly worse than the models at one year before bankruptcy. In terms of sensitivity, the models of H1 to H4 perform slightly better at t=-2 than an t=-1. The opposite can be observed for the models of H5. The percentage of correctly predicted companies is also on average lower two years before bankruptcy than one year before bankruptcy.

Table 6: Performance of prediction models two years before bankruptcy

Model	Sample	N	AUC	Sensitivity	Specificity	AR	Percentage of correctly predicted
H1 MDA	Estimation	123	0.737	0.182	0.949	47.4%	67.5%
	Hold-out	37	0.625	0.375	0.857	25.0%	64.9%
H2 MDA	Estimation	126	0.745	0.702	0.785	49.0%	75.4%
	Hold-out	32	0.875	0.200	0.727	75.0%	56.3%
H5 MDA set 2	Estimation	104	0.875	0.821	0.771	75.0%	79.8%
	Hold-out	28	0.719	0.688	0.750	43.8%	71.4%
H3 Logit	Estimation	126	0.829	0.489	0.924	65.8%	76.2%
	Hold-out	32	0.938	0.100	0.864	87.6%	62.5%
H5 Logit set 2	Estimation	104	0.479	0.232	0.938	0.0%	55.8%
	Hold-out	28	0.563	0.125	1.000	12.6%	50.0%
H5 Logit set 5	Estimation	106	0.817	0.672	0.813	63.4%	73.6%
	Hold-out	29	0.522	0.294	0.750	4.4%	48.3%
H4 NN	Estimation	117	0.676	0.610	0.855	35.2%	76.9%
	Hold-out	41	0.406	0.438	0.840	0.0%	68.3%
H5 NN set 2	Estimation	94	0.854	0.860	0.705	70.8%	78.7%
	Hold-out	38	0.781	0.864	0.813	56.2%	84.2%
H5 NN set 5	Estimation	92	0.854	0.800	0.786	70.8%	79.3%
	Hold-out	43	0.757	0.920	0.667	51.4%	81.4%

See footnotes of table 5 for interpretation of headers.

The model of Altman (1984) two years before bankruptcy does not perform as well as the same model one year before bankruptcy (AUC of 0.737<0.866). The results in the estimation and holdout sample are closer to each other than at one year before bankruptcy (difference between 0.737 and 0.625 < difference between 0.866 and 0.594). The model has an AUC lower than the threshold of 0.75, which implies that this model is not a good prediction model. this combined with the low sensitivity presents evidence for accepting H1 at two years before bankruptcy.

The MDA model of H2 performs slightly better in the estimation sample (0.754>0.737) than the model of H1 at two years before bankruptcy but performs better in the holdout sample (0.875>0.625). The sensitivity is notably higher (0.702>0.182), which implies that the model is better at predicting bankruptcies, than the model of H1. This result is not reproduced in the holdout sample (sensitivity of 0.2). Some evidence can be presented for accepting H2 at two years before bankruptcy, but the evidence is not overwhelming.

The Logit model performs better in terms of AUC than the model of H1 and H2 at two years before bankruptcy (0.829>0.745>0.737). The sensitivity of the model is poor in both the estimation sample (0.489) and the holdout sample (0.100). In percentage correctly predicted performs the Logit model slightly better than the re-estimated MDA model. The evidence in table 7 suggest that the Logit model is slightly better than the re-estimated MDA model and therefore this is enough evidence to accept hypothesis 3 and assume that the Logit model performs better than the model of H2.

Table 7 shows that the models of H2 and H3 perform better than the model of Altman at two years before bankruptcy. The cause could be that the model of Altman is optimised for the use one year before bankruptcy and the models of H2 and H3 are estimated on data of two years before bankruptcy.

The NN model of H4 performs worse than the re-estimated MDA and Logit model based on the AUC (0.676<0.737<0.829) value. The model of H4 is not a good prediction model, based on the AUC. The values represent almost a random model. the sensitivity of the model is more consistent over the estimation and hold-out sample, but not high enough to accurately predict bankruptcies. Th percentage of correctly predicted companies is comparable with the models of H2 and H3. Table 7 presents evidence for rejecting H4 at two years before bankruptcy.

The models of H5 perform better than the models of H1 to H4 in terms of sensitivity, apart from the Logit models). The MDA set, NN set 2 and 5 models have a higher sensitivity than the models of H1 to H4 and are more consistent over the estimation and holdout sample.

When comparing the MDA models, it can be noted that the MDA model of H1 does not perform well when compared to the re-estimated MDA model of H2 and the MDA model based on set 2. The MDA model based on ratio set 2 performs the best of the MDA models.

The Logit models of H3 and H5 set 2 perform better in terms of AUC than the Logit model based on Set 2. The downside of these models is that they do not reproduce the same results in the holdout sample as in the estimation sample. The second downside is that these three models have a low sensitivity, which implies that they are not the best models for predicting bankruptcies.

The NN models of H5 perform notably better than the NN of H4 and outperform all other models. Based on this information, arguments can be presented for accepting H5 at two years before bankruptcy.

6. Conclusion

A total of 91 different financial distress prediction models are used in this study, to assess which model in combination with a certain ratio set is most suited for financial distress prediction in the Netherlands. The MDA model of Altman (1984) is not estimated, but tested on the sample, functioning as a baseline for the other models. Thereafter the MDA method is used to estimate models consisting out of 6 timeframes before bankruptcy with 5 different sets of ratios. This totals the amount of MDA models used in this study to 31. The Logit and NN methods are used to estimate a total of 60 different models. 5 different ratio sets are used to estimate 6 different models for each ratio set (up to 6 years before bankruptcy).

6.1. Key findings

6.1.1. Best prediction model

Three different methods have been used to predict financial distress in the Netherlands. The results of the models vary, and it is complicated to present evidence for which method is superior to another.

The MDA model has proven itself in the past with the study of Altman (1968). Many scholars have applied or re-estimated this model. This study presents evidence for the MDA model not being the best model for financial distress prediction. The MDA model has the advantage that it is easy to use and relatively easy to interpret, but the model assumptions make it difficult to apply and generalise.

The results indicate that the model of Altman (1984) performs better in a Dutch setting than expected. The first hypothesis is neither rejected nor accepted at one year before bankruptcy but is accepted at two years before bankruptcy. The expectation was that the model would have a significant lower performance than the results indicate. The higher performance than expected is probably due to the ability of the model to correctly predict non-bankrupt companies. The model is not able to correctly predict bankrupt companies, which is more in line with the hypothesis.

The results also indicate that the MDA model performs better when re-estimated, but the difference in performance is not as high as expected. The main improvement of the re-estimated MDA model is the increase of sensitivity. The model is better at predicting bankrupt companies to be bankrupt at one and two years before bankruptcy than the model of Altman (1984). The results present no conclusive evidence for accepting or rejecting the hypothesis at one year before bankruptcy, but present evidence for accepting H2 at two years before bankruptcy. The results of hypothesis 1 and 2 are in line with the results of Altman et al. (2017). The model of '84 has decent performance and re-estimation yields slightly better result than the original model. The larger difference in performance as Grice and Ingram (2001) mention, between the model of Altman and the re-estimated cannot be confirmed in this study.

The re-estimated MDA model and the Logit model based on the same ratios have similar performance at one year before bankruptcy, but the Logit model performs slightly better at two years before bankruptcy. It seems as the Logit model performing slightly better, but the difference in performance is not great enough to give a conclusive acceptation or rejection of hypothesis 3. The results of the MDA and Logit methods are in line with the results Aziz and Dar (2006) and Jackson and Wood (2013). The Logit models perform slightly better than the MDA models used in this research.

The NN model of hypothesis four did not perform as well as hypothesised. The model resembles more a random model at one and two years before bankruptcy. Hypothesis 4 is rejected based on the results.

The models of Hypothesis 5 perform better than the models which use the ratios of Altman. The difference is easily observed at one year before bankruptcy. The best performing models differ in order compared with the models of H1 to H4. In H5 the MDA model and Logit model have comparable performance and the NN model almost has perfect performance. The Logit model performs worst at two years before bankruptcy, followed by the MDA model and the NN model performs best.

The results of the NN method are in line with Aziz and Dar (2006), Barboza et al. (2017) and Mselmi et al. (2017), in the models based on ratio set 2 and 5. The performance of the MDA models based on ratio set 2 are the lowest. In terms of AUC. The Logit method comes second and the NN method performs the best. This is not the case with the ratio set of Altman (1984). When this set of ratios is used, the performance of the NN model is not the highest. In that case the Logit method performs the best. The NN model is powerful and highly accurate in predicting financial distress. The drawback of the model is that weights of the ratios are not easily interpretable and it is difficult to explain the relation between the dependant and independent variable in the NN. Applying the NN model to another sample than the training and validation sample was not possible in the SPSS software. Therefore, the NN models created in this study cannot be applied outside this study.

6.1.2. Conclusion of main question

The main question investigates whether it is possible to predict financial distress in the Netherlands with an accuracy of 80%.

The MDA model of Altman (1984) did not predict financial distress accurately enough to achieve an accuracy percentage of 80%. Re-estimating the model yielded similar results. The accuracy was higher when the same ratios were used in a different model. The Logit model achieved in the holdout sample a percentage of correctly classified companies of higher than 80%, but not in the estimation sample. The NN model achieved in both the estimation as the holdout sample a result higher than 80% in terms of percentage of correctly predicted companies.

The accuracy is higher when ratio set 2 is used with the three different financial distress prediction methods. The MDA model achieves a percentage of correctly classified companies higher than 80% in the estimation sample, but not in the holdout sample. The Logit model achieves a Accuracy Ratio higher than 80% in the estimation sample, but not in the holdout sample and a percentage of correctly classified companies higher than 80% in both samples. The NN method achieves almost perfect results with the NN model based on ratio set 2. This model is in both the estimation and holdout sample almost perfect and confirms the main question that financial distress prediction can be predicted with an accuracy higher than 80%.

The accuracy of the models based on ratio set 5 are somewhat lower than the models based on ratio set 2, but higher than the models based on ratio set 1. The NN model achieves in both the training and testing sample an accuracy percentage higher than 80% in terms of percentage of correctly classified companies.

6.1.3. Ratios with predictive power

One of the major findings in this study is the use of different ratios to predict financial distress in the Netherlands. The results indicate that the ratios used by Altman (1968;1984) and Altman et al. (2017) (ratio set 1) are not the best ratios to use for financial distress prediction in the Netherlands. The ratio sets 2 and 5 are more suited for financial distress prediction in the Netherlands.

Both ratio set 2 and 5 consist mainly of ratios that give some indication about the amount of financial resources the company has at his disposal or how profitable the company is. Only ratio 13 of set 2 involves the liabilities of the company.

Based on the results, one may argue for the importance of having enough financial resource at the disposal for a company, when financial distress is immanent or assessed. Companies seem to be less in financial distress when financial resources are abundant.

The ratios in ratio set 2 and 5 are all ratios selected form the literature of financial distress prediction in other countries/economic regions. The literature investigated about specific ratios who could be used as predictors for the Netherlands seemed not the best ratios to use.

6.1.4. Selection of ratios

The ratios have been selected using different methods. The ratios selected with the use of t-test for difference in means (ratio set 2) and the ratios where both the t-teat and stepwise regression is applied (ratio set 5) are the most promising ratios in this study. The ratios which were selected using only the stepwise regression method are not suitable for predicting financial distress in the Netherlands. These results are in line with the study of Tsai (2009).

6.2. Limitations

A major limitation is the nature of the three models used, with the model assumptions. The MDA model has many assumptions, which could not be met in this study. The MDA method could be a powerful statistical tool but is not the most suited tool for this application. The NN model is proven to be the best model in this study, but because of the nature of the model it is difficult for someone else to use the same NN model estimated in this study on a different dataset. The NN model is only suited for researchers who are interested in the outcome and not the manner of calculating, because this cannot be done without computer programs (SPSS manual).

I also want to express my concerns for the lack of a universal expression of model performance in financial distress prediction studies. This study compares the different models based on the AUC, the AR, the percentage of correctly classified companies, the sensitivity and specificity of the model. As previously pointed out, many different methods are used to express the model performance and these cannot be compared with each other. Many scholars use the AUC statistic to assess the performance of a model, which is a derivative of the sensitivity and specificity, but the problem is that one does not know whether an AUC is good because the sensitivity is high or the specificity Is high. This limitation is mitigated in this study by reporting both the specificity and sensitivity next to the AUC value. One of the problems which might occur when comparing results with other studies is that accuracy values not always can be compared with each other. One might compare the accuracy in terms of AR with the accuracy measured in correct predictions divided by total observations, which, as is shown in tables 5, 6, 7 and 8, are different.

Another limitation of this study is the availability of financial data. Reach reports to have record of over 60.000 bankruptcies in their database, but on closer selection of the data, only 125 of these records could be used in this study. Only 125 bankrupt companies remained in the sample after selecting the companies which had most data available. The same goes for the non-bankrupt companies, but there are a lot more non-bankrupt companies in Reach and the quality of data is higher. This small sample is a major limitation of the study. The second limitation of the Reach database is the availability of financial data. Not every variable needed for this study was available in the Reach database and therefore many company records must be deleted.

The backlog in the Reach database is also one of the limitations of this study. Financial data is gathered from different companies between 2010 and 2017. Financial data between 2017 and 2015 was more difficult to come by than data between 2010 and 2015. This is due to the fact that not all most recent data is processed in the database.

6.3. Future research

Many subjects, briefly touched in this study could be further researched by others. A suggestion for future research and maybe a more interesting subject is the long-term prediction of financial distress. Ratio set 5 is able to accurately predict financial distress up to 6 years before bankruptcy. This is uncommon in financial distress prediction literature. Most studies only focus on a two to three-year period before bankruptcy. As can be seen in the results of this study, for most model the performance of the model declines when the period before bankruptcy is increases. Except for ratio set 5 with the Logit model and the NN model. at this moment it is unknown whether this is due to the sample, may it be coincidence or is it actual possible to predict financial distress 6 years before bankruptcy.

Another suggestion for future research is the application of the prediction methods used on a larger Dutch sample, if it is possible to obtain. A larger sample might lead to similar results, which then confirm the findings in this study. A larger sample might also lead to a sample which complies with the statistical assumptions, which improves the use of the MDA and Logit methods.

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Appendix

App. I: Prediction methods for financial distress.

Method category	Method
Statistical models	Linear discriminant analysis
	Logistic reasoning
	Multivariate discriminant analysis
	Quadratic discriminant analysis
	Factor analysis
	risk index models
	conditional probability models
	Univariate
	Linear probability model
	Logit model
	Probit model
	Cumulative sums
	Partial adjustment processes
Artificial intelligent models	Multi-layer perceptron
	backpropagation neural network
	self-organising map
	Learning vector quantization
	Radical basis function network
	Probabilistic neural network
	Recursively partitioned decision trees
	Case-based reasoning
	Neural networks
	Genetic algorithms
	Rough sets model
	auto-associative neural network
	Self-organising map
	Cascade correlation neural network
	Fuzzy logic techniques
Hybrid learning models	Genetic algorithm
	Annealing simulation
	Particle swarm optimization
	Ant colony optimization
Operational research models	Linear programming
	Data envelopment analysis
	Quadratic programming
Theoretical models	Balance sheet decomposition measures
	Gambler's ruin theory
	Cash Management Theory
	Credit risk theories
Decision tree models	CHAID
	C5.0
	QUEST
	CART
Semi-parametric methods	
Support vector machines	
Case-based reasoning	
evolutionary approaches	
rough sets	
soft computing	

App. II: Reference in literature of ratios

Ratios		Reference in literature									
Liquidity											
R1	Current ratio = Current assets / Current liabilities	Abdullah et al., 2008	Charitou et al., 2004	Chen 2011	Chen and Du 2009	Ciampi and Gordini 2013	Hu and Sathye 2015	Lin 2009	Van Gestel et al., 2006		
R2	Cash Ratio = Cash and cash equivalents / Current liabilities	Abdullah et al., 2008	Charitou et al., 2004	Chen 2011	Laitinen and Kankaanpaa 1999	Lensberg et al., 2006	Lin 2009				
R3	Debt Equity Ratio = Total liabilities / Equity	Chen 2011	Chen and Du 2009	Mselmi et al., 2017	Xie, Luo and Yu, 2011						
R4	Cash flow / Current liabilities	Chen 2011	Chen and Du 2009	Ciampi and Gordini 2013	Xie et al., 2011						
R5	Cash flow / Total liabilities	Almamy et al., 2016	Charitou et al., 2004	Agarwal and Taffler (2008)	Charalambakis 2015	Charitou et al., 2004					
R6	Current liabilities / Total assets	Agarwal and Taffler (2008)	Charitou et al., 2004	Charalambakis 2015							
Profitability											
R7	EBIT / Total Assets *	Altman et al., 2017	Abdullah et al., 2016	Alfaro et al., 2008	Almamy et al., 2016	Altman and Sabato 2007	Charalambakis 2015	Charitou et al., 2004	Manzaneque et al., 2016		
R8	Sales / Total Assets	Alfaro et al., 2008	Almamy et al., 2016	Charalambakis 2015	Lin 2009	Van Gestel et al., 2006	Xie, Luo and Yu, 2011				
R9	ROA = Net income / Total assets	Abdullah et al., 2008	Chen 2011	Chen and Du 2009	Laitinen and Kankaanpaa 1999	Lin 2009	Van Gestel et al., 2006	Xie, Luo and Yu, 2011	Laitinen and Suvas 2016		
R10	ROE = Net income / Equity	Chen 2011	Chen and Du 2009	Van Gestel et al., 2006							
R11	Profit rate = (Net income / Sales)	Hu and Sathye 2015	Van Gestel et al., 2006	Xie et al., 2011							
Liability											
R12	Equity / Total Liabilities *	Altman et al., 2017	Almamy et al., 2016	Charitou et al., 2004	Chen 2011	Chen and Du 2009	Lin 2009	Tinoco and Wilson (2013)	Laitinen and Suvas 2016		
R13	Solvency Ratio = EBIT / Total Liabilities	Charitou et al., 2004	Mselmi et al., 2017	Van Gestel et al., 2006							
R14	Total Liabilities / Total Assets	Abdullah et al., 2008	Agarwal and Taffler (2008)	Charitou et al., 2004	Ciampi and Gordini 2013	Donker et al. 2009	Hu and Sathye 2015	Laitinen and Kankaanpaa 1999	Lin 2009	Tian and Yu 2017	Tinoco and Wilson (2013)

Growth									
R15	Growth rate of net income (CY-PY)/PY	Abdullah et al., 2008	Lin 2009	Xie, Luo and Yu, 2011					
R16	Growth rate of EBIT (CY-PY)/PY	Lin 2009							
R17	Growth rate of equity (CY-PY)/PY	Lin 2009							
Size									
R18	Logarithm of Total assets	Agarwal and Taffler (2008)	Alfaro et al., 2008	Donker et al. 2009	Lensberg et al., 2006	Van Gestel et al., 2006			
R19	Logarithm of market value of equity	Abdullah et al,. 2016	Charalambakis 2015						
Structure									
R20	Retained Earnings / Total Assets *	Altman et al., 2017	Almamy et al., 2016	Altman and Sabato 2007	Charitou et al., 2004	Lin 2009	Manzaneque et al., 2016	Tian and Yu 2017	Xie, Luo and Yu, 2011
R21	Equity / TA	Charitou et al., 2004	Lensberg et al., 2006						
R22	Working Capital/Total Assets *	Almamy et al., 2016	Altman et al., 2017	Charitou et al., 2004					
R23	Cash and cash equivalents / Total assets	Alfaro et al., 2008	Altman and Sabato 2007						
R24	Current Assets to Total Assets Ratio	Alfaro et al., 2008	Chen 2011						
R25	Years of corporation	Abdullah et al,. 2016	Lensberg et al., 2006						
R26	Total Assets / Number of Employees	Ciampi and Gordini 2013							
R27	Standard deviation of ROA	Laitinen and Suvas (2016)							

App. III: Descriptive statistics

Descriptive statistics of sample

Bankrupt		N	Minimum	Maximum	Mean
	Years in business	125	1	137	26,18
	Total assets	125	€ -	€ 1.047.113.000,00	€ 57.065.925,40
	EBIT	119	€ -47.243.000,00	€ 41.104.000,00	€ -956.662,15
	Number of employees	97	1	6324	237,25
Non-bankrupt		**N**	**Minimum**	**Maximum**	**Mean**
	Years in business	125	3	118	28,74
	Total assets	125	€ 31.000,00	€ 1.516.384.000,00	€ 86.349.729,47
	EBIT	125	€ -25.902.000,00	€ 142.000.000,00	€ 4.725.794,11
	Number of employees	113	2	86750	1399,19

Descriptive statistics of ratios used

		N	Mean	Minimum	Maximum	Std. Deviation	Variance
R1 t-1	Non-bankrupt	300	1.755	0.000	9.790	1.313	1.724
	Bankrupt	45	1.014	0.014	4.255	0.858	0.735
R1 t-2	Non-bankrupt	299	1.677	0.000	9.055	1.240	1.537
	Bankrupt	126	1.365	0.007	9.254	1.580	2.496
R1 t-3	Non-bankrupt	299	1.630	0.074	9.849	1.199	1.437
	Bankrupt	127	1.485	0.009	8.672	1.522	2.316
R1 t-4	Non-bankrupt	298	1.634	0.002	9.015	1.188	1.411
	Bankrupt	123	1.434	0.008	8.007	1.397	1.952
R1 t-5	Non-bankrupt	295	1.590	0.000	8.603	1.131	1.279
	Bankrupt	112	1.336	0.007	7.541	1.145	1.312
R1 t-6	Non-bankrupt	285	1.576	0.000	6.874	1.044	1.089
	Bankrupt	98	1.465	0.075	9.261	1.382	1.909
R4 t=1	Non-bankrupt	292	0.209	-2.836	2.754	0.676	0.458
	Bankrupt	33	-0.128	-1.318	1.102	0.442	0.196
R4 t-2	Non-bankrupt	297	0.298	-2.111	2.380	0.534	0.286
	Bankrupt	119	-0.006	-2.367	2.553	0.557	0.310
R4 t-3	Non-bankrupt	298	0.335	-1.089	2.807	0.447	0.200
	Bankrupt	125	0.084	-1.219	2.615	0.443	0.196
R4 t-4	Non-bankrupt	274	0.318	-1.092	2.356	0.415	0.172
	Bankrupt	111	0.096	-1.815	2.508	0.411	0.169
R4 t-5	Non-bankrupt	254	0.303	-2.894	2.141	0.438	0.192
	Bankrupt	89	0.068	-0.800	1.252	0.231	0.053
R4 t-6	Non-bankrupt	222	0.339	-1.386	2.785	0.408	0.166
	Bankrupt	67	0.093	-1.027	0.806	0.258	0.067
R5 t-1	Non-bankrupt	295	0.131	-2.160	2.754	0.481	0.231
	Bankrupt	34	-0.149	-1.159	0.716	0.342	0.117
R5 t-2	Non-bankrupt	299	0.200	-2.028	2.380	0.414	0.172
	Bankrupt	125	-0.011	-1.805	2.553	0.477	0.227
R5 t-3	Non-bankrupt	300	0.214	-2.744	2.101	0.344	0.118
	Bankrupt	127	0.098	-0.962	2.659	0.444	0.197
R5 t-4	Non-bankrupt	275	0.204	-0.686	2.295	0.292	0.085
	Bankrupt	112	0.085	-0.669	2.376	0.294	0.086
R5 t-5	Non-bankrupt	256	0.202	-1.008	1.618	0.283	0.080
	Bankrupt	89	0.041	-0.324	0.515	0.141	0.020
R5 t-6	Non-bankrupt	223	0.216	-0.325	1.740	0.246	0.061
	Bankrupt	67	0.068	-0.592	0.784	0.206	0.042
R7 t-1	Non-bankrupt	293	0.053	-0.967	0.940	0.184	0.034
	Bankrupt	34	-0.105	-0.642	0.375	0.212	0.045
R7 t-2	Non-bankrupt	295	0.078	-1.000	0.841	0.139	0.019
	Bankrupt	121	-0.068	-0.803	0.878	0.251	0.063
R7 t-3	Non-bankrupt	301	0.078	-0.368	0.520	0.107	0.011
	Bankrupt	121	0.021	-0.571	0.953	0.227	0.051
R7 t-4	Non-bankrupt	293	0.072	-0.440	0.499	0.114	0.013
	Bankrupt	104	0.031	-0.443	0.938	0.176	0.031
R7 t-5	Non-bankrupt	284	0.070	-0.457	0.562	0.112	0.012
	Bankrupt	79	-0.030	-0.883	0.380	0.180	0.032
R7 t-6	Non-bankrupt	266	0.088	-0.357	0.776	0.115	0.013
	Bankrupt	43	0.018	-0.722	0.425	0.191	0.037

Continuation of appendix III, Descriptive statistics

		N	Mean	Minimum	Maximum	Std. Deviation	Variance
R9 t-1	Non-bankrupt	291	0.028	-0.993	0.716	0.177	0.031
	Bankrupt	35	-0.143	-0.986	0.331	0.246	0.060
R9 t-2	Non-bankrupt	295	0.057	-0.955	0.884	0.144	0.021
	Bankrupt	122	-0.092	-0.961	0.878	0.264	0.070
R9 t-3	Non-bankrupt	301	0.051	-0.566	0.393	0.104	0.011
	Bankrupt	122	-0.003	-0.575	0.953	0.212	0.045
R9 t-4	Non-bankrupt	294	0.048	-0.465	0.427	0.099	0.010
	Bankrupt	117	0.005	-0.505	0.938	0.166	0.028
R9 t-5	Non-bankrupt	284	0.043	-0.818	0.424	0.113	0.013
	Bankrupt	99	-0.042	-0.882	0.374	0.154	0.024
R9 t-6	Non-bankrupt	268	0.062	-0.244	0.565	0.094	0.009
	Bankrupt	71	-0.001	-0.773	0.224	0.135	0.018
R10 t-1	Non-bankrupt	292	0.080	-2.821	2.142	0.577	0.333
	Bankrupt	34	0.290	-1.507	2.264	0.797	0.635
R10 t-2	Non-bankrupt	287	0.159	-2.966	2.628	0.506	0.256
	Bankrupt	116	0.070	-2.661	2.861	0.891	0.795
R10 t-3	Non-bankrupt	295	0.169	-2.476	2.990	0.479	0.230
	Bankrupt	115	0.194	-2.601	2.818	0.797	0.635
R10 t-4	Non-bankrupt	292	0.146	-2.157	2.765	0.478	0.228
	Bankrupt	114	-0.013	-2.215	1.595	0.672	0.451
R10 t-5	Non-bankrupt	280	0.144	-1.461	2.203	0.378	0.143
	Bankrupt	91	0.046	-2.833	2.444	0.593	0.352
R10 t-6	Non-bankrupt	266	0.144	-2.695	1.489	0.392	0.154
	Bankrupt	69	0.106	-1.412	1.639	0.459	0.211
R11 t-1	Non-bankrupt	145	0.045	-0.565	0.912	0.106	0.011
	Bankrupt	26	-0.112	-0.575	0.139	0.181	0.033
R11 t-2	Non-bankrupt	141	0.026	-0.549	0.253	0.090	0.008
	Bankrupt	89	-0.029	-0.784	0.464	0.182	0.033
R11 t-3	Non-bankrupt	166	0.033	-0.254	0.224	0.065	0.004
	Bankrupt	91	0.009	-0.726	0.839	0.199	0.039
R11 t-4	Non-bankrupt	167	0.031	-0.441	0.302	0.079	0.006
	Bankrupt	90	-0.006	-0.792	0.471	0.144	0.021
R11 t-5	Non-bankrupt	166	0.024	-0.931	0.525	0.105	0.011
	Bankrupt	67	-0.012	-0.405	0.556	0.126	0.016
R11 t-6	Non-bankrupt	155	0.035	-0.345	0.757	0.092	0.008
	Bankrupt	47	-0.005	-0.553	0.233	0.095	0.009
R12 t-1	Non-bankrupt	287	1.033	0.000	5.488	1.090	1.189
	Bankrupt	24	0.299	0.007	1.607	0.371	0.138
R12 t-2	Non-bankrupt	279	0.896	0.000	4.791	0.901	0.812
	Bankrupt	88	0.515	0.004	3.860	0.735	0.541
R12 t-3	Non-bankrupt	282	0.894	0.000	4.944	0.912	0.833
	Bankrupt	102	0.492	0.000	4.462	0.690	0.476
R12 t-4	Non-bankrupt	282	0.842	0.000	4.669	0.795	0.632
	Bankrupt	105	0.469	0.010	4.542	0.672	0.451
R12 t-5	Non-bankrupt	281	0.825	0.000	4.416	0.780	0.609
	Bankrupt	91	0.403	0.010	2.065	0.414	0.171
R12 t-6	Non-bankrupt	271	0.806	0.000	3.485	0.681	0.464
	Bankrupt	87	0.471	0.018	2.513	0.522	0.273

Continuation of appendix III, Descriptive statistics

		N	Mean	Minimum	Maximum	Std. Deviation	Variance
R13 t-1	Non-bankrupt	293	0.049	-1.984	1.400	0.389	0.151
	Bankrupt	39	-0.158	-1.172	0.623	0.313	0.098
R13 t-2	Non-bankrupt	296	0.116	-1.735	1.496	0.310	0.096
	Bankrupt	121	-0.088	-1.331	0.812	0.239	0.057
R13 t-3	Non-bankrupt	301	0.124	-0.701	1.331	0.218	0.048
	Bankrupt	122	0.013	-1.051	1.778	0.305	0.093
R13 t-4	Non-bankrupt	293	0.110	-0.728	1.333	0.219	0.048
	Bankrupt	117	0.001	-0.826	1.033	0.190	0.036
R13 t-5	Non-bankrupt	284	0.102	-1.121	1.442	0.261	0.068
	Bankrupt	99	-0.028	-0.645	0.422	0.144	0.021
R13 t-6	Non-bankrupt	268	0.143	-0.419	1.585	0.240	0.058
	Bankrupt	71	0.023	-0.426	0.668	0.165	0.027
R20 t-1	Non-bankrupt	266	0.041	0.000	0.891	0.071	0.005
	Bankrupt	30	0.092	0.001	0.930	0.169	0.029
R20 t-2	Non-bankrupt	271	0.045	0.000	0.905	0.076	0.006
	Bankrupt	79	0.057	0.000	0.428	0.074	0.006
R20 t-3	Non-bankrupt	271	0.048	0.000	0.885	0.075	0.006
	Bankrupt	74	0.055	0.001	0.288	0.068	0.005
R20 t-4	Non-bankrupt	270	0.044	0.000	0.819	0.070	0.005
	Bankrupt	76	0.059	0.000	0.322	0.074	0.005
R20 t-5	Non-bankrupt	260	0.047	0.000	0.893	0.077	0.006
	Bankrupt	71	0.048	0.000	0.344	0.064	0.004
R20 t-6	Non-bankrupt	250	0.051	0.000	0.911	0.094	0.009
	Bankrupt	60	0.059	0.000	0.594	0.091	0.008
R21 t-1	Non-bankrupt	301	0.402	-0.267	0.981	0.228	0.052
	Bankrupt	38	0.065	-0.640	0.958	0.310	0.096
R21 t-2	Non-bankrupt	301	0.385	-0.331	0.965	0.232	0.054
	Bankrupt	117	0.123	-0.971	0.794	0.313	0.098
R21 t-3	Non-bankrupt	301	0.373	-0.670	0.978	0.241	0.058
	Bankrupt	118	0.197	-0.994	0.912	0.268	0.072
R21 t-4	Non-bankrupt	300	0.376	-0.859	0.998	0.239	0.057
	Bankrupt	117	0.197	-0.805	0.820	0.242	0.059
R21 t-5	Non-bankrupt	297	0.366	-0.713	0.987	0.240	0.058
	Bankrupt	109	0.197	-0.786	1.000	0.263	0.069
R21 t-6	Non-bankrupt	291	0.377	-0.594	0.997	0.234	0.055
	Bankrupt	97	0.235	-0.815	1.000	0.250	0.063
R22 t-1	Non-bankrupt	301	0.191	-0.708	0.907	0.253	0.064
	Bankrupt	40	-0.039	-0.965	0.958	0.356	0.126
R22 t-2	Non-bankrupt	301	0.174	-0.653	0.896	0.252	0.063
	Bankrupt	118	0.014	-0.939	0.840	0.358	0.128
R22 t-3	Non-bankrupt	301	0.168	-0.720	0.885	0.252	0.064
	Bankrupt	119	0.103	-0.856	0.829	0.313	0.098
R22 t-4	Non-bankrupt	301	0.164	-0.837	0.883	0.257	0.066
	Bankrupt	118	0.087	-0.766	0.835	0.331	0.110
R22 t-5	Non-bankrupt	298	0.161	-0.898	0.872	0.259	0.067
	Bankrupt	109	0.098	-0.801	1.000	0.339	0.115
R22 t-6	Non-bankrupt	291	0.169	-0.703	0.911	0.247	0.061
	Bankrupt	96	0.134	-0.917	1.000	0.297	0.088

List of companies in sample

Company name	Current status
College Style B.V.	Bankrupt
XS2TheWorld B.V.	Bankrupt
WR Accounting & Control B.V.	Bankrupt
Benerich Telecom & Network B.V.	Bankrupt
Flinter America N.V.	Bankrupt
Flinter Tide N.V.	Bankrupt
Flinter Trader N.V.	Bankrupt
Flinter Rose N.V.	Bankrupt
Touchbase B.V.	Bankrupt
Eltu B.V.	Bankrupt
Scivias Zorg B.V.	Bankrupt
Butters Rüben Expres B.V.	Bankrupt
Naabb BV	Bankrupt
Handelsonderneming Nicolai B.V.	Bankrupt
Ozhas B.V.	Bankrupt
Landmeier Wielersport B.V.	Bankrupt
Itec Systems B.V.	Bankrupt
Haag Vlechtwerken B.V.	Bankrupt
Wegako Bouw B.V.	Bankrupt
MLM Bouwbeheer B.V.	Bankrupt
Rafal Kunststof Techniek B.V.	Bankrupt
Seabricks Holding B.V.	Bankrupt
Tuincorrect B.V.	Bankrupt
Klaassen Home Connecting B.V.	Bankrupt
Postmasters Zaanstad B.V.	Bankrupt
D.B. Group B.V.	Bankrupt
bigSHIFT coöperatief U.A.	Bankrupt
Select Mail Amsterdam B.V.	Bankrupt
Hof van Saksen B.V.	Bankrupt
Transportbedrijf G. Oudt en Zoon B.V.	Bankrupt
Pouw Autoschade Groep B.V.	Bankrupt
Restige Ré Beheer B.V.	Bankrupt
D. van de Wetering B.V.	Bankrupt
NOVEK Group B.V.	Bankrupt
Conesco International Holding B.V.	Bankrupt
Prime Champ Logistics B.V.	Bankrupt
BVK Telecom B.V.	Bankrupt
Booijink Metaal Holding B.V.	Bankrupt
Flinter Atlantic N.V.	Bankrupt
Flinter Arctic N.V.	Bankrupt
DB Licensing B.V.	Bankrupt
USG Sourcing B.V.	Bankrupt
Ardenberg B.V.	Bankrupt
Arkos Capital Group N.V.	Bankrupt
Witteveen Mode B.V.	Bankrupt
Haegens International B.V.	Bankrupt
Madagascar Ibis Holding B.V.	Bankrupt
FG Worldwide B.V.	Bankrupt
EMA Autobedrijven B.V.	Bankrupt
La Ligna Investments B.V.	Bankrupt
La Ligna B.V.	Bankrupt
Keijsers Holding N.V.	Bankrupt
Fontijne Grotnes B.V.	Bankrupt
Ossfloor Tapijtfabrieken B.V.	Bankrupt
EMA Venlo B.V.	Bankrupt
Koninklijke Jansen, Post & Cocx B.V.	Bankrupt
Keijsers interior Projects B.V.	Bankrupt
Kaarsenfabriek Parcan B.V.	Bankrupt
Florie en Van den Heuvel B.V.	Bankrupt
Merkx Drukkerijen Beheer B.V.	Bankrupt
Turboned Holding B.V.	Bankrupt
Automotief Beheer B.V.	Bankrupt
Automobielbedrijf J. van Dijk & Dochters B.V.	Bankrupt

Company name	Current status
VDMA Eindhoven B.V.	Bankrupt
Koninklijke Aannemingmaatschappij van Waning B.V.	Bankrupt
Nijl B.V.	Bankrupt
Parallel Groep ETB Vos B.V.	Bankrupt
EBS B.V.	Bankrupt
Miedema Groep B.V.	Bankrupt
Reef Hout B.V.	Bankrupt
PBO Holding B.V.	Bankrupt
Present Time B.V.	Bankrupt
Solfruit International B.V.	Bankrupt
Prime Champ Packaging B.V.	Bankrupt
Point of View B.V.	Bankrupt
S.S.T. Staalsnijtechniek B.V.	Bankrupt
Amtraco Holding B.V.	Bankrupt
Flinter Aland N.V.	Bankrupt
SL Services B.V.	Bankrupt
Apollo Fruit B.V.	Bankrupt
New Fashion B.V.	Bankrupt
A-Film Benelux Holding B.V.	Bankrupt
Fl Sport B.V.	Bankrupt
V&D Group Holding B.V.	Bankrupt
MS Mode Group B.V.	Bankrupt
OAD Groep Holding B.V.	Bankrupt
Koops Furness N.V.	Bankrupt
Schoenenreus B.V.	Bankrupt
Zinvest Fashion B.V.	Bankrupt
Brova B.V.	Bankrupt
Kruidenier Groep B.V.	Bankrupt
Aktiesport B.V.	Bankrupt
Koninklijke Swets & Zeitlinger Holding N.V.	Bankrupt
Swets & Zeitlinger Group B.V.	Bankrupt
De Harense Smid B.V.	Bankrupt
The Phone House Netherlands B.V.	Bankrupt
BPG Group B.V.	Bankrupt
Phanos N.V.	Bankrupt
Scheer & Foppen Elektro Speciaalzaken B.V.	Bankrupt
AREND-SOSEF B.V.	Bankrupt
ACI Adam B.V.	Bankrupt
Libridis Groep B.V.	Bankrupt
Rasenberg Holding B.V.	Bankrupt
iCentre Group B.V.	Bankrupt
Van Straten Groep B.V.	Bankrupt
Van Straten Bouw B.V.	Bankrupt
TCN UROP SE	Bankrupt
Pouw Automotive B.V.	Bankrupt
Eurocommerce Holding B.V.	Bankrupt
Ferdinand Stinger Holding B.V.	Bankrupt
PDC B.V.	Bankrupt
Paradigit Retail B.V.	Bankrupt
TCN Assets B.V.	Bankrupt
V.P. Holding B.V.	Bankrupt
TE Holding Group B.V.	Bankrupt
Slavenburg B.V.	Bankrupt
J.E. Baas Plantenservice B.V.	Bankrupt
Phanos Vastgoed B.V.	Bankrupt
Trianel Energie B.V.	Bankrupt
Koster Metalen B.V.	Bankrupt
SunConnex B.V.	Bankrupt
O.W. Bunker (Netherlands) B.V.	Bankrupt
Trinity Group B.V.	Bankrupt
EMA Holding B.V.	Bankrupt
Solfruit Beheer B.V.	Bankrupt

Company name	Current status
Mapper Lithography Holding B.V.	Non-Bankrupt
Bejo Zaden B.V.	Non-Bankrupt
Somnium Recreatie B.V.	Non-Bankrupt
Van de Graaf en Meeusen Holding B.V.	Non-Bankrupt
Ostoy Trading B.V.	Non-Bankrupt
RF Solutions B.V.	Non-Bankrupt
Waalwijk Egg Powders B.V.	Non-Bankrupt
Internationale Handelmaatschappij "Demeter" B.V.	Non-Bankrupt
VIB Netwerken Gelderland B.V.	Non-Bankrupt
Van Oord Handel en Transport B.V.	Non-Bankrupt
Licorne Petroleum Nederland B.V.	Non-Bankrupt
Bergh Special Products B.V.	Non-Bankrupt
SRA (Samenwerkende Registeraccountants en Accountants-Administratieconsulenten)	Non-Bankrupt
X Trade B.V.	Non-Bankrupt
Shakira Holdings B.V.	Non-Bankrupt
Van Amstberg Capital Management B.V.	Non-Bankrupt
Cavotec Nederland B.V.	Non-Bankrupt
Kalvermesterij Hooijer B.V.	Non-Bankrupt
P. van Gennip Holding B.V.	Non-Bankrupt
Bimmerman Projectafbouw B.V.	Non-Bankrupt
Hinke Fongers Beheer B.V.	Non-Bankrupt
Office Service Partners B.V.	Non-Bankrupt
Instituut voor Toegepaste Haptonomie (I.T.H.) B.V.	Non-Bankrupt
Losi B.V.	Non-Bankrupt
Pillar Group B.V.	Non-Bankrupt
Herkon B.V.	Non-Bankrupt
Storms Totaal B.V.	Non-Bankrupt
RINGSPANN Benelux B.V.	Non-Bankrupt
Chassé Theater Beheer N.V.	Non-Bankrupt
Bouwonderneming Van Bekkum B.V.	Non-Bankrupt
Beheermaatschappij Oosterbaan Nijmegen B.V.	Non-Bankrupt
Huibers Holding B.V.	Non-Bankrupt
Beton Industrie Veendam B.V.	Non-Bankrupt
Houdstermaatschappij Rijmar B.V.	Non-Bankrupt
Exalto Beheer Hardinxveld B.V.	Non-Bankrupt
S.J. Staadegaard en Zonen B.V.	Non-Bankrupt
Aannemersbedrijf Batenburg B.V.	Non-Bankrupt
Loyalty Management Netherlands B.V.	Non-Bankrupt
Eteck Energie Bedrijven B.V.	Non-Bankrupt
C.A. Oskam Holding B.V.	Non-Bankrupt
Inraco Nederland B.V.	Non-Bankrupt
Zuidlease B.V.	Non-Bankrupt
Beheersmaatschappij Gebr. Van Kleef B.V.	Non-Bankrupt
TradeWork B.V.	Non-Bankrupt
Jord Oil & Gas Systems B.V.	Non-Bankrupt
Vixia B.V.	Non-Bankrupt
Flexpoint Diensten Groep B.V.	Non-Bankrupt
Keniaanse Investeringsmaatschappij B.V.	Non-Bankrupt
OGD Beheer B.V.	Non-Bankrupt
Fitland Groep B.V.	Non-Bankrupt
B.V. de Sportfondsen	Non-Bankrupt
Sportfondsen Groep B.V.	Non-Bankrupt
Vegro Verpleegartikelen B.V.	Non-Bankrupt
Vegro Holding B.V.	Non-Bankrupt
Van Maanen Food Groep B.V.	Non-Bankrupt
Uitzendbureau 65plus B.V.	Non-Bankrupt
3D Fashion B.V.	Non-Bankrupt
Fonville Schoonmaakbedrijven B.V.	Non-Bankrupt
ATS Global B.V.	Non-Bankrupt
Wildschut Holding B.V.	Non-Bankrupt
Seven Pharma B.V.	Non-Bankrupt
Van Rooijen Beheer B.V.	Non-Bankrupt
Laurens Groep B.V.	Non-Bankrupt

Company name	Current status
Health Angels B.V.	Non-Bankrupt
H.J.L. Cornelissen Holding B.V.	Non-Bankrupt
Oegema Transport Dedemsvaart B.V.	Non-Bankrupt
Coöperatieve Vereniging PoZoB U.A.	Non-Bankrupt
Lakagroei B.V.	Non-Bankrupt
Pleasantville B.V.	Non-Bankrupt
Wiltec B.V.	Non-Bankrupt
Klein Poelhuis Beheer B.V.	Non-Bankrupt
Oegema Transport Dedemsvaart B.V.	Non-Bankrupt
Coöperatieve Vereniging PoZoB U.A.	Non-Bankrupt
Lakagroei B.V.	Non-Bankrupt
Pleasantville B.V.	Non-Bankrupt
Wiltec B.V.	Non-Bankrupt
Klein Poelhuis Beheer B.V.	Non-Bankrupt
WIJ van Kroonenburg Management B.V.	Non-Bankrupt
SW Participatie B.V.	Non-Bankrupt
Portena Vastgoed B.V.	Non-Bankrupt
Load-Lok International B.V.	Non-Bankrupt
A.C. Hartman Beheer B.V.	Non-Bankrupt
Stichting Georganiseerde Eerstelijnszorg Zoetermeer	Non-Bankrupt
Sandean Holding B.V.	Non-Bankrupt
Starre Group B.V.	Non-Bankrupt
Van den Ban Group Holding B.V.	Non-Bankrupt
Bidfood B.V.	Non-Bankrupt
Stage Entertainment B.V.	Non-Bankrupt
Randstad Holding Nederland B.V.	Non-Bankrupt
Raben Group N.V.	Non-Bankrupt
USG People B.V.	Non-Bankrupt
AB Vakwerk Groep B.V.	Non-Bankrupt
Stern Groep N.V.	Non-Bankrupt
Partou Holding B.V.	Non-Bankrupt
Horizon Meat Services B.V.	Non-Bankrupt
Black Star Groep B.V.	Non-Bankrupt
Schenker Logistics Nederland B.V.	Non-Bankrupt
B.V. Voortzetting Jan Linders Supermarkten	Non-Bankrupt
Riwal Holding Group B.V.	Non-Bankrupt
Visscher Caravelle Holding B.V.	Non-Bankrupt
Coolblue Holding B.V.	Non-Bankrupt
Hessing B.V.	Non-Bankrupt
Heisterkamp Beheer II B.V.	Non-Bankrupt
Heisterkamp Beheer I B.V.	Non-Bankrupt
Visscher Caravelle Participaties B.V.	Non-Bankrupt
The Makers Holding B.V.	Non-Bankrupt
Klaria Beheer B.V.	Non-Bankrupt
Luba Uitzend Buro B.V.	Non-Bankrupt
FleuraMetz Holding B.V.	Non-Bankrupt
Swiss Sense Holding B.V.	Non-Bankrupt
Walmarkt Holding B.V.	Non-Bankrupt
ManpowerGroup Netherlands B.V.	Non-Bankrupt
Broekhuis Holding B.V.	Non-Bankrupt
NCOI Holding B.V.	Non-Bankrupt
Beheermaatschappij De 4 Elementen B.V.	Non-Bankrupt
Optisport Exploitaties B.V.	Non-Bankrupt
ATTERO Holding N.V.	Non-Bankrupt
Citadel Enterprises B.V.	Non-Bankrupt
Adecco Nederland Holding B.V.	Non-Bankrupt
Bastion Holding B.V.	Non-Bankrupt
Queens Bilderberg (Nederland) B.V.	Non-Bankrupt
Centraal Boekhuis B.V.	Non-Bankrupt
Yusen Logistics (Benelux) B.V.	Non-Bankrupt
Valkenhorst Participatie II B.V.	Non-Bankrupt
Eden Hotel Group B.V.	Non-Bankrupt

App. IV: Ratio selection

1. t-test

The t-test method is used to determine whether there is a significant difference between two group's means. It helps to answer the underlying question: do the two groups come from the same population, and only appear differently because of chance errors, or is there some significant difference between these two groups (Tsai, 2009). The null hypothesis of the T-test assumes the equality of means between the bankrupt and the non-bankrupt group. The means of the bankrupt and non-bankrupt groups are significantly different when the null hypothesis is rejected (P<0.05).

The t-test shows that the ratios R1, R4, R5, R7, R9, R11, R12, R13, R21 and R27 are different for the bankrupt and non-bankrupt groups for all timeframes. The other ratios, of which financial data is collected did not have a significant difference in means between the bankrupt and non-bankrupt group. The significance is therefore not reported in the table below. R10 and R20 are reported in the table below despite having no difference in means, because these ratios are used in hypothesis 1 to 4.

t-test for Equality of Means between bankrupt and non-bankrupt group					
Ratio	Sig.	Ratio	Sig.	Ratio	Sig.
R1 t-1	0.000	R9 t-1	0.000	R13 t-1	0.002
R1 t-2	0.030	R9 t-2	0.000	R13 t-2	0.000
R1 t-3	0.294	R9 t-3	0.008	R13 t-3	0.000
R1 t-4	0.137	R9 t-4	0.010	R13 t-4	0.000
R1 t-5	0.044	R9 t-5	0.000	R13 t-5	0.000
R1 t-6	0.409	R9 t-6	0.000	R13 t-6	0.000
R4 t-1	0.006	R10 t-1	0.145	R20 t-1	0.113
R4 t-2	0.000	R10 t-2	0.314	R20 t-2	0.251
R4 t-3	0.000	R10 t-3	0.754	R20 t-3	0.469
R4 t-4	0.000	R10 t-4	0.022	R20 t-4	0.119
R4 t-5	0.000	R10 t-5	0.144	R20 t-5	0.911
R4 t-6	0.000	R10 t-6	0.529	R20 t-6	0.554
R5 t-1	0.001	R11 t-1	0.000	R21 t-1	0.000
R5 t-2	0.000	R11 t-2	0.009	R21 t-2	0.000
R5 t-3	0.004	R11 t-3	0.261	R21 t-3	0.000
R5 t-4	0.000	R11 t-4	0.024	R21 t-4	0.000
R5 t-5	0.000	R11 t-5	0.030	R21 t-5	0.000
R5 t-6	0.000	R11 t-6	0.010	R21 t-6	0.000
R7 t-1	0.000	R12 t-1	0.000	R22 t-1	0.000
R7 t-2	0.000	R12 t-2	0.000	R22 t-2	0.000
R7 t-3	0.009	R12 t-3	0.000	R22 t-3	0.027
R7 t-4	0.028	R12 t-4	0.000	R22 t-4	0.024
R7 t-5	0.000	R12 t-5	0.000	R22 t-5	0.081
R7 t-6	0.024	R12 t-6	0.000	R22 t-6	0.249

2. Correlation matrix

Correlation matrix is to confer the correlation of two quantitative groups, as well as to analyse whether one group affects the other one. A correlation coefficient is the result of a mathematical comparison of how closely related two variables are. The relationship between two variables is said to be highly correlated if a movement in one variable results or takes place at the same time as a similar movement in another variable. To select appropriate variables affecting much more parts of the result by this technique could obtain related advantages. The correlation matrix is used combined with the Cronachs alpha to determine whether the selected ratios measure the same construct. A reliability analysis is used in SPSS to determine the Cronbachs alpha for the ratios with a significant difference in means. The Cronbachs alpha was developed to measures the internal consistency of a test. The internal consistency measures the extent to which all items measure the same concept. The Cronbachs alpha ranges between 0 and 1, where a score of below 0.5 is poor and a score above 0.8 is good.

A correlation matrix is made for the ratios which have a significant difference in means (based on the t-test). This resulted for the ratios at time t-1 in a Cronbachs alpha of 0.411, for time t-2 0.399 and for time t-3 0.451. Generally a Cronbachs alpha below 0.5 is unacceptable. Therefore, ratios were deleted to increase the Cronbachs alpha.

The following items were deleted for time t-1 in order to increase Cronbachs alpha until the highest score was achieved: R8, R6, R14, R24, R18, R19 and R12. The Cronbachs alpha after deleting these ratios is increase to 0.849, which is good. One can be confident for these ratios measuring the same construct in the data. The correlations of the ratios are reported in table 7. The results at t-3 are similar to the results of t-1.

Table 7: Correlation matrix at time t-1

Time t-1	R4	R5	R7	R9	R11	R13	R21	R22	R27
R4	1.000								
R5	0.732	1.000							
R7	0.407	0.535	1.000						
R9	0.508	0.670	0.934	1.000					
R11	0.756	0.579	0.479	0.576	1.000				
R13	0.645	0.919	0.675	0.773	0.620	1.000			
R21	0.399	0.465	0.210	0.342	0.342	0.379	1.000		
R22	0.195	0.307	0.292	0.364	0.219	0.415	0.559	1.000	
R27	0.508	0.670	0.934	1.000	0.576	0.773	0.342	0.364	1.000

Cronbachs alpha 0.849

The following items were deleted for time t-2 in order to increase Cronbachs alpha until the highest score was achieved: R8, R14, R6, R24, R18, R19, R12, R27, R22, R4, R21 and R12. The Cronbachs alpha after deleting these ratios is increase to 0.921, which is excellent. One can be confident for these ratios measuring the same construct in the data. The correlations of the ratios are reported in table 8.

Table 8: Correlation matrix at time t-2

Time t-2	R5 t-2	R7 t-2	R9 t-2	R13 t-2
R5 t-2	1.000			
R7 t-2	0.684	1.000		
R9 t-2	0.712	0.931	1.000	
R13 t-2	0.934	0.755	0.795	1.000

Cronbachs alpha 0.921

The choice was made to not include the other time periods (t-3, t-4, t-5, t-6) because the same ratios would be in the correlation matrix. Overall two sets of ratios might have predictive value for the sample, based on these tests.

First the set of t-1 consisting out of the ratios R4, R5, R7, R11, R13, R21 and R27. This outcome is almost the same as the outcome at time t-3. The second set of ratios is the set of time t-2 consisting of four ratios: R5, R7, R9 and R13.

3. stepwise regression

To select the optimal set of predictors and improve the performance of the models, ratio selection is also undertaken by using stepwise regression. When using regression to build models, one common technique to find the best combination of predictor variables is stepwise regression. Although there are many variations, the most basic procedure is to find the single best predictor variable and add variables that meet some specified criterion the result is a combination of predictor variables, all of which have significant coefficients. (Tsai, 2009). In the stepwise regression method, the ratios enter after each other into the model, depending on the significance value of the ratios together. A ratio is inserted in the model with a significance value of 0,05 and excluded from the model with a significance value of 0,1. All ratios collected in literature are used as input for the stepwise regression.

Table 9: Summary of stepwise regression models

Time	Model	Ratios in model	R	R Square
t-1	4	R3 R11 R12 R21	0.690	0.476
t-2	8	R1 R8 R10 R12 R18 R19 R21 R22	0.881	0.777
t-3	3	R4 R15 R19	0.405	0.164
t-4	3	R15 R18 R21	0.419	0.176
t-5	4	R7 R19 R24 R26	0.460	0.212
t-6	5	R16 R19 R24 R26 R27	0.556	0.309

Stepwise regressions have been calculated for each individual time period. The results differ per period. Only the best models have been reported in table 9. A model that explains more than 30% of the variance in the independent variable could be considered as a good model. This means that when the R square is higher than 0.3 it is a good model.

Model 4 is the best model of t-1, which consists out of the ratios R3, R11, R12 and R21. 47,6% of the variance in the dummy variable for bankruptcy is explained by this set of ratios. The best model of t-2 has a higher R square of 0.777 which means that 77.7% of the variance in the dummy variable can be explained by the ratios in model 8 of t-2.

A correlation matrix is made from the results of the stepwise regression. The correlation matrix indicated that there was not internal consistency between the ratios selected with stepwise regression, but when some items are deleted, the results would be better.

Cronbachs alpha at time t-2 suggest that the outcome of the stepwise regression of t-2 is low. The reliability test gives a value of Cronbachs alpha of 0.148. The reliability analysis suggests that when R8 is deleted Cronbachs alpha increases to 0.612. When R10 is deleted the Cronbachs alpha increases to 0.627. This is only a marginal increase a therefore this item is not deleted. Chronbachs alpha becomes lower when R18 is deleted and therefore R18 remains in the selection of variables. Table 10 shows the correlation matrix for this set of ratios.

Table 10: Correlation matrix of stepwise regression results at time t-2

	R1 t-2	R10 t-2	R12 t-2	R18 t-2	R19 t-2	R21 t-2	R22 t-2
R1 t-2	1.000						
R10 t-2	0.150	1.000					
R12 t-2	0.533	0.085	1.000				
R18 t-2	-0.041	-0.020	-0.039	1.000			
R19 t-2	0.111	0.027	0.233	0.907	1.000		
R21 t-2	0.488	0.133	0.887	-0.019	0.343	1.000	
R22 t-2	0.692	0.163	0.490	-0.135	0.079	0.568	1.000

Cronbachs alpha of 0.612

A negative correlation is usually a red flag in reliability analysis, but in this case, the internal cohesion does not increase when deleting R18. As matter of fact, the Cronbachs alpha is lower when R18 is deleted.

Overall stepwise regression and reliability analysis suggest that the ratios R1, R10, R12, R18, R19, R21 and R22 having some degree of predictive value and should be tested for constructing a financial distress prediction model.

4. Stepwise regression based on t-test

The method of stepwise regression is also used in combination with the t-test, where the ratios which have significant differences in means are used as input into the stepwise regression. The models created with the stepwise regression using the results of the t-test as a basis seem to have a similar R square as the models created without using the t-test.

Table 11: Summary of stepwise regression models with t-test as basis

	Model	Ratios in model	R	R Square
t-1	3	R11 R12 R21	0.607	0.368
t-2	7	R5 R8 R9 R12 R18 R21 R22	0.850	0.722
t-3	2	R4 R19	0.381	0.145
t-4	2	R18 R21	0.384	0.147
t-5	4	R7 R12 R19 R24	0.426	0.181
t-6	3	R19 R24 R27	0.433	0.188

Judging from the R square in table 11, model 7 at time t-2 could have some degree of predictive value. The R square of the other models is not high enough. A correlation matrix is made based on this results in table 12.

Table 12: Correlation matrix of stepwise regression based on t-test at t-2

	R5 t-2	R9 t-2	R11 t-2	R21 t-2	R22 t-2
R5 t-2	1.000				
R9 t-2	0.649	1.000			
R11 t-2	0.505	0.714	1.000		
R21 t-2	0.438	0.482	0.344	1.000	
R22 t-2	0.332	0.370	0.274	0.611	1.000

Cronbachs alpha 0.756

The Cronbachs alpha is not as high as the selection of the ratios using only the t-test but is acceptable. In this manner of testing the ratios R5, R9, R11, R21 and R22 seem to have some degree of predictive value.

5. Final ratio sets

The ratio sets as input for the MDA and Logit model must be absent of multicollinearity. Therefore, the multicollinearity is tested for each set of ratios in terms of the VIF statistic (app. VIII).

The ratios determined by the t-test (R4, R5, R7, R11, R13, R21 and R27) have a high multicollinearity in the ratios R7, R13 and R27. A possible explanation therefore is that R27 the std. of ROA has common factors with the other ratios. Therefore, R27 was deleted, which resulted in VIF statistics within margin of 10 (only R13 has a VIF of 10.219).

The second set of ratios determined by the t-test (R5, R7, R9 and R13) have high multicollinearity in the ratios R7 and R9 due to a shared common factor, the total assets. The ratio with the highest VIF was chosen to delete, after which the VIF is within acceptable margin.

The third set of ratios is determined by stepwise regression (R1, R10, R12, R18, R19, R21 and R22) have a high multicollinearity in three ratios (R18, R19 and R21). This is due to the fact that R18 and R19 are logarithms of the variables in R21. R18 and R19 were deleted because all information also lies in R21. Afterwards the multicollinearity is within acceptable margin.

The final set of ratios was determined with a combination of t-test and stepwise regression (R5, R9, R11, R21 and R22) and has no multicollinearity issues.

Overall four sets of ratios have been selected to be used in the MDA, the Logit and the Neural Networks model. Set 1 is the ratio set of Altman, which were used in H1 to H4. The ratio sets 2, 3, 4 and 5 are selected using ratio selection methods and used in the financial distress prediction models of H5.

- Ratio set 1 R7, R12, R20 and R22
- Ratio set 2 R4, R5, R7, R13 and R21
- Ratio set 3 R5, R9 and R13
- Ratio set 4 R1, R10, R12, R21 and R22
- Ratio set 5 R5, R9, R11, R21 and R22

App. V: Testing of assumptions

1. Normal distribution of data, Equality of variance and equality of means

		Shapiro-Wilk for normality of data. Sig.	Levene's Test for Equality of Variances Sig.	t-test for Equality of Means Sig.
R1 t-1	Non-bankrupt	0.000	0.087	0.000
	Bankrupt	0.089		
R1 t-2	Non-bankrupt	0.000	0.322	0.030
	Bankrupt	0.035		
R1 t-3	Non-bankrupt	0.000	0.158	0.294
	Bankrupt	0.045		
R1 t-4	Non-bankrupt	0.000	0.406	0.137
	Bankrupt	0.008		
R1 t-5	Non-bankrupt	0.000	0.846	0.044
	Bankrupt	0.006		
R1 t-6	Non-bankrupt	0.000	0.262	0.409
	Bankrupt	0.088		
R4 t-1	Non-bankrupt	0.000	0.283	0.006
	Bankrupt	0.000		
R4 t-2	Non-bankrupt	0.000	0.689	0.000
	Bankrupt	0.129		
R4 t-3	Non-bankrupt	0.000	0.254	0.000
	Bankrupt	0.342		
R4 t-4	Non-bankrupt	0.000	0.107	0.000
	Bankrupt	0.105		
R4 t-5	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.033		
R4 t-6	Non-bankrupt	0.000	0.003	0.000
	Bankrupt	0.000		
R5 t-1	Non-bankrupt	0.000	0.644	0.001
	Bankrupt	0.000		
R5 t-2	Non-bankrupt	0.000	0.929	0.000
	Bankrupt	0.003		
R5 t-3	Non-bankrupt	0.000	0.635	0.004
	Bankrupt	0.101		
R5 t-4	Non-bankrupt	0.000	0.204	0.000
	Bankrupt	0.010		
R5 t-5	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.031		
R5 t-6	Non-bankrupt	0.000	0.035	0.000
	Bankrupt	0.000		
R7 t-1	Non-bankrupt	0.000	0.023	0.000
	Bankrupt	0.032		
R7 t-2	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.213		
R7 t-3	Non-bankrupt	0.000	0.000	0.009
	Bankrupt	0.735		
R7 t-4	Non-bankrupt	0.000	0.018	0.028
	Bankrupt	0.000		
R7 t-5	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.037		
R7 t-6	Non-bankrupt	0.000	0.001	0.024
	Bankrupt	0,692		

Continuation of appendix V, Testing of assumptions

		Shapiro-Wilk for normality of data. Sig.	Levene's Test for Equality of Variances Sig.	t-test for Equality of Means Sig.
R9 t-1	Non-bankrupt	0.000	0.002	0.000
	Bankrupt	0.021		
R9 t-2	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.002		
R9 t-3	Non-bankrupt	0.000	0.000	0.008
	Bankrupt	0.578		
R9 t-4	Non-bankrupt	0.000	0.012	0.010
	Bankrupt	0.000		
R9 t-5	Non-bankrupt	0.000	0.024	0.000
	Bankrupt	0.000		
R9 t-6	Non-bankrupt	0.000	0.354	0.000
	Bankrupt	0.015		
R10 t-1	Non-bankrupt	0.000	0.001	0.145
	Bankrupt	0.020		
R10 t-2	Non-bankrupt	0.000	0.000	0.314
	Bankrupt	0.000		
R10 t-3	Non-bankrupt	0.000	0.000	0.754
	Bankrupt	0.001		
R10 t-4	Non-bankrupt	0.000	0.000	0.022
	Bankrupt	0.001		
R10 t-5	Non-bankrupt	0.000	0.019	0.144
	Bankrupt	0.360		
R10 t-6	Non-bankrupt	0.000	0.012	0.529
	Bankrupt	0.036		
R11 t-1	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.797		
R11 t-2	Non-bankrupt	0.000	0.001	0.009
	Bankrupt	0.459		
R11 t-3	Non-bankrupt	0.000	0.000	0.261
	Bankrupt	0.612		
R11 t-4	Non-bankrupt	0.000	0.023	0.024
	Bankrupt	0.000		
R11 t-5	Non-bankrupt	0.000	0.255	0.030
	Bankrupt	0.007		
R11 t-6	Non-bankrupt	0.000	0.549	0.010
	Bankrupt	0.631		
R12 t-1	Non-bankrupt	0.000	0.001	0.000
	Bankrupt	0.000		
R12 t-2	Non-bankrupt	0.000	0.088	0.000
	Bankrupt	0.001		
R12 t-3	Non-bankrupt	0.000	0.005	0.000
	Bankrupt	0.008		
R12 t-4	Non-bankrupt	0.000	0.015	0.000
	Bankrupt	0.005		
R12 t-5	Non-bankrupt	0.000	0.000	0.000
	Bankrupt	0.000		
R12 t-6	Non-bankrupt	0.000	0.002	0.000
	Bankrupt	0.000		

Continuation of appendix V, Testing of assumptions

		Shapiro-Wilk for normality of data. Sig.	Levene's Test for Equality of Variances Sig.	t-test for Equality of Means Sig.
R13 t-1	Non-bankrupt	0.000	0.871	0.002
	Bankrupt	0.015		
R13 t-2	Non-bankrupt	0.000	0.286	0.000
	Bankrupt	0.004		
R13 t-3	Non-bankrupt	0.000	0.650	0.000
	Bankrupt	0.007		
R13 t-4	Non-bankrupt	0.000	0.067	0.000
	Bankrupt	0.002		
R13 t-5	Non-bankrupt	0.000	0.007	0.000
	Bankrupt	0.117		
R13 t-6	Non-bankrupt	0.000	0.014	0.000
	Bankrupt	0.002		
R20 t-1	Non-bankrupt	0.000	0.000	0.113
	Bankrupt	0.000		
R20 t-2	Non-bankrupt	0.000	0.215	0.251
	Bankrupt	0.000		
R20 t-3	Non-bankrupt	0.000	0.127	0.469
	Bankrupt	0.000		
R20 t-4	Non-bankrupt	0.000	0.012	0.119
	Bankrupt	0.000		
R20 t-5	Non-bankrupt	0.000	0.507	0.911
	Bankrupt	0.000		
R20 t-6	Non-bankrupt	0.000	0.595	0.554
	Bankrupt	0.000		
R21 t-1	Non-bankrupt	0.097	0.216	0.000
	Bankrupt	0.136		
R21 t-2	Non-bankrupt	0.554	0.032	0.000
	Bankrupt	0.436		
R21 t-3	Non-bankrupt	0.002	0.495	0.000
	Bankrupt	0.055		
R21 t-4	Non-bankrupt	0.000	0.624	0.000
	Bankrupt	0.017		
R21 t-5	Non-bankrupt	0.000	0.902	0.000
	Bankrupt	0.625		
R21 t-6	Non-bankrupt	0.012	0.851	0.000
	Bankrupt	0.134		
R22 t-1	Non-bankrupt	0.450	0.069	0.000
	Bankrupt	0.068		
R22 t-2	Non-bankrupt	0.372	0.000	0.000
	Bankrupt	0.184		
R22 t-3	Non-bankrupt	0.727	0.052	0.027
	Bankrupt	0.374		
R22 t-4	Non-bankrupt	0.038	0.017	0.024
	Bankrupt	0.002		
R22 t-5	Non-bankrupt	0.005	0.002	0.081
	Bankrupt	0.053		
R22 t-6	Non-bankrupt	0.032	0.096	0.249
	Bankrupt	0.247		

2. Multicollinearity

The ratio sets as input for the MDA and Logit model must be absent of multicollinearity. Therefore, the multicollinearity is tested for each set of ratios in terms of the VIF statistic (app. VIII).

The ratios determined by the t-test (R4, R5, R7, R11, R13, R21 and R27) have a high multicollinearity in the ratios R7, R13 and R27. A possible explanation therefore is that R27 the std. of ROA has common factors with the other ratios. Therefore, R27 was deleted, which resulted in VIF statistics within margin of 10 (only R13 has a VIF of 10,219).

The second set of ratios determined by the t-test (R5, R7, R9 and R13) have high multicollinearity in the ratios R7 and R9 due to a shared common factor, the total assets. The ratio with the highest VIF was chosen to delete, after which the VIF is within acceptable margin.

The third set of ratios is determined by stepwise regression (R1, R10, R12, R18, R19, R21 and R22) have a high multicollinearity in three ratios (R18, R19 and R21). This is due to the fact that R18 and R19 are logarithms of the variables in R21. R18 and R19 were deleted because all information also lies in R21. Afterwards the multicollinearity is within acceptable margin.

The final set of ratios was determined with a combination of t-test and stepwise regression (R5, R9, R11, R21 and R22) and has no multicollinearity issues.

Table 13: Multicollinearity statistic

	Collinearity Statistics	
Ratio set 1	Tolerance	VIF
R7 EBIT / Total Assets	0.900	1.111
R12 Equity / Total Liabilities	0.829	1.206
R20 Retained Earnings / Total Assets	0.993	1.007
R22 Working Capital / Total Assets	0.779	1.283
Ratio set 2	Tolerance	VIF
R4 Cash flow / Current liabilities	0.300	3.329
R5 Cash flow / Total liabilities	0.118	8.479
R7 EBIT / Total Assets	0.124	8.073
R11 Gross profit rate = Net income / net sales	0.315	3.171
R13 Net income / Total Liabilities	0.098	10.219
R21 Equity / Total Assets	0.667	1.499
Ratio set 3	Tolerance	VIF
R5 Cash flow / Total liabilities	0.184	5.437
R13 Net income / Total Liabilities	0.143	7.001
R9 ROA = Net income / Total assets	0.326	3.068
Ratio set 4	Tolerance	VIF
R1 Current ratio = Current assets / Current liabilities	0.531	1.883
R10 ROE = Net income / Equity	0.930	1.075
R12 Equity / Total Liabilities	0.194	5.156
R21 Equity / Total Assets	0.180	5.543
R22 Working Capital / Total Assets	0.448	2.232
Ratio set 5	Tolerance	VIF
R5 Cash flow / Total liabilities	0.478	2.091
R9 ROA = Net income / Total assets	0.235	4.247
R11 Gross profit rate = Net income / net sales	0.408	2.451
R21 Equity / Total Assets	0.498	2.010
R22 Working Capital / Total Assets	0.643	1.554

App. VI: MDA method computing and estimation process

1. Model of Altman (1984)

The Z-score model of Altman (1984) is computed in SPSS and gives a value when all financial data is available for that particular company. When one or more ratios are missing, in computing the Z-score, a missing value will be given to the company. This is preferred over giving the company a value based on three or less ratios out of four, because the Z-score would not be interpretable when it is not based on all four ratios. Altman's Z-score has been calculated for 1 to 6 years before bankruptcy of a company, where t-1 is one year before bankruptcy and t-6 is 6 years before bankruptcy.

Table 14: Performance of MDA model of Altman (1984)

Time	Sub sample	AUC	Sensitivity	Specificity	AR	Percentage correctly classified (included Grey Area)	Percentage correctly classified (Excluded Grey Area)
t-1	Estimation	0.866	0.353	0.947	73.2%	72.2%	83.9%
	Holdout	0.594	0.000	0.857	18.8%	64.3%	75.0%
t-2	Estimation	0.737	0.182	0.949	47.4%	58.0%	67.5%
	Holdout	0.625	0.375	0.857	25.0%	58.5%	64.9%
t-3	Estimation	0.515	0.120	0.986	3.0%	56.0%	63.7%
	Holdout	0.594	0.083	0.950	18.8%	54.1%	62.5%
t-4	Estimation	0.590	0.133	0.973	18.0%	59.1%	65.5%
	Holdout	0.625	0.111	0.895	25.0%	52.9%	64.3%
t-5	Estimation	0.521	0.053	0.971	4.2%	59.0%	64.5%
	Holdout	0.594	0.286	1.000	18.8%	62.1%	78.3%
t-6	Estimation	0.460	0.045	0.985	0.0%	70.7%	74.7%
	Holdout	0.563	0.250	1.000	12.6%	61.5%	72.7%

The AUC of Altman's Z-score one year before bankruptcy is good (AUC of 0.866) and is higher than the highest AUC (AUC of 0.787 AR of 57.4%) for the Netherlands in the study of Altman et al. (2017). The AUC of is even higher than the best AUC in the study of Altman et al. (2017). The rule of thumb of the AUC, which implies that a model has predictive power when the AUC is 0.75 or higher only applies for the time t-1. At the other times the model is not suitable for predicting financial distress. The AUC's of the time t-3 to time t-6 are poor. An AUC close to 0.5 resembles a model without any predictive capabilities.

The sensitivity results of the model is very low in all time periods. This implies that the models performs poor at predicting bankruptcies. The specificity is for all timeframes in both samples high or almost perfect. This implies that the model is good at predicting non-bankruptcies.

The percentage of correctly classified companies is on average lower when the grey zone is included in calculating the percentage (amount of correctly predicted results divided by the total observations). When the grey area is excluded in calculating the performance in this manner, the accuracy percentage is higher. Altman (1968) did not include the grey zone in calculating the accuracy, and therefore the grey zone will also be excluded in this study.

The model of Altman (1983) seems to be a model which is not good at predicting bankruptcies, but good at predicting non-bankruptcies, based on the results in table 16. The model might achieve decent results in a sample true to the total population, because there a lot more non-bankrupt companies in the true population than in the sample of this study.

2. (Re-)estimation of MDA method

The MDA model is estimated for all ratio sets for all time periods. The results are presented in table 15. The model's performance is different with each ratio set. The model is re-estimated for each time period before bankruptcy, with the financial data of that particular year before bankruptcy. In other words, the model of t-1 is a different model than the model of t-2 etc.

Table 15: Estimation results of MDA method

Ratio set	Time	AUC	Sensitivity	Specificity	AR	Percentage correctly classified
Ratio set 1: R7, R12, R20 and R22	t-1	0.491	0.000	0.988	0.0%	85.6%
	t-2	0.829	0.447	0.937	65.8%	75.4%
	t-3	0.588	0.429	0.922	17.6%	73.0%
	t-4	0.463	0.106	0.935	0.0%	62.1%
	t-5	0.463	0.100	0.918	0.0%	62.8%
	t-6	0.500	0.100	0.969	0.0%	0.0%
Ratio set 2: R4, R5, R7, R11, R13 and R21	t-1	0.979	0.429	0.959	95.8%	84.1%
	t-2	0.854	0.839	0.729	70.8%	78.8%
	t-3	0.750	0.800	0.482	50.0%	65.3%
	t-4	0.729	0.818	0.560	45.8%	69.5%
	t-5	0.438	0.364	0.872	0.0%	66.3%
	t-6	0.458	0.154	0.944	0.0%	73.5%
Ratio set 3: R5, R9 and R13	t-1	0.500	0.160	0.937	0.0%	77.5%
	t-2	0.633	0.604	0.811	26.6%	71.0%
	t-3	0.708	0.568	0.745	41.6%	65.8%
	t-4	0.708	0.554	0.678	41.6%	61.8%
	t-5	0.467	0.185	0.877	0.0%	56.8%
	t-6	0.567	0.109	0.939	13.4%	59.8%
Ratio set 4: R1, R10, R12, R21 and R22	t-1	0.500	0.000	1.000	0.0%	84.3%
	t-2	0.402	0.343	0.833	0.0%	61.6%
	t-3	0.559	0.459	0.907	11.8%	70.0%
	t-4	0.560	0.400	0.814	12.0%	61.4%
	t-5	0.734	0.439	0.855	46.8%	67.1%
	t-6	0.701	0.449	0.901	40.2%	71.7%
Ratio set 5: R5, R9, R11, R21 and R22	t-1	0.600	0.429	0.980	20.0%	85.9%
	t-2	0.692	0.793	0.583	38.4%	69.8%
	t-3	0.688	0.758	0.404	37.6%	59.3%
	t-4	0.708	0.758	0.510	41.6%	64.6%
	t-5	0.617	0.571	0.830	23.4%	70.8%
	t-6	0.796	0.733	0.750	59.2%	74.2%

When assessing the AUCs of the model, it points out that the sets 1, 2 and 5 have models with an AUC higher than 0.75. The models of ratio set 3 and 4 do not have AUCs of 0.75 or higher. Most models have an AUCs represent a model without any predictive power (approximately 0.5).

The sensitivity of most models is low, apart from some models based on ratio set 2 and 5. The model based on ratio set 1 at time t-2 has the highest sensitivity rate of the models of ratio set 1. Based on the good AUC and the highest sensitivity of the models based on set 1, will this model be used as a basis for the re-estimation of the model of Altman (1984).

The model of ratio set 2 at time t-2 is chosen to be used as a basis for the variant of the MDA method model with other or additional ratios. This model is chosen over the model at t-1 because the sensitivity rate of the model is notably higher, thus better at predicting bankruptcies.

The models based on ratio set 5 show some promising results but are notably lower than the results of ratio set 2.

2.1. MDA model based on ratio set 1

The MDA model of ratio set 1 is estimated based on the results of time t-2. This time period resulted in the best performance of the model. the assumptions of the model are tested in the same function as estimation of the model (using SPSS).

The Box's M tests the assumption of equality of variance-covariance matrices in the groups. A Box's M indicated by a small p-value indicates violation of this assumption. However, when the sample size is large, Box's M is usually high. Box's M for this model has a P value of P<0.001. This implies that the group variances are unequal for this model.

When Wilks Lambda is significant one may rely on the model producing statistical significant predictions. Wilks' Lambda is for this model excellent (p<0.001).

The MDA equation is determined by the Canonical Discriminant Function coefficients, which gives weights on the ratios and a constant value (eq.9).

Eq.8: Re-estimated MDA model

$$Z = -0.359 + 7.966R_7 + 1.017R_{12} + 0.052R_{20} - 2.586R_{22}$$

Some differences arise when comparing the original MDA Z-score model with the re-estimated model. First the constant is negative and second the ratios R20 and R22 have less influence over the outcome of the model. There is also a difference in the classification of the companies. The original model has three outcome possibilities, but the re-estimated model has only the outcome of bankrupt or non-bankrupt. The classification of the re-estimated model is done via the function at group centroids of the bankrupt (-0.731) and non-bankrupt companies (0.435). The value exactly in the middle is the cut-off point (-0.148, which determines whether a company is bankrupt (Z<-0.148) or non-bankrupt (Z>-0.148).

2.2. MDA model based on ratio set 2

The MDA model of ratio set 2 is estimated based on the results of time t-2. This time period resulted in the best performance of the model. the assumptions of the model are tested in the same function as estimation of the model (using SPSS).

The Box's M tests the assumption of equality of variance-covariance matrices in the groups. A Box's M indicated by a small p-value indicates violation of this assumption. However, when the sample size is large, Box's M is usually high. Box's M for this model has a P value of P<0.001. This implies that the group variances are unequal for this model. When Wilks Lambda is significant one may rely on the model producing statistical significant predictions. Wilks' Lambda is for this model excellent (p<0.001).

The MDA equation is determined by the Canonical Discriminant Function coefficients, which gives weights on the ratios and a constant value (eq.10).

Eq.9: Estimated MDA model based on ratio set 2

$$Z = -0.530 + 2.485R_4 + 3.532R_5 + 2.745R_7 - 3.680R_{11} - 1.876R_{13} - 0.114R_{21}$$

The classification of the re-estimated model is done via the function at group centroids of the bankrupt (-0.568) and non-bankrupt companies (0.662). The value exactly in the middle is the cut-off point (0.047), which determines whether a company is bankrupt (Z<0.047) or non-bankrupt (Z>0.047).

2.3. Results of estimation of the MDA method

Table 16 presents the results of the estimated models based on ratio set 1 and 2. These results are obtained by inserting the financial data in the equations 8 and 9.

Table 16: Results of MDA models based on ratio set 1 and 2

Ratio set	Time	Sample	AUC	Sensitivity	Specificity	AR	Percentage correctly classified
Ratio set 1: R7, R12, R20 and R22	t-1	Estimation	0.727	0.462	0.738	45.4%	70.1%
		Holdout	0.906	0.500	0.696	81.2%	66.7%
	t-2	Estimation	0.745	0.702	0.785	49.0%	75.4%
		Holdout	0.875	0.200	0.727	75.0%	56.3%
	t-3	Estimation	0.505	0.551	0.792	1.0%	69.8%
		Holdout	0.875	0.385	0.783	75.0%	63.9%
	t-4	Estimation	0.458	0.426	0.714	0.0%	60.5%
		Holdout	0.844	0.636	0.727	68.8%	69.7%
	t-5	Estimation	0.458	0.475	0.671	0.0%	60.2%
		Holdout	0.906	0.667	0.789	81.2%	75.0%
	t-6	Estimation	0.551	0.450	0.831	10.2%	74.1%
		Holdout	0.875	0.571	0.765	75.0%	70.8%
Ratio set 2: R4, R5, R7, R11, R13 and R21	t-1	Estimation	0.896	1.000	0.816	79.2%	85.7%
		Holdout	0.833	1.000	0.667	66.6%	71.4%
	t-2	Estimation	0.875	0.821	0.771	75.0%	79.8%
		Holdout	0.719	0.688	0.750	43.8%	71.4%
	t-3	Estimation	0.792	0.631	0.625	58.4%	62.8%
		Holdout	0.739	0.765	0.714	47.8%	74.2%
	t-4	Estimation	0.813	0.618	0.640	62.6%	62.9%
		Holdout	0.652	0.667	0.636	30.4%	65.5%
	t-5	Estimation	0.792	0.667	0.596	58.4%	62.5%
		Holdout	0.718	0.769	0.667	43.6%	72.0%
	t-6	Estimation	0.896	0.769	0.750	79.2%	75.5%
		Holdout	0.646	0.625	0.667	29.2%	64.7%

App. VII: Logit method estimation process

1. Estimation of model

Because there is no formula for this model, it must be estimated into this sample. Before estimating the Logit model, the assumption of absence of multicollinearity must be verified. No other assumptions have to be tested. The Logit models are estimated in the same manner as the MDA models. The model is estimated for each individual ratio set at each timeframe, and therefore the model at t-1 is a different model than the model at t-2 etc.

Table 17: Estimation results of Logit method on matched pairs training sample

Ratio set	Time	AUC	Sensitivity	Specificity	AR	Percentage correctly classified
Ratio set 1: R7, R12, R20 and R22	t-1	0.625	0.077	1.000	25.0%	87.6%
	t-2	0.829	0.489	0.924	65.8%	76.2%
	t-3	0.569	0.449	0.896	13.8%	72.2%
	t-4	0.463	0.128	0.922	0.0%	62.1%
	t-5	0.463	0.075	0.918	0.0%	61.9%
	t-6	0.500	0.100	0.969	0.0%	76.5%
Ratio set 2: R4, R5, R7, R11, R13 and R21	t-1	1.000	0.500	0.959	100.0%	85.7%
	t-2	0.875	0.839	0.750	75.0%	65.3%
	t-3	0.750	0.785	0.500	50.0%	65.3%
	t-4	0.750	0.818	0.580	50.0%	70.5%
	t-5	0.438	0.485	0.872	0.0%	71.3%
	t-6	0.438	0.308	0.917	0.0%	75.5%
Ratio set 3: R5, R9 and R13	t-1	0.475	0.120	0.968	0.0%	79.2%
	t-2	0.700	0.648	0.779	40.0%	66.3%
	t-3	0.700	0.589	0.735	40.0%	66.3%
	t-4	0.742	0.578	0.667	48.4%	62.4%
	t-5	0.542	0.308	0.864	8.4%	61.6%
	t-6	0.733	0.413	0.864	46.6%	67.9%
Ratio set 4: R1, R10, R12, R21 and R22	t-1	0.542	0.176	0.989	8.4%	86.1%
	t-2	0.552	0.403	0.821	10.4%	67.5%
	t-3	0.560	0.486	0.837	12.0%	67.5%
	t-4	0.702	0.538	0.779	40.4%	66.3%
	t-5	0.693	0.455	0.795	38.6%	64.4%
	t-6	0.701	0.510	0.901	40.2%	74.2%
Ratio set 5: R5, R9, R11, R21 and R22	t-1	0.579	0.429	0.960	15.8%	84.4%
	t-2	0.754	0.793	0.646	50.8%	57.7%
	t-3	0.588	0.727	0.404	17.6%	57.7%
	t-4	0.708	0.758	0.510	41.6%	64.6%
	t-5	0.796	0.619	0.766	59.2%	69.7%
	t-6	0.958	0.767	0.833	91.6%	80.3%

When assessing the AUCs of the model, it points out that the sets 2 and 5 have models with an AUC higher than 0.75. The models of ratio set 3 and 4 do not have AUCs of 0.75 or higher.

The sensitivity of most models is low, apart from some models based on ratio set 2 and 5. The model based on ratio set 1 at time t-2 has the highest sensitivity rate of the models of ratio set 1. Based on the good AUC and the highest sensitivity of the models based on set 1, will this model be used as a basis for the re-estimation of the model of Altman (1984).

The model of ratio set 5 at time t-6 performs the best out of these models. It is remarkable that a model is able to accurately predict financial distress at t-6.

The model of ratio set 2 at t-2 seems also a good model for predicting financial distress and complies with the terms for a decent predictive model (AUC above 0.75; high sensitivity and a good specificity). This model is chosen over the model of set 2 at time t-1 because that model has a lower sensitivity rate. The emphasis of this study lies on predicting financial distress and therefore a high sensitivity is chosen over the highest AUC.

1.1. Logit model based on ratio set 1

This Logit model is based on the same ratios as used by Altman (1984). The results of table 19 indicate that the model estimated at t-2 performs best with this ratio set. Therefore, this model is used to create the Logit model in equation 10 and will be tested at the holdout sample.

The formula of eq. 10 gives a value P, which can be interpreted as odds a company has for being (non-)bankrupt. The company is classified as bankrupt when eq. 8 results in a score higher than 0.5. A company is financial healthy when the value for P is below 0.5. The results of the model are presented in table 20.

Eq.10: Logit model based on ratio set 1

$$p = \frac{\exp(-0.110 - 10.046R_7 - 1.353R_{12} - 0.417R_{20} + 2.961R_{22})}{1 + \exp(-0.110 - 10.046R_7 - 1.353R_{12} - 0.417R_{20} + 2.961R_{22})}$$

1.2. Logit model based on ratio set 2

This Logit model is based on ratio set 2, which is acquired in the ratio selection process. The model at t-1 has the best AUC but has a low sensitivity. The model at t-2 has a good AUC and a high sensitivity and therefore this model is used to create equation 11 and to test at the holdout sample.

The formula of eq. 11 gives a value P for each company, which can be interpreted as odds a company has for being (non-)bankrupt. The company is classified as bankrupt when the equation results in a score higher than 0.5. A company is financial healthy when the value for P is below 0.5. The results of the model are presented in table 20.

Eq.11: Logit model based on ratio set 2

$$p = \frac{\exp(-1.020 - 3.241R_4 - 4.350R_5 - 7.902R_7 + 8.534R_{11} + 2.812R_{13} + 0.014R_{21})}{1 + \exp(-1.020 - 3.241R_4 - 4.350R_5 - 7.902R_7 + 8.534R_{11} + 2.812R_{13} + 0.014R_{21})}$$

1.3. Logit model based on ratio set 5

The ratios used in this model are also acquired during the ratio selection process. The model at t-6 yields the best results and therefore this model is used to create equation 12 and will be tested on the holdout sample.

The formula of eq. 12 gives a value P for each company, which can be interpreted as odds a company has for being (non-)bankrupt. The company is classified as bankrupt when the equation results in a score higher than 0.5. A company is financial healthy when the value for P is below 0.5. The results of the model are presented in table 20.

Eq.12: Logit model based on ratio set 5

$$p = \frac{\exp(1.324 - 27.350R_5 + 5.437R_9 + 3.791R_{11} + 0.343R_{21} + 3.203R_{22})}{1 + \exp(1.324 - 27.350R_5 + 5.437R_9 + 3.791R_{11} + 0.343R_{21} + 3.203R_{22})}$$

1.4. Results of estimation of the Logit method

Table 18 presents the results of the estimated models based on ratio set 1, 2 and 5. These results are obtained by inserting the financial data in the equations 10, 11 and 12.

Table 18: Results of Logit models with ratio set 1, 2 and 5

Ratio set	Time	Sample	AUC	Sensitivity	Specificity	AR	Percentage correctly classified
Ratio set 1: R7, R12, R20 and R22	t-1	Estimation	0.764	0.231	0.444	52.8%	72.2%
		Holdout	0.906	0.250	0.410	81.2%	63.0%
	t-2	Estimation	0.829	0.489	0.924	65.8%	76.2%
		Holdout	0.938	0.100	0.864	87.6%	62.5%
	t-3	Estimation	0.588	0.408	0.922	17.6%	72.2%
		Holdout	0.938	0.231	0.870	87.6%	63.9%
	t-4	Estimation	0.532	0.234	0.831	6.4%	60.5%
		Holdout	0.875	0.455	0.773	75.0%	66.7%
	t-5	Estimation	0.560	0.275	0.863	12.0%	65.5%
		Holdout	0.906	0.556	0.842	81.2%	75.0%
	t-6	Estimation	0.597	0.350	0.908	19.4%	77.6%
		Holdout	0.938	0.429	0.882	87.6%	75.0%
Ratio set 2: R4, R5, R7, R11, R13 and R21	t-1	Estimation	0.979	0.357	0.959	95.8%	82.5%
		Holdout	0.750	0.500	1.000	50.0%	92.9%
	t-2	Estimation	0.479	0.232	0.938	0.0%	55.8%
		Holdout	0.563	0.125	1.000	12.6%	50.0%
	t-3	Estimation	0.500	0.138	1.000	0.0%	53.7%
		Holdout	0.529	0.059	1.000	5.8%	48.4%
	t-4	Estimation	0.479	0.091	0.960	0.0%	50.5%
		Holdout	0.500	0.500	0.500	0.0%	37.9%
	t-5	Estimation	0.479	0.152	0.979	0.0%	63.8%
		Holdout	0.612	0.308	0.917	22.4%	60.0%
	t-6	Estimation	0.479	0.077	0.972	0.0%	73.5%
		Holdout	0.625	0.250	1.000	25.0%	64.7%
Ratio set 5: R5, R9, R11, R21 and R22	t-1	Estimation	0.896	1.000	0.820	79.2%	85.9%
		Holdout	0.875	1.000	0.750	75.0%	78.6%
	t-2	Estimation	0.817	0.672	0.813	63.4%	73.6%
		Holdout	0.522	0.294	0.750	4.4%	48.3%
	t-3	Estimation	0.754	0.545	0.684	50.8%	61.0%
		Holdout	0.630	0.474	0.786	26.0%	60.6%
	t-4	Estimation	0.875	0.548	0.765	75.0%	64.6%
		Holdout	0.604	0.571	0.636	20.8%	59.4%
	t-5	Estimation	0.854	0.738	0.681	70.8%	70.8%
		Holdout	0.658	0.733	0.583	31.6%	66.7%
	t-6	Estimation	0.958	0.767	0.833	91.6%	80.3%
		Holdout	0.733	0.800	0.667	46.6%	73.7%

App. VIII: NN method estimation process

The NN method is estimated slightly different than the MDA and Logit method. The NN method does not produce an equation as is with the MDA and Logit method. The NN function in SPSS only reports the estimation process and the results. Therefore, only the best results are presented in table 19 (results of ratio set 1, 2 and 5) and the results of ratio set 3 and 4 are not used and not reported.

Table 21 displays the best results of the ratio sets 1, 2 and 5. Set 2 has almost a perfect performance in both the training sample and the validation sample at time t-1. The model performs also well at t=-2 in both the training sample and validation sample. At t-3 the model performs notably worse than at t-1 and t-2. The AUCs are decent, but the sensitivity rates are notably lower. The AUCs of ratio set 5 are lower than the highest AUC of set 2, but more stable over different time periods. The specificity of the models is good at time t-2 and t-6, but decent at t-1 and t-5. As is the same with the AUC, the accuracy is lower.

Overall the model of ratio set 2 performs well on short term financial distress prediction and the model based on ratio set 5 performs better at long term financial distress prediction.

Table 19: Results of NN models with ratio set 1, 2 and 5

Ratio set	Time	Sample	AUC	Sensitivity	Specificity	AR	Percentage of correctly classified
Ratio set 1: R7, R12, R20 and R22	t-1	Estimation	0.500	0.000	1.000	0.0%	87.3%
		Holdout	0.500	0.000	1.000	0.0%	84.4%
	t-2	Estimation	0.676	0.610	0.855	35.2%	76.9%
		Holdout	0.406	0.438	0.840	0.0%	68.3%
	t-3	Estimation	0.361	0.761	0.782	0.0%	77.4%
		Holdout	0.938	0.688	0.818	87.6%	76.3%
	t-4	Estimation	0.454	0.333	0.929	0.0%	69.6%
		Holdout	0.438	0.462	0.793	0.0%	69.0%
	t-5	Estimation	0.417	0.314	0.848	0.0%	66.3%
		Holdout	0.500	0.500	0.962	0.0%	80.0%
	t-6	Estimation	0.472	0.313	0.944	0.0%	80.0%
		Holdout	0.969	0.545	0.893	93.8%	79.5%
Ratio set 2: R4, R5, R7, R11, R13 and R21	t-1	Estimation	1.000	0.909	1.000	100.0%	98.0%
		Holdout	1.000	0.800	0.957	100.0%	92.9%
	t-2	Estimation	0.854	0.860	0.705	70.8%	78.7%
		Holdout	0.781	0.864	0.813	56.2%	84.2%
	t-3	Estimation	0.896	0.672	0.750	79.2%	70.5%
		Holdout	0.782	0.667	0.731	56.4%	70.2%
	t-4	Estimation	0.708	0.833	0.556	41.6%	72.2%
		Holdout	0.672	1.000	0.400	34.4%	65.9%
	t-5	Estimation	0.479	0.611	0.897	0.0%	76.0%
		Holdout	0.804	0.500	1.000	60.8%	83.3%
	t-6	Estimation	0.479	0.235	0.929	0.0%	66.7%
		Holdout	0.514	0.000	0.941	2.8%	76.2%
Ratio set 5: R5, R9, R11, R21 and R22	t-1	Estimation	0.800	0.538	0.947	60.0%	84.3%
		Holdout	0.750	0.667	0.958	50.0%	92.6%
	t-2	Estimation	0.854	0.800	0.786	70.8%	79.3%
		Holdout	0.757	0.920	0.667	51.4%	81.4%
	t-3	Estimation	0.733	0.703	0.707	46.6%	70.5%
		Holdout	0.735	0.857	0.767	47.0%	80.4%
	t-4	Estimation	0.733	0.810	0.628	46.6%	73.3%
		Holdout	0.680	0.800	0.684	36.0%	75.0%

	t-5	Estimation	0.838	0.564	0.841	67.6%	71.1%
		Holdout	0.792	0.611	0.867	58.4%	72.7%
	t-6	Estimation	0.896	0.769	0.697	79.2%	72.9%
		Holdout	0.789	0.929	0.833	57.8%	88.5%