BANKRUPTCY PREDICTION FOR DUTCH PRIVATE FIRMS USING THE ALTMAN Z-SCORE MODEL

Master thesis

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ABSTRACT

This thesis aims to evaluate the predictive ability of the Altman z-score model (1983) in the Netherlands. It starts with discussions on what bankruptcy is, how the Dutch bankruptcy systems works and how the various bankruptcy prediction models work.

The Altman z-score model is a multiple discriminant analysis considering five financial ratios, which consider liquidity, size, productivity, solvency, and efficiency of a firm's assets. The model gives z-scores in three classifications, the 'safe' or 'bankrupt' zone or the zone in between named 'grey zone'. In this thesis it is studied whether bankrupt and non-bankrupt firms are correctly classified in the right zone. The classification accuracy of three versions of the Altman z-score model are analysed and compared.

The sample consisted of financial data from around 16.000 Dutch private limited liability firms from the years 2007 to 2015. Accuracy classifications were analysed for one through three years prior bankruptcy. The results suggested that bankrupt firms do not have z-scores falling in the distress zone and non-bankrupt firms do score in the as safe predicted zone. This indicates the Altman z-score model is not directly useful for Dutch private firms. Even after re-estimation by the coefficients by logistics regression analysis, the model does not provide an useful prediction tool.

In conclusion, the findings coincide with that of prior research that results of bankruptcy prediction that used Altman models should be interpreted cautiously and the classification ability is likely to differ per time-period and country studied. Results of this study suggests that the predictive ability of the model in the Netherlands is lower, with around 30 to 45% classification accuracy, compared to previous studies in other countries, which report around 70 to 90% classification accuracy. When using the Altman z-score model in practice, it would be useful to re-estimate the coefficients on a more specific sample and perhaps take more ratios into consideration.

TABLE OF CONTENTS

1. INTRODUCTION

1.1 BACKGROUND

Through the last few years, some remarkable bankruptcies were in the news in the Netherlands, like the 'OAD Groep', 'MacIntosh' and 'Vroom & Dreesmann'. These businesses were active for decades before they were declared bankrupt. The bankruptcies were in the news, because they were relative big employers in their industries (OAD: loss of jobs for around 1200 employees and for V&D; around 10000) and the settlements of the bankruptcies were taking a long or still is taking time. When bankrupt, the people and parties involved or related, called the stakeholders, often have a loss, whether it is financial or non-financial like loss of jobs, service or others. Therefore from stakeholder's perspective, such as employees, customers, investors or creditors, it is interesting to evaluate the likelihood of bankruptcies. For example in business to business markets, the proposed payment conditions can be influenced by the likelihood of bankruptcy or financial distress. Furthermore, bankruptcy or financial distress often is a longer-term phenomenon and the earlier firms can become aware of their position the better decisions they can take to turn around the company and perhaps avoid bankruptcy (Bal, 2016).

Bankruptcy prediction models are generally tools to predict whether or not a firm will go bankrupt based on financial data. One of the most popular bankruptcy prediction model, scientifically and in practice, is the Altman z-score model which originated in 1968 (Siddiqui, 2012). Altman revised this z-score model in 1983, including one which made it also applicable for private firms.

In this thesis the sample researched will consist of Dutch private firms. Private firms are organizations that do not trade their shares publicly and have fewer obligations than public firms. The private firms used in this research are all 'private limited liability organization' ('Besloten Vennootschap met beperkte aansprakelijkheid') and this is the most common entity in the Netherlands.

In the Netherlands the z-score model was and still is used as a prediction tool by many investors and financial professionals who use it as one of their methods for their analyses. In 1989 it even warned truck manufacturer 'DAF', which later went into financial distress and bankruptcy in 1993 (Financieel Dagblad, 2013). So when a firm is predicted by the model as distressed, the firms will not always be able to turn the situation around. Although bankruptcy cannot always be avoided in those cases, it might caution potential creditors and investors.

Grice & Ingram (2001) concluded that the Altman z-score model is not as effective in classifying firms in later studies (1985-1991) as it was in studies at the time (1968 and 1983) of development. Grice and Ingram's results also indicated that Altman's model is useful for predicting financial distress conditions but less accurate in predicting bankruptcy. In this thesis, the intend is to examine the predictive ability in a Dutch environment.

1.2 OBJECTIVE

The main focus of this thesis is to evaluate the predictive ability of the revised Altman z-score model (1983) for privately held firms in the Netherlands. It is interesting to explore the predictive ability as it can show the usability of the Altman z-score model in the Netherlands. In other words, whether it is usable as a forecasting or early warning tool for Dutch firms in their decision making. Altman's z-score model of 1983 is a revised version of the original model from 1968, which uses multiple discriminant analysis to derive a linear combination of financial ratio variables that discriminate between bankrupt and non-bankrupt firms.

The problem statement can be described in different ways. As there are many different bankruptcy prediction models (Kumar & Ravi, 2007) and each has their own results and effects in environments, industries and times, there is no real clarity about the validity of Altman's z-score model in the Netherlands. In other words, it is not scientifically shown that the z-score model works accurate or has predictive abilities in the Netherlands. Therefore research needs to be done to address the predictive accuracy of Altman's z-score model in a sample of Dutch 'private limited liability firms'(B.V.'s) in a more recent time.

The problem statement and literature research led to the following research question:

What is the predictive ability of the revised z-score model for private firms in the Netherlands?

This research question can be seen as a descriptive question, as it seeks to provide an accurate description of how predictive the z-score model is, as in how much of the sample is correctly distinguished between bankrupt and non-bankrupt firms. In order to increase our understanding of the Altman z-score and bankruptcy prediction in the Netherlands, this study intends to address the following sub-questions:

- What is bankruptcy?
- How does the Dutch bankruptcy system work?
- What are bankruptcy prediction models?
- How do the Altman z-score models (1968 and 1983) work?
- How did other researchers test the Altman z-score models?
- What are the prediction accuracies of the z-score model one to three years prior to bankruptcy?

The first five sub-questions will be answered in the literature review. A global question of this study is also whether, by looking purely and solely at financial data and performance, in the years prior to the bankruptcy, it is possible to infer the probability of bankruptcy in the Netherlands.

1.3 RELEVANCE

The reason why the Altman z-score model is chosen to study is that it is the most popular (Siddiqui, 2012; Ohlson, 1980; Wu, Gaunt & Gray, 2010) and one of the most scientifically studied and reviewed bankruptcy prediction tool. Often the z-score model was not studied individually but compared to other models or measurement methods. Studies suggested that Altman's revised z-score model is one of the most effective multiple discriminant analysis (Siddiqui, 2012). Another reason for the popularity of the Altman z-score is that the later versions are appropriate for both public and private firms, and for both manufacturers and service companies, which makes it a popular tool for investors, auditors, and stakeholders (Kim & Choi, 2013). So the usability is high with the revised z-score model.

The data analysed in this thesis is from private Dutch firms, so the Altman z-score model from 1983 for private firms is studied at first. In addition, another revised model from the same year 1983 will be tested as well as a new model with re-estimated coefficients based on the sample of this thesis. Furthermore, the popularity of the Altman z-score originates from the usability compared to another prediction model. The chosen model gives clear results predicting a firm in three zones and the scores also make comparing between firms relatively simple to analyze. The usability and the working of the Altman z-score model will be further discussed in section 2.3.

The aimed contribution of this thesis to the existing literature is an exploration of the usability of the Altman z-score in the Netherlands. When looking at the existing literature of the Altman z-score in the Netherlands, most prior research was not specifically focused on the Netherlands or not just only focused on the Altman z-score, but these articles also focused on other countries or models. This study differentiates from prior research as it analyses a Netherlands specific sample in a recent timeframe (2009 to 2016), and solely focusses on the Altman z-score model.

The revised Altman z-score model is an accounting based model and a reason not to study a market-based model is that there are no market variables available for private firms, as their shares are not publicly traded or listed. The main goal of this thesis is to verify whether the Altman z-score model can be useful for predicting bankruptcy of Dutch private firms.

1.4 STRUCTURE

The remainder of this paper is organized as follows. Chapter 2 will start with a literature review on bankruptcy in general and in the Netherlands, after which bankruptcy prediction models, and the Altman's z-score model in particular, will be reviewed. Afterward relevant literature on bankruptcy prediction models will be discussed. At the end of chapter 2 the focus will be on hypothesis development. Chapter 3 will discuss the research method, the data collection and the sample. Then chapter 4 will discuss the results of the research. Finally chapter 5 will draw the conclusions based on these results.

2. LITERATURE REVIEW

2.1 BANKRUPTCY

In the literature, the phenomenon bankruptcy is sometimes called failure. The term bankruptcy in this study will refer to, as like the Altman study (1968), firms that are legally bankrupt. This will mean firms that are *legally declared bankrupt* by Dutch Bankruptcy law. This generally happens by a court order when a firm is unable to pay debts owed to creditors.

Financial Distress

Financial distress is a broad concept that contains several situations in which firms face financial difficulty (Geng, Rose and Chen, 2015). The most common terms used to describe these situations are 'bankruptcy', 'failure', 'insolvency', and 'default'. Hillier et al. (2010) see financial distress as a situation where the firms operating cash flows are not sufficient to satisfy current obligations and the firm is forced to take corrective action. They also state that financial distress is hard to define precisely, partly because of a variety of events like dividend reductions, plants closings, losses, layoffs, CEO resignations, plummeting share prices among others. Furthermore, Hillier et al. (2010) discussed that financial distress can be somewhat linked to insolvency.

In most countries, bankruptcy has two basic options; liquidation or reorganization. So bankruptcy may not always end up in a disappearance of the company, and firms may be split up, sold to a new buyer, or restructured during the process. Dutch bankruptcy law will be more extensively discussed later on in section 2.2.1. For now, it is important to bear in mind that financial distress does not necessarily mean the same as bankruptcy and that there are several sides of financial distress.

2.1.1 CAUSES

As discussed earlier, the main reason that a bankruptcy or financial distress happens is that the operating cash flow is not sufficient to satisfy the current obligations. In other words, not all the financial duties can be met, which can have several types of reasons. When looking at purely financial reasons it can be a combination of too high costs and not enough income. According to the Dutch Central Agency of Statistics (Centraal Bureau voor de Statistiek) the causes of Dutch bankruptcies can be distinguished in the following groups (van Elswijk, Jansen, Duijkers, Moerman, 2016):

-Mismanagement: administrative issues, low accounting knowledge, employee issues, organizational issues, insufficient debtor monitoring, under- and over financing, high finance charges, marketing fails, lack of preparation of entrepreneurship.

-Economic factors: increased competition, sales or price drops, market changes, foreign and other economic changes.

-Managerial issues.

-Bankruptcies of parent, sister or related organizations.

-Other causes, like lawsuits, tax-related confiscations, a credit stop or suspicious acts.

Some common factors of financial distress can be distinguished in internal and external business conditions are given in table 1.

Table 1 Common business conditions leading to financial distress

Internal	**External**
Mismanagement	Competition increase
Inappropriate location	Supplier cost increase
Loss/keeping of employees	Market events
	Shifts in consumer preferences

When looking at mismanagement, for example, it can be that there was a lack of planning or weak decision making. Location is especially important for stores of retail businesses and loss of key employees can mean that an employee with for the business key knowledge or skills went away permanently (due whatever reason) and was not adequately replaced. On the other hand keeping loyal employees can as well cause high costs because reorganizing and letting go of loyal personnel is hard for most firms.

An increase in competition can induce to be outperformed by similar sellers on elements of the marketing mix (price, product, distribution, promotion), whereby the number of sales and or the profit margin goes down. Supplier cost increase can also cause the profit margin to decrease if sale prices are not adjusted accordingly. The conditions in table 1 are not mutually exclusive as for example a market event like the development of a new technology can cause a shift in consumer preference, the demand for earlier technology might be shifted by new developments.

Additionally, table 1 is definitely not complete and there are more common factors causing financial distress. These can be financial problems like inability to secure new or additional funding. Even if more financing is secured, high debt can cause difficulties with the cash flow because of the interest that needs to be paid. Other underlying problems of firm bankruptcies can be lawsuits, tax-related problems, conflicts (for example between the property owner and management), debtors in financial distress, criminal activity, illness, disasters and accidents (even though having insurance coverage).

The Dutch Central Agency of Statistics also states that from the material published by the curators, there cannot always be given one exact reason for each bankruptcy, often there are several causes kept by curators (van Elswijk et al., 2016) .

2.1.2 EFFECTS

When a bankruptcy happens there are various stakeholders that will be affected or related to the bankruptcy.

Creditors

All who are owed money by a firm are called creditors. These creditors can be divided in various types. The most obvious are often the investors of the firm. These can be the owners, partners and or shareholders who, in case of a bankruptcy, will question whether or what part of their investment they will be able to recover. Suppliers of the bankrupt firm who have not been paid yet can also be in uncertainty, if they are very dependent on the bankrupt firm a ‘domino effect’ can threaten. A ‘domino effect’ means that one bankruptcy can set off a chain of more bankruptcies. In bankruptcies, creditors generally are not paid in full what they are due, as there are also direct bankruptcy costs involved like legal and administrative fees.

Property owners are also considered creditors and can have claims of unpaid rent. Furthermore, these landlords will often not be able to rent out their property immediately to a new debtor after a bankruptcy. There are three main groups of creditors, which are unsecured, secured and preferred creditors. These types of creditors and the priority rules of payments after bankruptcy will be further discussed in section 2.2.1 of this thesis.

Employees

On one hand, employees are also creditors if they are still owed some salaries or other work-related income. On the other hand, most employees are big stakeholders who will probably lose their jobs immediately in case of a bankruptcy. Furthermore, employees can experience uncertainty after a bankruptcy about work changes or retirement plans they had with the bankrupt firm, and probably have to search for new jobs, which may or may not be equally rewarding for them.

Debtors

Debtors like customers of a seized bankrupt business can also notice effect as for example service or after-service of the product or machine they purchased is not possible anymore. Also with bankruptcies in the retail businesses, it can happen that purchased gift cards or store credits will lose its worth as there cannot be purchased anything with them anymore at the bankrupt store.

Other stakeholders

Competitors can possibly notice various effects of losing a competing bankrupt firm, for example, an increase in sales or work orders, or better terms with a supplier or the loan market. Although there is no scientific evidence for these effects in the Netherlands. Business partners can also be influenced by a bankruptcy and for instance forced into dropping project what would have been done together.

Depending on the legal form of the firm, the firm management can sometimes be held liable for the bankruptcy. And even when it is limited liability company (like a B.V.) in the Netherlands the firm can be held personally liable if there are reasons therefore like serious maladministration (‘onbehoorlijk bestuur’ called in Dutch). Examples of maladministration are management errors or fraudulent behavior.

Recovery rates

Recovery rates are the rates of what amount is recovered from the money owed to the creditors. The study by Couwenburg (2001) suggested that firm size of the bankrupt firm has an important effect on survival and recovery rates in the Netherlands. With the firm size, the recovery rates of the creditors of a bankrupt firm go up. Findings by Couwenburg and De Jong (2008) indicate that such firm characteristics are more important determinants of recovery rates than the legal procedures in the bankruptcy process.

Finally, the effects depend on whether the firm activities are seized immediately, partly or later after being declared bankrupt. Often when the business activities are continued for some time after bankruptcy it is for the reason to achieve a higher yield of the liquidation.

Concluding there can be different effects on various stakeholders after a bankruptcy filing and just a few were mentioned here. Effects of bankruptcy are not exclusively financial losses on investments, but also nonmonetary as losses in social stability and market trust.

2.2 BANKRUPTCY IN THE NETHERLANDS

2.2.1 DUTCH BANKRUPTCY LAW

The current Dutch bankruptcy code is quite old (1896) and the last few years there has been some discussion going on about reforming or replacing it. Although still no major reformations have happened or are planned for the Dutch bankruptcy code (Hummelen, 2014). A Dutch firm in financial distress has three options; an informal reorganization, suspension of payment or filing for bankruptcy. Summarizing Boot & Ligterink (2000), Couwenberg (2001) and Couwenberg & De Jong (2008), the Dutch bankruptcy system consists of the following three paths:

Informal reorganization

Informal reorganization means that the firm in financial difficulties tries to set agreements with their debt holders and or creditor in an informal way, so not by formal bankruptcy law. This happens mostly on an initiative by the creditor, most of the times this will be a bank since from their position they could and should acknowledge financial problems at an early stage. Because the negotiations are outside the bankruptcy law, it is necessary that all creditors agree with the intended reorganization. Therefore the negations get more difficult when there are more creditors. In the Netherlands most of the times banks are the most dominant creditors, therefore the role of banks is valuable in bankruptcies and in the debate about bankruptcy law.

Suspension of payments

Requesting suspension of payments can only be done by the debtor itself and the court will accept it when there is a prospect of fulfillment for creditors. The suspension of payments procedure aims at firms in financial distress with sufficient prospects to recover in a short time. If more than a quarter of the amount from the on the creditor meeting present unsecured claims or a third of the unsecured creditors oppose to the suspension then the suspension of payments will be rejected. Most firms will then end up in bankruptcy, but if the court provides a suspension of payments an administrator will be appointed who will be responsible together with the management for the business operations. The management will keep the power, but have to cooperate with the administrator. The purpose of suspension of payment is to provide the opportunity to the management to set things in order to prevent bankruptcy. An agreement can be offered to the creditors like a postponed payment in combination with possible partly remission. Secured and preferential creditors fall outside the suspension of payment arrangements and newer financing get higher priority during the suspension of payments. Basically, in the suspension procedure, the distressed firm can offer settlements to the ordinary creditors. If the suspension procedure fails, the distressed firm cannot try the suspension of payments procedure again and neither offer the exact same settlement composition in the bankruptcy procedure.

Filing for bankruptcy

Bankruptcy can be filed by both the creditors as the debtor firm self. After the debtor has been declared bankrupt by the court, a trustee (curator) is appointed. Purpose of the bankruptcy is to liquidate all the assets of the firm, whereby the interest of the creditors goes first. The proceeds have to be distributed among the creditors. Another important difference with the suspension of payments is that with bankruptcy leases and contracts can be canceled easier with the transfer of assets. Although liquidation has a preference, the curator can choose to continue the business or parts of the business as going concern if a higher yield, and thus recovery rate, can be achieved by this.

Priority rules

Couwenberg & de Jong (2008) also shortly summarizes the priority rules in the distribution of the yield after a bankruptcy in the Netherlands:

There is a leading principle for the distribution of proceeds which holds that every creditor has an equal right to proportional payment. However, this principle of equality creditor is an exception rather than a rule. The Dutch law includes a number of statutes, which includes priority rules that provide preferences for certain creditors over another. The highest priority goes to the administrative costs, estate-financing and taxes accrued during the possible period of continuation in bankruptcy. Secured claims are entitled to receive the proceeds of the sale of the collateral, while any unpaid part is treated as unsecured claims. Next in line of priority are the audit, tax, wage and unsecured claims.

2.2.2 DIFFERENCES WITH FOREIGN SYSTEMS

To give some further insight into the Dutch system some differences across countries in bankruptcy law and system will be discussed. Blazy, Chopard & Fimayer (2008) defined the following four types of bankruptcy systems based on the combination of bankruptcy rules:

- Social pro debtor model
- Entrepreneurial pro debtor model
- Repressive model
- Pro secured creditors model

The social pro debtor model ingrates an automatic stay on creditor’s claims and the manager holding its place during reorganizations. Furthermore, the privileged creditor’s claims (state or workers) have priority over secured creditors. This type of model is, for example, active in France and favors the firm’s continuation and protect the interest of workers.

The Netherlands has an entrepreneurial pro debtor, which differs in the absolute priority rule, though the management keeps rights to run the firm’s operation while a reorganization plan is being formed. The Dutch system promotes continuation without giving priority to workers on the firm’s assets. A repercussion of such a debtor-friendly system may be that borrowers strategically file for bankruptcy in order to renegotiate their debt and labor contracts.

The repressive model differs in the way that the debtor is not responsible for the business operations during the bankruptcy process. This means that during a reorganization the bankrupt manager is replaced by an official appointed by the court or by the creditors. This type of model is used in the United Kingdom.

The pro secured creditors model also protects the interest of secured creditors, no automatic stay on the creditor’s claim exists and the absolute priority rule is enforced. This type of model is active in the countries Belgium and Germany.

Blazy et al. (2008) also suggested that the differences in bankruptcy models across countries especially reflects the differences in legal traditions. Differences in creditor’s rights across countries lead banks to adjust their lending and reorganization practices to mitigate costly aspect of bankruptcy law, for example, French banks respond to a creditor-unfriendly code by requiring more collateral than lenders elsewhere (Davydenko & Franks, 2008).

In the United States, financially distressed firms can file for Chapter 11 bankruptcy (similar to reorganization) or for Chapter 7 bankruptcy (similar to liquidation). The other aspects of the US bankruptcy system are practically the same as European systems (Hillier et al. 2010).

These classifications demonstrate that country-level differences exist in bankruptcy rules and in the objectives of national bankruptcy codes. The Netherlands has a reorganization focused bankruptcy system with protection of secured creditors and the management. Neighbouring countries like Germany, UK and Belgium are less focused on a reorganization system.

2.2.3 CASE STUDIES

OAD

Bankruptcies and the Dutch bankruptcy system will now be discussed with references to some cases. The case that will be discussed first is the bankruptcy in 2013 of Dutch travel agency OAD Groep. OAD is a family business with a long history, which had at its most successful years a turnover of almost 1 billion euros and more than 1500 employees. Similar to the sample of this research OAD is a private firm.

As mentioned in section 2.2.1 the role of the bank during financial distress of a firm is often the most dominant, like in the case of the bankruptcy of the travel agency OAD (Woudt, 2014). It is also possible that a different type of creditor plays a major role, which for example was the case with the department store 'Vroom & Dreesmann', where the real estate owners played a major role.

During liquidation, the curator can decide to continue parts of the business as going concern if a higher yield can be achieved. This was also the case with the bankruptcy of travel agency OAD, where for example the bus travel part of the business was continued by a former director of OAD. Furthermore, some of the travel bureaus were sold to a former competitor.

Woudt (2014) suggests that the bankruptcy of OAD could have been avoided in the final phase with a few million euro while in contrast in the year 2006 OAD had a turnover of almost one billion euros. This could suggest that bankruptcy could have been avoided with just a fraction of the turnover it had earlier. OAD's case corresponds with the conclusion of the Couwenberg & de Jong (2006) study which found that the assistance of banks is of crucial importance to the success of restructuring, but that some firms do not benefit from this assistance.

When looking further at the financial data from two years before the bankruptcy of OAD (OAD Groep Holding b.v.) and filling in the revised Altman z-model (1983), the result is that it is clearly a case that falls into the non-bankrupt prediction zone (z-score of 6.82). This means that this case is a Type I error; a bankrupt firm falsely predicted as non-bankrupt. Type I and type II errors will be more discussed later on in section 3.1. When looking at the four-variable Altman z-score model (1983) (later on discussed) OAD scores a z-score of 0.16 two years before the bankruptcy, with which it does fall into the bankruptcy prediction zone.

MacIntosh

The Dutch retail group MacIntosh was declared bankrupt in 2015. This is a publicly listed firm, but the reasons for the bankruptcy will be discussed shortly as an example. Although only the listed holding company was officially declared bankrupt, the shops and stores of the several MacIntosh formats stayed open and continued their business activities (press release, 2015). The curator tried to sell on as many of group companies as to the interest of all the stakeholders. The MacIntosh format Scapino was for example quite quickly sold to the previous owner and founder of the scapino format.

According to a first bankruptcy report released by the curator, the directors give five main reasons for the failure of MacIntosh. Firstly the recession led to oversupply, pressure on prices, dropping turnover and dropping margin. The bad weather pattern in the fall of 2014 and 2015 have intensified this. Secondly, the development of the online segment went at the expense of the traditional demand and offered extra supply, MacIntosh had to invest severely more into the online marketing of all the formats. Furthermore, there were limited resources to invest and make costs, there was a restraint which caused the shops and formats to get outdated, and less invested in brand development. Next to these, there were not many possibilities to intervene in the growing number of poor running shops as to the relatively long-term leases of buildings. Finally, the high overhead cost of a listed complex organization with a rather big number of formats, each with its own products, brand development, and direct sourcing compared to a business model in which third-party brands are purchased by wholesale, lead to the bankruptcy of MacIntosh group.

The Altman z-score(1983) of MacIntosh in the last year prior the bankruptcy is falling in the grey zone (2.36). So some financial distress could be derived from the Altman z-score a year before the bankruptcy, but still not correctly predicted as bankrupt.

V&D

The Dutch chain of department stores ‘Vroom & Dreesman’ was also declared bankrupt in 2015. It had a long history of 129 years and their stores were housed at prominent buildings in most Dutch cities. V&D was tried to be sold as going concern, and for that reason the stores stayed open for some time, but it eventually failed and about 10.000 jobs employees lost their jobs. Only the subsidiary restaurant La Place was sold on partially.

Some reasons for the failure according to the first bankruptcy reports are the rise of online shopping and the expensive prestigious real estate. V&D had compared to competitors a loyal labour staff, although that was also more costly. The real estate was sold in past (2004) by V&D, and while there were more and more vacancies in Dutch shopping streets, the rents were expensive for V&D. Through negotiations in 2015 with the real estate owners the rents were lowered, next to this the workforce was reduced by 400, but eventually this could not prevent the bankruptcy. The final straw for the bankruptcy was the relatively warm weather in the months November and December in 2015 which caused reduced sales.

The Altman z-score (1983) of ‘V&D Group Holding B.V.’ two years before bankruptcy was falling in the grey zone (1.51), and a four variable z-score falling in the distress zone (-0,55). The result of the z-scores of these cases is a clear indication of the potential, of testing the predictive accuracy, aimed at in this thesis.

2.3 BANKRUPTCY PREDICTION MODELS

In the literature various words are used for the phenomenon bankruptcy predictions, words like forecasting power, ability or accuracy are given next to classifying performance of financial distress, insolvency and failures. In general bankruptcy prediction models are tools to predict whether or not a firm will go bankrupt based on the current financial data.

2.3.1 TYPES

A lot of research is done in the field of bankruptcy prediction, motivated by the importance of accurate and timely strategic business decisions. Next to accuracy also understand-ability and transportability can be seen as important criteria of prediction models. The first research in bankruptcy prediction was done by Beaver (1966). Altman (1968) elaborated on this work and reconfirmed the usefulness of ratio analysis. Altman's study demonstrated the use of multiple variate analysis instead of univariate analysis. Multivariate analysis refers to a technique where multiple variables are analyzed from the data, including dealing with causes and relationships instead of univariate analysis with only one variable.

In bankruptcy prediction models the dependent variable commonly is dichotomous where a firm is 'firm is filed for bankruptcy' or 'firm remains solvent'. Independent variables are most of the times accounting ratios drawn from the financial statement, which include a measure of profitability, liquidity, and leverage. Sometimes also market-driven variables as the volatility of stock return and past excess returns or firm-characteristics like firm-size and corporate diversification are used in prediction models. The accounting-based models developed by Altman (1968) and Ohlson (1980) have emerged as the most popular bankruptcy prediction models and are often used by empirical accounting researchers as indicators of financial distress (Wu, Gaunt & Gray, 2010). The literature reported that the predictive ability of each model varies over time, different models perform relatively better at certain times, and the study by Wu et al. (2010) confirmed this.

In the literature, there are different conceptualizations of grouping the different types of bankruptcy predictions models. Some papers base the types of the prediction technique, some of what kind of info is used to predict and some of the analyzing method. Furthermore, some models are more narrowly focused than other models (Bellovary, Giacomino & Akers, 2007). The prediction models can be divided into two main categories which are parametric models and non-parametric based models (Singh & Mishra, 2016). Parametric based model considers all the data within a finite number of parameters, while non-parametric based models use a flexible number of parameters, and often grows as it learns from more data. With parametric based models more assumptions can be made about the data regarding the nature of the underlying population distribution. For non-parametric tests these assumptions regarding the underlying population are not necessary.

Parametric models can be grouped into accounting and market-based models which both could be univariate and multivariate and generally uses financial information. The Altman z-score model research in this thesis is such multivariate accounting model. Market-based models can then again be divided into structural and reduced form models (Singh Mishra, 2016). Examples of non-parametric of models are the types of neural networks, hazard models, fuzzy models, genetic algorithms and hybrid model.

Kumar and Ravi (2007) also identified two broad categories; statistical and intelligent techniques. The difference between statistical and intelligent techniques is approximately the same as parametric and non-parametric, as statistical techniques follow certain assumptions (like linearity), while intelligent techniques have a learning part. Furthermore, Kumar and Ravi (2007) grouped families of techniques into statistical techniques, neural networks, case-based reasoning, decision trees, operational research, evolutionary approaches, rough set-based techniques, other techniques subsuming fuzzy logic, support vector machine and isotonic separation and soft computing subsuming seamless hybridization of all the mentioned techniques. Siddiqui (2012) sees after univariate and multiple discriminant analyses, the logit and probit analysis, recursive partitioning algorithm and neural networks as the most significant types of prediction models.

Bellovary et al. (2007) reviewed various bankruptcy prediction studies, their accuracy analysis suggested that multivariate discriminant analysis and neural networks are the most promising, regarding the highest accuracy rates. The number of factors which were considered in the Bellovary et al. study ranged from one to 57. The factor most common in multiple studies is the ratio of net income to total assets (return on assets). The second most common factor is the ratio of current assets to current liabilities (current ratio). These findings also suggested that higher model accuracy is not guaranteed with a greater number of factors. Furthermore, some models are more narrowly focused than other models, for example on industry or environment specific. The Bellovary et al. study also considered how early the model is able to accurately predict bankruptcy, the earlier it is able, the more valuable the model will be.

So various types and classifications of bankruptcy prediction models exist. For this study, it is considered not necessary to go more into depth and explain each of the above mentioned types of models. The focus of this study will be the parametric, statistical and multivariate Altman z-score models. The original model which had a market-based component will now be first discussed, where after the, purely accounting based, revised model will be explained.

2.3.2 ORIGINAL ALTMAN Z-SCORE MODEL

The model that will be analysed in this research will be the Altman z-score model consisting of five financial ratios. The Altman model originated from his study in 1968. The multiple discriminant analysis technique was selected as appropriate for bankruptcy prediction as a combination of ratios can be analyzed simultaneously.

The original discriminant function is as follows:

$Z1 = 0.012*X1 + 0.014*X2 + 0.033*X3 + 0.006*X4 +0.999*X5.$

Where

$Z1$= overall index

X1= working capital/total assets

X2= retained earnings/total assets

X3= earnings before interest and taxes/total assets

X4= market value equity/book value of total liabilities

X5= sales/total assets.

The z-score resulting from this equation is a basis for the classification of firms into prediction zones as distressed, non-distressed or a grey zone in between.

The working capital/total assets ratio considers liquidity and size characteristics. The working capital is defined as the difference between the current assets and current liabilities, and a firm with consistent operating losses will have declining current assets relative to total assets. The retained earnings/total assets ratio is implicitly considering a firm age element as relative younger firms will probably have lower scores because they had less time to build up retained earnings. This reflects the fact that bankruptcy is higher in the early years of firms. The EBIT/total assets ratio measures the true productivity of the firm's assets, without the influence of any tax or interest factors.

The market value equity/book value of total liabilities ratio adds a market value dimension and shows how much the firm's value can decline before the liabilities exceed the assets and the firm becomes insolvent. The sales/total assets ratio is an asset turnover ratio that indicates the efficiency of the firm's assets. In the equation it is the least significant ratio on an individual basis, but because of its relation to the other variables in the model, it has a relatively big contribution to the overall discriminant function.

In the original Altman study (1968) the z-score model classified 95% of the sample correct in the year prior bankruptcy. The sample in 1968 consisted of 66 firms whereof 33 were bankrupt and 33 were non-bankrupt. The firms having a z-score greater than 2.99 fall into the non-bankrupt group and firms with a z lower than 1.81 are all predicted bankrupt, while firms with a score between 1.81 and 2.99 fall into the "grey zone".

2.3.3 REVISED ALTMAN Z-SCORE MODEL

The 1983 version of the Altman z-score model that will be used in this thesis basically works in the same way as the original, but it is revised for privately held firms and both manufacturing and non-manufacturing firms. The revised model uses the book value of equity instead of market value of equity and the coefficients of the variables are re-estimated as are the cut-off points for distress, grey and safe zones. The results of Altman's study in 2000 suggested several conclusion, including that the relative predictive ability decreases together with the increase of the lead time. However, the z-score model was accurate in predicting distress two to three years prior bankruptcies.

The function of this revised z-score model is:

Z2= 0.717*X1 + 0.847*X2 + 3.107*X3 + 0.420*X4 + 0.998*X5.

Where

X1=working capital/total assets

X2=retained earnings/total assets

X3=EBIT/total assets

X4=book value equity/total liabilities

X5=sales/total assets

And the cut-off points are z-scores above 2.9 for the "safe" zone, under 2.9 and over 1.23 for the "grey" zone, and z-score under 1.23 for the "distress" zone. Firms in the safe zone are considered 'Safe' based on financial figures only, while scores in the distress zone indicate a strong probability of distress within a year, while the grey zone was defined by Altman (1968) as a zone of ignorance, because of the susceptibility of error classification.

Summarizing the financial variables which are used in Altman's bankruptcy prediction model are; from the income statement: net sales and EBIT (or operating profit), and from the balance sheet: current and total assets, current and total liabilities, retained earnings and the book values of equity (net worth). Furthermore based on Altman's (2000) conclusions it is best to test the accuracy of the z-score model one to three years prior bankruptcies and not more years prior bankruptcies.

2.3.4 FOUR-VARIABLE ALTMAN Z-SCORE MODEL

Altman (1983) also developed a four-variable Z-score model without the Sales / Total Assets ratio. Literature (Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2016) mentioned that there is a potential industry effect influencing financial distress analysis. Firms in different industries tend to report different levels of the same financial ratios, which may have an effect on the boundary between bankrupt and non-bankrupt firms. Altman (1983) recognized this potential industry effect due to the wide variation among industries in assets turnover and therefore excluded the X5 (sales / total assets) ratio in the estimations.

The four-variable Z-score model has sometimes been given various names like a model for US-non manufacturing, for foreign (non-US) markets or for emerging countries. What was concluded by the Altman et al. (2016) study is that this four-variable model works consistently across different countries, because it minimalizes the potential industry effect.

The function of this z-score model is:

Z3 = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25

Where the variables are the same ratios as the revised Altman z-score model (1983). Although a constant is added to the function and the zones are adjusted to:

Distress zone below 1.1, the grey zone between 1.1 and 2.6, and the safe zone above 2.6.

The EBIT/Total Assets Ratio (X3), contributed the most to the discrimination power in this version of the model (Altman et al. 2016). The classification result for this four-variable model was identical to the revised five-variable model. In the international study by Altman et al. (2016) this four-variable model had the most focus, because it had the widest scope.

2.4 PRIOR RESEARCH

In this section, prior research on the accuracy of bankruptcy prediction models will be discussed. The empirical results of key research for the development of the Altman z-score model as well as studies that tested the z-score with their own samples from other environments and time frames.

Bankruptcy prediction research in the Netherlands

Influential research on bankruptcy prediction in the Netherlands were the studies from Bilderbeek (1977) and van Frederiklust (1978). They encountered small sample sizes of 85 and 40 firms, but their study however added evidence that financial ratios indicate information on bankruptcy prediction (Altman, 1984). Also, an influential researcher on financial distress from the Netherlands was Pompe, although he did his researches with Belgian data. Pompe & Bilderbeek (2000) suggested that no longer publishing a yearly financial statement by a firm can be seen as the material moment of bankruptcy. Pompe (2001) also tested hypotheses on the effects of firm age and size on the predictive power of a model. Results showed that firm young than 8 years were more difficult to predict than older firms and the size effect was only partly supported, the middle-sized firms were most successfully predicted. Another study by Pompe (2005) showed that there is no fixed order in which categories of ratios start being predictive in years before bankruptcy.

Prediction accuracy testing

Testing the predictive ability or accuracy has been done in various studies over the years. In this section, relevant studies will be discussed on how they tested and analyzed bankruptcy prediction models, in particular, Altman's z-score, on various samples from different environments. These studies analyzed the predictive results of the z-score model itself or compared the predictive ability to alternative models or sometimes even simple measures like prior year losses (Agarwal & Taffler 2007). The results of the study by Agarwal and Taffler also suggested that in terms of predictive accuracy, there is little difference between the market-based and accounting models.

One of the key resembling studies is the study by Grice & Ingram (2001). Grice & Ingram used data from the United States, as did most studies on bankruptcy prediction, from the years 1985 to 1991 from 1002 firms, whereof 148 were distressed and 854 were non-distressed. Of the 148 distressed firms, 92 were bankrupt. The study also tested the z-score model's ability to assess financial distress conditions other than bankruptcy. The study evaluated the classification accuracy using the full sample plus subsets of the sample like only bankrupt firms in the distressed group or only manufacturing firms. The accuracy was calculated by dividing the number of firms correctly predicted by the total number of firms in the sample, this is the same way it will be done in this thesis. Grice & Ingram also used the Altman z-score with re-estimated coefficients to compare the results with those using Altman's original model (Z1).

Using the original Altman's z-score model on Grice & Ingram's sample resulted in an overall accuracy of 57.8% correctly classified. Other results of their study suggested that Altman's model is more useful for predicting financial distress of manufacturing firms (69.1% accuracy) than for non-manufacturing firms and using the Altman z-score model with re-estimated coefficients resulted in an overall accuracy of 88.1%. Thus Grice & Ingram suggested that significantly better classification results can be achieved when the original coefficients (Z1) of the Altman z-score model are re-estimated.

Research is done in a simpler manner by Machek, who focused on a bankrupt only sample of firms from the Czech Republic. The study was focused on whether the models, among others the Altman's z-score model for private firms (Z2), correctly predicted bankruptcies one to five years in advance. The results gave percentages of correct predictions of bankruptcies and compared these percentages with the results of other bankruptcy prediction models like the Kralicek Quick Tests (1991) and the Taffler model (1997). The results showed percentages of correct predictions between 37 and 45 % over the different years for the Altman model. The predictive ability of Quick test and Taffler model in this study seemed limited, while the usefulness, in predicting financial distress in the Czech environment, of the Altman's z-score was confirmed. Furthermore, the results showed that the z-score model does not significantly lose predictive ability over course of time. Thus it will be interesting to see if that will be the same for the sample used in this thesis, whether or not the predictive ability decreases as the years' prior bankruptcy increase.

The Altman z-score model for private firms (Z2) was also tested in the Czech Republic by Karas Reznakova, Bartos & Zinecker (2014). The results were about the same as Machek (2014) with a predictive accuracy of the z-score model of 50.1%. A re-estimation of the z-score model was also included in their study and the main reason they did re-estimation was that they saw results falling the grey zone as failing to evaluate firms. As the number of firms in the grey zone led to a significant limitation on the practical usage of the model according to the authors, the model was revised for the Czech Republic by recalculating the discriminant function including the boundaries of the grey zone. The number of firms in the grey zone was reduced by 69% and the accuracy rate increased to 77.9%.

Another study that tested the extent to which Altman's z-score were able to predict bankruptcy was the study by Alkhatib & Al Bzour (2011). Although this was a rather small study based on data from 32 Jordanian firms, it gave a simple example of testing prediction accuracy. The accuracy of bankruptcy prediction was in the first, the second and the third year prior bankruptcy 100%, the results thus suggested that Altman's z-score model is able to predict accurately during the five years prior bankruptcy. Furthermore, Wang & Campbell (2010) studied the predictive ability of various z-score models on a sample of 1336 Chinese publicly listed firms from the year 1998 till 2008. Failure was defined as a firm that has been delisted from the stock exchange during the studied period. This study only tested the predictive accuracy of one year prior the failure. The original Altman model scored a predictive accuracy of 83.33% while the re-estimated Altman models scored an accuracy rate of 87.5%. Although these accuracy rates were lower than the by Wang & Campbell re-estimated z-score model (95.83%), the results though do validate the usefulness of Altman's z-score models in predicting bankruptcies and de-listings in China.

A study by El Khoury & Al Beaïno (2014) compared results from Altman's z-score model against classifications from the banks in Lebabon. Results in this study suggested that the z-score model can accurately classify similar to banking classifications. Kim & Choi (2013) on the other hand compared the results of the z-score model in South Korea to financial performances measures as profitability (return on assets) and implied cost of capital. Kim & Cho's results supported evidence that the Altman z-score model can be used as a bankruptcy classification criteria on South Korean firms.

Coefficient re-estimation research

Begley, Ming & Watts (1996) and Hillegeist, Keating, Cram & Lundstedt (2004) revised Altman's original z-score model by re-estimating the coefficient on their new data from US samples. Hillegeist et al (2004) suggest that the reasons for the change in associations between accounting variables and the probability of bankruptcy for the United States are the changes in legal environments and the changes in accounting rules, which causes differences in how accounting variables are measured. Begley et al. (1996) also mention this by stating that the changes in bankruptcy laws in the United States in the late 1970s allowed for greater strategic use of bankruptcy. In their revised models the coefficients have substantially changed, which also suggested that the relationship between accounting variables and the probability of bankruptcy is not stable over time. However, both studies found out that their revised models perform about equal or less well than the original model. Although the use of multiple discriminant analysis decreased, it remained a generally accepted standard method for comparative studies (Balcaen & Ooghe, 2006).

Like this literature review, the review of Altman et al. (2016) also showed that the results for z-score models have been various over studies, sometimes scoring around 50% of accuracy and sometimes around 90% accuracy. Thus in the Altman et al. (2016) study, they assess various factors on the performance of the z-score model through an international comparison. The Altman et al. (2016) used, similar to this thesis, the Orbis database to collect data from 32 European and 3 non-European countries. The hypothesized factors affecting the model's performance were coefficient re-estimation, estimation method, year, size, age, industry, and country. The results of Altman et al. (2016) showed that original coefficients are extremely robust across countries and over time. The effects of bankruptcy year and size were stronger, but these had strong variations between countries, furthermore, the results showed that the effects of age, industry, and country were marginal. The study thus suggested that the z-score model performs well in an international context, however, it is possible to derive a more efficient country model for most countries by re-estimating the model.

In table 2 an overview will be given of a few relevant studies with their methods and main findings.

Table 2 Overview relevant bankruptcy prediction accuracy research

Author, year.	**Sample locations and years**	**Findings** (1 year prior bankruptcy accuracy %)	**Remarks**
Grice & Ingram, 2001	United States, 1985-1991	Altman's model' is more useful for predicting financial distress of manufacturing firms than for non-manufacturing firms and using the Altman z-score model with re-estimated coefficients resulted in higher overall accuracy. (57.8% original z-score)	Used original Altman model (Z1), and did re-estimation.
Wang & Campbell, 2010	China, 1998-2008.	Confirms usefulness z-score models in predicting firms de-listings (83.33 % original z-score)	Used original Altman model (Z1), and did re-estimation.
Machek, 2014	Czech-Republic, 2007-2012	Usefulness in predicting financial distress of Altman z-score was confirmed. Results showed that the z-score model does not significantly lose predictive ability over course of time, even until 5 years prior bankruptcy. (44,33 %)	Used a bankrupt only sample.
Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2016	32 European countries and Columbia, China & US, 2007-2010.	General z-score model works reasonably well for most countries (around 75% prediction accuracy). Classification accuracy can increase by re-estimations.	Did re-estimation using logistic regression analysis and different additional variables.

Summarizing the prior research and table 2 it can be considered that in most prior research the accuracy rates of the z-score model for bankrupt firms deviate from around 50% to 80% accuracy. Thus it can be expected that the results of this thesis on the accuracy rates can also be around this range.

Furthermore the literature review suggests that re-estimation should also be done in this research. As the Netherlands and the time period researched is a different environment than that the model was designed in, the results can be expected to be inaccurate if the model will be used in its original form.

2.5 CONCLUSIONS

Before going further to the empirical section of this thesis some general answers can be given on the first four sub-questions.

Relating to this thesis an answer to the first sub-question 'What is bankruptcy?' is that bankruptcy is a state which is declared by the court on firms who are unable to pay debts owed to its creditors. Bankruptcy is often preceded by a situation of financial distress, which can have various overlapping causes. After a bankruptcy filing, there are various effects on various stakeholders, which are not just purely financial effects.

The second sub-question was 'How does the Dutch bankruptcy system works?'. In the Netherlands the firms in financial distress have the options of informal reorganization, suspension of payments and filing for bankruptcy. Filing for bankruptcy can also be done by creditors and if the firm is declared bankrupt a trustee is appointed, who aims to liquidate or sell business parts as going concern, whereby the interest of the creditors goes first. The yield is then distributed according to certain priority rules. Compared to neighboring countries the Netherland has a more on reorganization focused code instead of liquidation focused.

Next was the third the sub-question which relates to what bankruptcy prediction models are. Generally, bankruptcy prediction models are tools to predict whether or not a firm will go bankruptcy based on financial data. These models can be based both on various statistical techniques as well as various intelligent (non-parametric) techniques.

The fourth sub question went more into depth as to how the Altman z-score model works. The Altman z-score model is a multiple discriminant analysis considering five financial ratios, which consider liquidity, size, productivity, solvency, and efficiency of a firm's assets. The function of the model gives scores in three classifications, the 'safe' or 'bankrupt' zone or the zone in between named 'grey zone'.

To come to answers on the fifth sub question the rest of this thesis will be focused on the empirical part of the research. The prior resembling research will be used in setting up the research design.

2.6 HYPOTHESES

As mentioned in section 2.4, Altman et al. (2016) showed that the original coefficients of the z-score model are extremely robust across countries and over time. The in 1983 revised version of the Altman z-score model (Z2) will be analyzed in the Dutch private firm environment. As this model (Z2) suggests, bankrupt firms should have z-scores under 1.23 to be in the predicted bankruptcy zone and non-bankrupt firms should have z-scores above 2.9 to be in the 'as safe predicted' zone.

It is interesting to test how the model (Z2) performs in a different environment and time-period as it was originated from. As suggested by the intention of the model and by the studies that tested the Altman z-score (Grice & Ingram, 2001, Wang & Campbell, 2010, Macheck, 2014, Altman et al., 2016, etc.), firms that are declared bankrupt should have a z-score falling in distress zone. Thus the first and main hypothesis of this thesis is as follows:

H1: Bankrupt firms have z-scores falling in the distress zone.

Similar, it was the intention of Altman model that non-bankrupt firms will have such financial ratios that they distinguish themselves from the bankrupt firms with help of the model, as they score a z-score in the safe zone. Following the arguments of the first hypothesis this leads to a second hypothesis as follows:

H2: Non-bankrupt firms have z-scores falling in the safe zone.

These first two hypotheses will be tested on the 1983 revised version of the Altman z-score model (Z2), which is the main focus of this research. Furthermore the four-variable revised version of 1983 (Z3) will also be tested.

Literature (Altman et. al., 2016) mentioned that there is a potential industry effect influencing on financial distress analysis. Firms in different industries tend to report different levels of the same financial ratios, which may have an effect on the boundary between bankrupt and non-bankrupt firms. Altman (1983) recognized this potential industry effect due to the wide variation among industries in assets turnover and therefore excluded the X5 (sales / total assets) ratio in estimating Z3. Altman et al., 2016 also showed that the four-variable Altman z-score (Z3) works consistently well internationally. The third hypothesis aims to analyse differences in the classification performance of this model (Z3) compared to the previously tested (Z3). This leads to the following hypothesis:

H3: The four-variable Altman z-score model (Z3) increases the classification accuracy compared to the revised Altman z-score model (Z2).

Altman (1983) recommended using data as near to the present as possible when developing a bankruptcy prediction model. Firms financial behaviour and business environment change significant over time. Thus the importance of the financial ratios, as reflected by the coefficients, may differ from the original model. Therefore studies (Altman et. al, 2016, Grice & Ingram, 2001) suggested that it is possible to derive a more efficient model for most countries by re-estimating the model.

Based on the sample used in this thesis, re-estimation is done of the coefficients of the financial ratios of Z2. Like Grice & Ingram (2001) did, the re-estimation of this thesis is done by using logistic regression analysis. Based on the logistic regression analysis a re-estimated three-variable model (Z4) is estimated. The aim is to support prior evidence that re-estimation will improve classification performance, by testing the potential increase of Z^4 classification performance compared to Z4. This is expressed by the fourth hypothesis:

H4: Coefficient re-estimation by regression analysis (Z4) increases the classification accuracy compared to the revised Altman z-score model (Z2).

It can be noted that all the four hypotheses are explicitly about classification accuracy. It is common (Grice & Ingram, 2001, Altman et al. 2016, Machek, 2014) that the accuracy rates decline as the more years prior the bankruptcy. So in addition, the classification accuracy of bankrupt firms will be analysed in the three years prior bankruptcy (t-1 to t-3).

3. RESEARCH DESIGN

In this chapter the empirical phase of this research will start. The research methodology will be made clear, the specifications of the model will then be given, whereafter the sample selection and the data collection will be described.

3.1 METHODS

The research method resembles that of the studies by Grice and Ingram (2001) and Altman et al. (2016). From the results of the hypotheses, conclusions can be stated on the current state of predictive accuracy of the Altman z-score model in the Netherlands.

An additional question can be how much percentage the model should classify accurate to state that it is able to predict accurately. Other prior studies compared the accuracy with other models accuracy or against another factor as bankruptcy year, number of years prior bankruptcy, industry, firm age, firm size, country or others. A study by Altman et al. (2016) offered evidence that the z-score model worked reasonably well for most countries with prediction accuracy rates around 75 percent. Thus if one-year prior bankruptcy the accuracy rate is above 75 percent, it can be suggested as accurate.

3.1.1 MODEL SPECIFICATION

The first model used for analyzing is the revised Altman z-score model for private firms from 1983 (Z2). This revised model used the book value of equity instead of market value of equity and new weights (coefficients) are assigned to the variables. This formula of the model is as follows:

$$Z2=0.717*X1 + 0.847*X2 + 3.107*X3 + 0.420*X4 + 0.998*X5$$

And the zones are: $Z<1.23$ = “distress” zone, $1.23< Z < 2.9$ = “grey” zone, $Z>2.9$ = “safe” zone.

The following definitions for the variables are used:

X1: is the same (Working Capital / Total Assets)

X2: was Retained Earnings / Total Assets; Shareholders Income / Total Assets is used. Shareholders income is collected from the Profit and Loss account. It was the income after taxes minus the minority interests.

X3: was EBIT/Total Assets. Operating Results / Total Assets is used. Operating result was always the same as EBIT, when EBIT was available in the data. Therefore operating result was used, because sometimes EBIT was missing.

X4: Book Value of Equity / Book Value of Total Liabilities. Shareholders’ Funds / Total Debt is used. Seems that in the database of the sample another terminology is used for Equity value, which was the same case for Total Liabilities, wherefore Total Debt is used.

X5: is the same (Net Sales / Total Assets)

3.1.2 ROBUSTNESS CHECKS

Secondly the four-variable Altman z-score model (Z3) is tested. This model has the same ratios, except for X5 (net sales / total assets) which is left out. This was done by Altman (1983) because he recognized a wide variation in assets turnover among industries, this made the model work more consisted internationally. In the formula there is also a constant added:

Z3= 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25

The zones are: Z<1.1 = "distress" zone, 1.1< Z < 2.6= "grey" zone, Z>2.6 = "safe" zone.

In this study a revision is done of the Altman z-score model by re-estimation the coefficients with regression analysis. The regression analysis was done on the t-1 sample, which is further discussed in section 3.2 and 3.4 of this thesis. After winsorizing the variables at the 99th and 1st percentile, only the significant ratios were included in the equation, which gave the following formula:

Z4= 2.001*X1 + 7.614*X3 + -0.288*X5 + 7.014

The cut-off point of this formula for the safe and distress zone is 0,5, there is no grey zone obtained from the logistic regression analysis.

3.1.3 TYPE I & TYPE II ERRORS

Type I and Type II errors can be distinguished by using the sample groups of bankrupt and non-bankrupt firms. The first hypothesis was 'Bankrupt firms have z-scores falling in the distress zone' In the first hypothesis, Type I error means that the hypothesis is rejected and thus that the bankrupt firm does not fall in the distress zone. Type II error means that non-bankrupt firms are falsely scoring a z-score in the distress zone. It is generally agreed upon that Type I errors are more costly than Type II errors for several reasons including loss of business (audit clients), damage to a firm's reputation, and potential lawsuits or court costs (Bellovary et al. 2007). Table 3 gives a synopsis of what type I and II errors are according to the hypothesis that 'bankrupt firms have z-scores falling in the distress zone'.

Table 3 Overview type I and type II errors

	Bankrupt	Non-bankrupt
Predicted: Bankrupt	Accurate percentage	Type I error
Predicted: Non-bankrupt	Type II error	Accurate percentage

This overview helps in defining the classification accuracy in the tests of hypotheses H3 and H4.

3.2 SAMPLE SELECTION AND DATA

The data for this study is collected from the REACH database, published by Bureau van Dijk. REACH contains income statements and balance sheet information for millions of firms. Following Altman et al. (2016) the requirements for the empirical data are that the firms are unlisted and non-financial, the firm-owners must have limited liability, so partnership and sole proprietors are left out, and there is a minimum requirement for the size of firms. Balcaen and Ooghe (2006) also suggested that financial ratios in very small firms are generally too unstable for a bankruptcy prediction model. In this thesis the same minimum of total assets is used as Altman et al. (2016) used, which is 100.000 euros. The private firms used in this research are all 'private limited liability organization' ('Besloten Vennootschap met beperkte aansprakelijkheid') and this is the most common entity in the Netherlands.

The status of the firms was bankrupt or active (non-bankrupt) and the B.V. was based in the Netherlands. To not limit the scope of the model in this study, bankrupt firms from all industry groups were collected. Based on the primary industries (SBI-codes) of the bankrupt firms all the non-bankrupt firms of those same industries were collected. Furthermore because there are many private limited liability entities organized under holdings in the Netherlands, only the data from firms with consolidated accounts were used.

Many firms in the sample had the primary industry code of a holding. It was chosen to keep these holdings included in the sample. Collecting based on the subsidiary industry codes was tried, however most holdings consisted out of multiple subsidiaries, so this was not done in this research.

For t-1 the sample consisted out of firm data from 2009 to 2015, for t-2 from 2007 to 2015, for t-3 from 2007 to 2014. The financial information was not always available in the database for each year. Only firms with complete financial parameters available for one year were included in the sample. For example when variable X5 was not available for a bankrupt firm in the year t-1, t-1 for that firm was not included, but it occurs that t-2 for that firm is completely available and thus was included. This is also the reason that the counts of firms through the years t-1 to t-3 variates. More on the counts of the definitive sample used can be found in the section of descriptive statistics.

Pompe & Bilderbeek (2000) suggested that no longer publishing a yearly financial statement by a firm can be seen as the material moment of bankruptcy. In this thesis this will be not considered as our database gave the true moment (year) of the declaration of bankruptcy. A check was included on whether the year of last available data was t-1, t-2 or t-3. Furthermore it was checked whether non-bankrupt firms last available data was from 2016 or later.

Outliers

Outliers are observations that lie at an abnormal distance from other values in a sample. There are various approaches on how to flag these outliers and how to handle them. Two common approaches are trimming and winsorizing. Trimming excludes outliers, while winsorizing replaces these extreme values with certain percentiles (the trimmed minimum and maximum).

Altman et al. (2016) winsorized the independent variables at the 1 and 99 percent level to minimize extreme outliers. This will also be done in this research. Furthermore, trimming was also done for this research, but it did not result in significant differences to winsorizing, so it will be left out the results in this thesis.

3.3 DESCRIPTIVE STATISTICS

An overview of the descriptive statistics of the full sample is presented in table 4. For each financial ratio for each of the years and both of the groups, the count, mean, median, minimum, maximum and standard deviation can be analysed. Furthermore the aim of table 4 is to compare the variables and to observe mean differences between the bankrupt and non-bankrupt firms. Therefore a t-test with a confidence level of 95% is conducted.

The comparison of bankrupt and non-bankrupt variable means is indicating that work capital/ total assets (X1), shareholders income / total assets (X2), operating results/ total assets (X3) and shareholders funds / total debt (X4) were lower in the bankrupt group that in the non-bankrupt group for all the three years. These variables X1 through X4, are all significant at the 1% level, indicating an extremely significant difference in these variables between the bankrupt and non-bankrupt groups. The discriminant coefficient for these show positive signs, so these results are as what one would expect. In other words, the greater a firm's bankruptcy potential the lower is the score for each variable.

For the net sales/ total assets ratio (X5) the mean difference shows the opposite and in the first and third year prior bankruptcy slightly less significant. This implies that bankrupt firms score higher in the X5 ratio than non-bankrupt firms. This matches the studies by Altman (1983) and Altman et. al (2016) that the estimated four-variable model without the X5 ratio performs better in an international environment.

The shareholders funds/ total debt ratio (X4) shows the biggest mean difference, which corresponds with the descriptive statistics of all the data of Altman et al. (2016). Grice & Ingram (2001) also has corresponding mean differences for X1 through X3 in the same direction. For X4 and X5 Grice & Ingram's study did not show a significant difference between the groups. For the non-bankrupt group the mean only exceeds the median significantly for the X4 ratios, which indicates a positively skewed distribution for the shareholder fund/ total debt ratio (X4).

We currently cannot yet expect whether in the classification results there will be Type I or Type II errors. For now, most of the ratios of the Altman z-score model do show some potential to classify between bankrupt and non-bankrupt correctly in this sample. The next chapter will further look at accuracy tests and explore this more.

Table 4 Descriptive statistics

	Bankrupt						Non-bankrupt						T-test	
t-1	N	Mean	Median	Min.	Max.	St. Dev	N	Mean	Median	Min.	Max.	St. Dev.	Mean Diff.	Sig.
X1	21	-0.177	-0.159	-0.623	0.676	0.319	11296	0.138	0.130	-0.623	0.748	0.247	-0.315	***
X2	21	-0.168	-0.110	-0.425	0.040	0.180	11296	0.030	0.030	-0.425	0.349	0.102	-0.198	***
X3	21	-0.151	-0.098	-0.376	0.056	0.177	11296	0.058	0.052	-0.376	0.416	0.107	-0.208	***
X4	21	0.107	0.104	-0.422	1.957	0.529	11296	0.883	0.511	-0.422	8.208	1.271	-0.776	***
X5	21	2.756	1.612	0.173	7.121	2.356	11296	1.740	1.486	0.039	7.121	1.267	1.016	**
t-2														
X1	171	-0.055	-0.041	-0.598	0.764	0.315	15928	0.151	0.143	-0.598	0.764	0.244	-0.207	***
X2	171	-0.113	-0.064	-0.427	0.202	0.158	15928	0.035	0.033	-0.427	0.359	0.100	-0.148	***
X3	171	-0.100	-0.044	-0.453	0.270	0.169	15928	0.061	0.055	-0.453	0.430	0.113	-0.160	***
X4	171	0.210	0.125	-0.413	8.215	0.743	15928	0.870	0.510	-0.413	8.215	1.253	-0.659	***
X5	171	2.275	1.932	0.090	7.076	1.624	15928	1.785	1.533	0.040	7.076	1.281	0.490	***
t-3														
X1	168	0.013	0.007	-0.578	0.772	0.289	13060	0.152	0.143	-0.578	0.772	0.244	-0.139	***
X2	168	-0.050	-0.021	-0.400	0.310	0.123	13060	0.034	0.032	-0.400	0.350	0.097	-0.084	***
X3	168	-0.046	-0.010	-0.438	0.412	0.144	13060	0.060	0.055	-0.438	0.424	0.111	-0.106	***
X4	168	0.271	0.152	-0.393	8.746	0.769	13060	0.874	0.507	-0.393	8.746	1.292	-0.603	***
X5	168	1.968	1.569	0.039	6.846	1.518	13060	1.784	1.537	0.039	6.846	1.264	0.183	**

X1= Working Capital / Total Assets, X2= Shareholders Income / Total Assets, X3= Operating Result / Total Assets, X4=Shareholders funds / total debt, X5= Net Sales / Total Assets

***= 1% significance, **=5% significance, *=10% significance (statistical significance level)

3.4 COEFFICIENT RE-ESTIMATION

Like mentioned in section 3.1.2 a coefficient re-estimation with regression analysis is done based on the t-1 part of the sample. Table 5 presents the correlation matrix of the variables. The correlations matrix is a comparison of how closely related two variables are. Table 5 shows that there are not very high correlations between variables, and most are even negative correlations. For example, the biggest negative correlation is between the variables shareholders income / total assets (X2) and operating results / total assets (X3) with a correlation of -0.834.

Table 5 Correlation matrix

	Constant	X1	X2	X3	X4	X5
Constant	1.000					
X1	0.208	1.000				
X2	0.147	-0.153	1.000			
X3	0.068	-0.051	-0.834	1.000		
X4	-0.534	-0.453	-0.104	-0.054	1.000	
X5	-0.626	0.033	0.037	0.009	0.119	1.000

X1= Working Capital / Total Assets, X2= Shareholders Income / Total Assets, X3= Operating Result / Total Assets, X4=Shareholders funds / total debt, X5= Net Sales / Total Assets

Table 6 presents the steps of the regression analyses based on the significance of each variables beta (coefficient). In the first step only the constant and variables of operating results / total assets (X3) and net sales / total assets (X5) are statistically significant. At the second step of the regression the variable working capital / total assets (X1) also is significant at the 95% significance level. The net sales / total assets ratio (X5) gives a negative coefficient. This negative coefficient would mean that the higher the net sales / total assets the more probability on bankruptcy in this sample. Eventually only the significant ratios are included in the equation which gave the following formula:

$$Z4= 2.001*X1 + 7.614*X3 + -0.288*X5 + 7.014$$

Table 6 Regression Analysis

		B	Sig.			B	Sig.
Step 1	X1	1.618	0.094	Step 2	X1	2.001	0.016
	X2	-0.728	0.782		X3	7.614	0.000
	X3	8.026	0.003		X5	-0.288	0.011
	X4	0.444	0.440		Constant	7.014	0.000
	X5	-0.275	0.016				
	Constant	6.782	0.000				

X1= Working Capital / Total Assets, X2= Shareholders Income / Total Assets, X3= Operating Result / Total Assets, X4=Shareholders funds / total debt, X5= Net Sales / Total Assets

4. RESULTS

In this chapter, the results of the empirical part of this research are analysed and discussed.

4.1 DESCRIPTIVE STATISTICS Z-SCORES

Table 7 represents the descriptive statistics of the three z-score models tested over the three years. As done in the descriptive statistics of the variables, a t-test for mean differences, between the bankrupt and non-bankrupt group, is conducted with a confidence interval of 95%.

Table 7 Descriptive statistics z-scores

	Bankrupt						Non-Bankrupt						T-test	
t-1	N	Mean	Median	Min.	Max.	St. Dev.	N	Mean	Median	Min.	Max.	St. Dev.	Mean Diff.	Sig.
Z2	21	2.058	1.348	-1.186	5.004	2.074	11296	2.411	2.244	-2.003	10.646	1.500	-0.353	
Z3	21	0.640	1.150	-5.190	8.658	3.734	11296	5.567	5.197	-5.190	19.131	3.012	-4.927	***
Z4	21	4.718	5.456	0.851	7.291	2.146	11296	7.228	7.224	0.851	11.385	1.088	-2.510	***
t-2														
Z2	171	1.913	1.583	-1.892	7.360	1.703	15928	2.472	2.305	-2.223	10.620	1.511	-0.559	***
Z3	171	2.069	2.500	-5.544	16.895	3.671	15928	5.677	5.335	-5.544	20.945	2.973	-3.607	***
Z4	171	5.487	5.845	0.326	8.793	1.844	15928	7.263	7.266	0.342	11.753	1.112	-1.776	***
t-3														
Z2	168	1.903	1.589	-0.556	7.120	1.616	13060	2.473	2.306	-1.949	10.356	1.492	-0.570	***
Z3	168	3.151	2.893	-5.201	18.494	3.042	13060	5.683	5.334	-5.201	21.486	2.976	-2.532	***
Z4	168	6.125	6.297	1.264	9.519	1.495	13060	7.261	7.266	0.549	11.741	1.101	-1.136	***

***= 1% significance, **=5% significance, *=10% significance (statistical significance level)

For non-bankrupt firms the mean and median are close to each other, which indicates symmetry of distributions. For the failed firms however, the median differs more from the mean in various directions, which indicates skewed distributions. It shows especially more difference between mean and median in t-1, so this suggests that the more year prior bankruptcy the more symmetry there is in the distribution of bankrupt firms in this sample.

A comparison of the mean differences indicates that the z-scores are lower for bankrupt firms than for non-bankrupt firms. Although for Z2 in t-1 the mean difference is not significant, the other differences are all significant at the 1% level. The significant differences correspond with the expectations that the higher the z-score, the lower the bankruptcy potential. This coincides with the results of other studies like Altman et al. (2016) and Grice & Ingram (2001). What does not coincide with the expectation and these other studies is that for Z2 the mean differences get bigger the more years prior bankruptcy. For Z3 and Z4 though, the mean differences do get smaller, as expected, the more years prior bankruptcy.

4.2 TESTING MAIN HYPOTHESES

The main and first hypothesis of this thesis was:

H1: Bankrupt firms have z-scores falling in the distress zone.

To test the first hypothesis a one sample t-test of the bankrupt firms is done against the value 1.23, which is the border of the grey zone. The results are presented in the left-sided part of table 8. The results suggest that for Z2 the true mean of bankrupt firms in t-1 higher than the grey zone (p=0.082, mean difference=0.828). For t-2 (p=0.000, mean difference=0.683) and t-3 (p=0.000, mean difference=0.673) the means are also higher than the grey zone. This is evidence that the main hypothesis cannot be supported for the revised z-score of 1983 (Z2).

When testing the same for the four-variable z-score model (Z3) against the zone border of z<1.1, the mean difference in t-1 is lower than the grey-zone, though insignificant (p=0.579, mean difference=-0.579). For t-2 (p=0.001, mean difference=0.969) and t-3 (p=0.000, mean difference 2.051) the mean difference is significant, thus the first hypothesis can also be rejected for the four-variable model (Z3).

The results of the one-sample t-test, on the in this study re-estimated z-score model (Z4) are about the same (t-1; p=0.000, mean difference=4.218. t-2; p=0.000, mean difference=4.987. t-3; p=0.000, mean difference=5.625). So overall these results suggest that there is no evidence to support the first hypothesis.

Table 8 One sample t-tests

		Bankrupt				Non-bankrupt			
Model	Year	Mean	Test value	Mean diff.	Sig. (2-tailed)	Mean	Test value	Mean diff.	Sig. (2-tailed)
Z2	t-1	2.058	1.23	0.828	0.082	2.411	2.9	-0.489	0.000
	t-2	1.913	1.23	0.683	0.000	2.472	2.9	-0.428	0.000
	t-3	1.903	1.23	0.673	0.000	2.473	2.9	-0.427	0.000
Z3	t-1	0.640	1.1	-0.460	0.579	5.567	2.6	2.967	0.000
	t-2	2.069	1.1	0.969	0.001	5.677	2.6	3.077	0.000
	t-3	3.151	1.1	2.051	0.000	5.683	2.6	3.083	0.000
Z4	t-1	4.718	0.5	4.218	0.000	7.228	0.5	6.728	0.000
	t-2	5.487	0.5	4.987	0.000	7.263	0.5	6.763	0.000
	t-3	6.125	0.5	5.625	0.000	7.261	0.5	6.761	0.000

In table 8 the results of the t-test of mean differences of the non-bankrupt against the upper grey zone borders are also presented. The aim of the right-sided part of the table is to test the second hypothesis of this thesis.

H2: Non-bankrupt firms have z-scores falling in the safe zone.

The second hypothesis looks at the non-bankrupt firms and one-sample t-tests are done again the upper grey zone border values. For the revised 1983 model (Z2) the means are significantly (at the 1% level) smaller than the score to fall in the safe zone for each year (t-1;

p=0.000, mean difference=-0.489. t-2; p=0.000, mean difference=-0.428. t-3; p=0.000, mean difference=-0.427). This result suggests that there is no evidence to support the second hypothesis for the Z2 model.

The results for the four-variable model (Z3) though do support the second hypothesis. The non-bankrupt scores significantly higher than the score to fall in the safe zone, so they fall, as expected, within that prediction zone (t-1; p=0.000, mean difference=2.967. t-2; p=0.000, mean difference=3.077. t-3; p=0.000 mean difference is 3.083).

With the 0.5 zone border for the in this study re-estimated model (Z4), the results also support the second hypothesis (t-1; p=0.000, mean difference=6.728. t-2; p=0.000, mean difference=6.746. t-3; p=0.000 mean difference is 6.742). Non-bankrupt firms scores statistically significant higher Z4 scores than the 0.5 cut-off point, thus correctly predicting non-bankrupt firms as non-bankrupt. Although a recommendation for future research can be that when re-estimating coefficients, the zone-borders should also be re-estimated.

Compared to the conclusion of the Altman et. al (2016) and Grice & Ingram (2001) studies, that the Altman z-score model can predict bankrupt and non-bankrupt relatively correctly, these results suggest otherwise. In the sample of this thesis the results suggest that bankrupt firms are not correctly classified in the bankruptcy prediction zone. For non-bankrupt firms the results suggest that only the Z3 and Z4 models classify them in the correct non-bankrupt prediction zone.

4.3 CLASSIFICATION ACCURACY

Table 9 presents the classification and the accuracy percentages of the z-score models (Z2, Z3 & Z4) for each of the three years. Calculating these accuracy rates is done similar to Grice & Ingram (2001), by dividing the number of correctly predicted firms by the total number of firms.

When looking at the left side and middle section of table 9 a conclusion can be given on the third hypothesis of this thesis. The third hypothesis was as follows:

H3: The four-variable Altman z-score model (Z3) increases the classification accuracy compared to the revised Altman z-score model (Z2).

For the Z2 model the accuracy of bankrupt firms in t-1 is about 43 percent. In t-2 and t-3 the predictive accuracy of bankrupt firms stays around 40 percent. For non-bankrupt firms the predictive accuracy, for the three years, is around 33 percent correctly predicted. The accuracy of the four-variable Altman z-score model (Z3) is in t-1 for bankrupt firms around 48 percent. It then lowers in t-2 and t-3 to 34% and 18% for bankrupt firms. For non-bankrupt firms the correct predictions are around 90 percent. These results partially support the third hypothesis that the four-variable model increases the classification accuracy. In t-1 it does has increased classification accuracy, but for t-2 and t-3 it has just better classification accuracy for non-bankrupt firms.

So these result only partially support the third hypothesis. This does not correspond with the results of prior studies (Altman, 1983, Altman et al, 2016, Grice & Ingram, 2001) that the four variable model (Z3) improves the classification of samples across non-US countries. It does coincide with the notion that non-bankrupt firms are better classified in the right prediction zone. But predicting non-bankrupt firms correctly as non-bankrupt is not the only aim of a bankruptcy prediction model.

The left and right side of table 9 (Z2 and Z4) helps to discuss the fourth hypothesis, which was as follows:

H4: Coefficient re-estimation by regression analysis (Z4) increases the classification accuracy compared to the revised Altman z-score model (Z2).

The Z4 model gives, just in t-2, two right predictions for bankrupt firms. The rest of the bankrupt firms in the sample are falsely predicted as non-bankrupt by the re-estimated model (Z4). So the number of Type II errors is high, while there are no Type I errors. The non-bankrupt firms are all correctly predicted, but the value is questionable when almost none of the bankrupt firms are correctly predicted. Therefore these results suggest that there is not enough evidence, certainly for bankrupt firms, to support the fourth hypothesis. The revised model of 1983 (Z2) is in this sample still a better prediction model.

Re-estimation of coefficients based on logistic regression analysis did improve the classification accuracy in studies by Altman et al. (2016) and Grice & Igram (2001). While in this study the re-estimation did not work out as expected, future research suggestions can be useful based on re-estimation method and cut-off point determination. Moreover future research recommendation will be discussed in section 5.3 of this thesis.

Table 9 Classification results

	Z2					Z3					Z4				
Prediction	Bankrupt		Non-bankrupt		Total	Bankrupt		Non-bankrupt		Total	Bankrupt		Non-bankrupt		Total
Zone	N	%	N	%	N	N	%	N	%	N	N	%	N	%	N
t-1															
Distress	9	42.86%	2416	21.39%	2425	10	47.62%	504	4.46%	514	0	0.00%	0	0.00%	0
Grey	4	19.05%	5317	47.07%	5321	6	28.57%	746	6.60%	752	0	0.00%	0	0.00%	0
Safe	8	38.10%	3563	31.54%	3571	5	23.81%	10046	88.93%	10051	21	100.00%	11296	100.00%	11317
Total	21	100.00%	11296	100.00%	11317	21	100.00%	11296	100.00%	11317	21	100.00%	11296	100.00%	11317
t-2															
Distress	68	39.77%	3207	20.13%	3275	59	34.50%	611	3.84%	670	2	1.17%	2	0.01%	4
Grey	60	35.09%	7409	46.52%	7469	29	16.96%	984	6.18%	1013	0	0.00%	0	0.00%	0
Safe	43	25.15%	5312	33.35%	5355	83	48.54%	14333	89.99%	14416	169	98.83%	15926	99.99%	16095
Total	171	100.00%	15928	100.00%	16099	171	100.00%	15928	100.00%	16099	171	100.00%	15928	100.00%	16099
t-3															
Distress	66	39.29%	2610	19.98%	2676	31	18.45%	485	3.71%	516	0	0.00%	0	0.00%	0
Grey	62	36.90%	6128	46.92%	6190	46	27.38%	809	6.19%	855	0	0.00%	0	0.00%	0
Safe	40	23.81%	4322	33.09%	4362	91	54.17%	11766	90.09%	11857	168	100.00%	168	1.29%	336
Total	168	100.00%	13060	100.00%	13228	168	100.00%	13060	100.00%	13228	168	100.00%	13060	100.00%	336

Excluding grey zone

Like Karas et al. (2014) there will also be an analysis of the results without considering the grey zone scores. Suggested is that results falling in the grey zone could both be considered as failing to evaluate or be considered as predicted as financially distressed. In this additional section grey zone scores are considered as failing to evaluate.

Table 10 Classification results without grey zones

	Z2					Z3				
Prediction	Bankrupt		Non-bankrupt		Total	Bankrupt		Non-bankrupt		Total
Zone	N	%	N	%	N	N	%	N	%	N
t-1										
Distress	9	52.94%	2416	40.41%	2425	10	66.67%	504	4.78%	514
Safe	8	47.06%	3563	59.59%	3571	5	33.33%	10046	95.22%	10051
Total	17	100.00%	5979	100.00%	5996	15	100.00%	10550	100.00%	10565
t-2										
Distress	68	61.26%	3207	37.65%	3275	59	41.55%	611	4.09%	670
Safe	43	38.74%	5312	62.35%	5355	83	58.45%	14333	95.91%	14416
Total	111	100.00%	8519	100.00%	8630	142	100.00%	14944	100.00%	15086
t-3										
Distress	66	62.26%	2610	37.65%	2676	31	25.41%	485	3.96%	516
Safe	40	37.74%	4322	62.35%	4362	91	74.59%	11766	96.04%	11857
Total	106	100.00%	6932	100.00%	7038	122	100.00%	12251	100.00%	12373

Z4 is not included as they had no results in the grey zones

Table 10 presents a comparison of the classification of the revised model (Z2) and the four-variable model (Z3) without the grey zone prediction included. For t-1 the results still support the third hypothesis that the four-variable model increases the classification accuracy (66.67% and 95.22% against 52.94% and 59.5%). For t-2 and t-3 these results supports this less, as for bankrupt firms the accuracy is higher with the first revised model (Z2).

The results of Karas et al. (2014) suggested that the overall accuracy of z-score models could be increased by excluding the grey zone. This indeed is the case in this thesis, because the number of firms in the grey zone, and thus incorrectly predicted, are left out, which is the logical reason for a higher overall accuracy percentage.

5. CONCLUSIONS

5.1 FINDINGS

The objective of this study was to evaluate the predictive ability of the revised Altman z-score model (Z2) for privately held firms in the Netherlands. It was tested how this model performed and how the classification performance was compared to the four-variable Altman z-score model (Z3) and a re-estimated model (Z4). For these tests four hypotheses were formulated. The data consists of around 16.000 firms (bankrupt or non-bankrupt) from the years 2007 to 2015.

The findings indicated that the classification accuracy of Altman's model from 1983 (Z2) declined when applied to this Dutch sample. The results of the analyses suggested that for bankrupt firms in the Netherlands the revised z-score model (Z2) is not a significantly good classification model. One year prior the bankruptcy only around 43 percent is correctly predicted bankrupt, while prior studies (Grice & Ingram, 2001, Altman et al., 2016) suggested higher accuracies from 70 to 90 percent correctness. The classifications of non-bankrupt firms do show around the same accuracy rates. When testing the second hypothesis, there is no significant evidence to support the hypothesis that non-bankrupt firms have z-scores falling in the safe zone using Z2. The results of the four-variable model (Z3) do support this second hypothesis, although the classification accuracy does not significantly increase compared to the Z2 model.

Overall the results in this study do not support the hypotheses that bankrupt firms have z-score falling in the distress (H1), that non-bankrupt firms have z-scores falling in the safe zone (H2) and that coefficient re-estimation by regression analysis increases the classification accuracy (H4). The third hypothesis that the four-variable model increases the classification accuracy (H3) could only be supported partially by the results. An overall conclusion can be that the Altman z-score model is not directly useful for the Dutch private firms in its original form. Even after re-estimation of coefficients done in the way of this thesis, the Altman z-score model would not be considered as an useful prediction model compared to the results of other studies.

Reasons for the lower classification accuracies in this thesis compared to other studies (Grice & Ingram, 2001, Altman et al., 2016), probably lays in notes that can be mentioned about the methodology and the data-set. This will be further discussed in the next section 5.2 of limitations.

In conclusion, the findings coincide with that of Grice & Ingram (2001) that results of bankruptcy prediction studies that used Altman's model should be interpreted cautiously. Plus that the classification ability of the model is likely to differ for each time-period or country studied. The findings of this thesis also correspond with the conclusion of Altman et al. (2016) that after coefficient re-estimation the variations in results potentially differ stronger among countries. This Dutch sample appears to be one of that stronger variations in classification performance.

Finally answering the main research question of this thesis of: 'What is the predictive ability of the revised z-score model for private firms in the Netherlands?'. The predictive ability of Z2 in the Netherlands is lower, with around 30 to 45% classification accuracy, compared to previous studies in other countries and environments, which report around 70 to 90% classification accuracy. The main conclusion of this study is then that the predictive ability of the revised Altman z-score model for private firms (Z2) in the Netherlands is lower than prior studies.

5.2 LIMITATIONS

Similar to other bankruptcy prediction research this thesis has some limitations. This study purely looked at the accounting-based prediction model of Altman. There was no inclusion of other types of models as done by prior research (e.g. Machek, 2014). A common suggested limitation of accounting-based prediction models is that accounting variables can be manipulated by for example depreciation methods.

This study researched only private limited liability firms and thus had to check for the consolidated account in collecting the data. This led to many firms being identified as active in holding industries, while matching bankrupt and non-bankrupt firms were based on industry. This could potentially have biased the results, as all the holding firms are not actually active in the same industry, like for example in the retail industry. Furthermore the sample consisted of a rather large quantity of non-bankrupt firms compared to the bankrupt group. This difference in counts of both groups potentially biased the results of testing the hypotheses and also the re-estimation of the coefficients.

Furthermore to not limit the scope of the model in this study, bankrupt firms from all available industry groups were collected. Together with the previous paragraph, it should be mentioned that are other approaches to match bankrupt with non-bankrupt firms, but moreover this in the next section of future research suggestions (5.3).

Additionally the study focussed on the time period from 2007 to 2015. A limitation of this thesis can be that the specific time period is not discussed in depth (i.e. the global financial crisis). Partially to not broaden the study more and due to time limitations, some potential quality improvements are left out. Some future research suggestions to address this will be given in the next section.

5.3 FUTURE RESEARCH SUGGESTIONS

This study attempted to evaluate the predictive ability of the Altman z-score model in the Netherlands. While performing this study some questions have emerged which will be discussed shortly. In this thesis a re-estimation of the coefficients was done using logistics regression analysis. Other studies (Balcaen & Ooghe, 2006 & Karas et al., 2014) suggested re-estimations of the coefficient by multiple discriminant analysis, so this could be a future research opportunity.

Further research on bankruptcy prediction in the Netherlands could also focus more on other potential variables like firm size, age and other financial ratios. Furthermore this study only focusses on private limited liability firms, but future research could analyse the Altman model on other Dutch entity forms, or even focus on more on public firms. In this study only Altman z-scores models are analysed, but there are also research opportunities to compare other types of models on a Dutch sample.

Additionally future research on bankruptcy prediction in the Netherlands could approach the matching of bankrupt and non-bankrupt firms differently, more industry specific and or cases specific. Less country specific future research would also be able to extend analyses of bankruptcy prediction to the mentioned areas. When using the Altman z-score model in practice, it would be useful to re-estimate the coefficients on a more specific sample and take more ratios into consideration.

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REFERENCES

Alkhatib, K., & Al Bzour, A. E. (2011). Predicting corporate bankruptcy of Jordanian listed companies: using Altman and Kida models. *International Journal of Business and Management*, 6(3), 208-215.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609.

Altman, E. I. (1984). The success of business failure prediction models: an international survey. *Journal of Banking & Finance*, 8(2), 171-198.

Altman, E. I. (2000). Predicting financial distress of companies: revisiting the z-score and ZETA models. *Stern School of Business, New York University*, 9-12.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2016). Financial distress prediction in an international context: a review and empirical analysis of Altman's z-score model. *Journal of International Financial Management & Accounting*, 27(0), 1-41.

Altman, E. I., Danovi, A., & Falini, A. (2013). Z-score models' application to Italian companies subject to extraordinary administration. *Journal of Applied Finance*, 23(1).

Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: does it really have predictive ability? *Accounting and Business Research*, 37(4), 285-300.

Bal, G. R. (2016). Prediction of financial distress using Altman z-score: a study of select FMCG companies. *Indian Journal of Applied Research*, 5(9), 129-131.

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. *The British Accounting Review*, 38(1), 63-93.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71-111.

Begley, J., Ming, J., & Watts, S. (1996). Bankruptcy classification errors in the 1980s: an empirical analysis of Altman's and Ohlson's models. *Review of Accounting Studies*, 1(4), 267-284.

Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education*, 33, 1-42.

Bilderbeek, J. (1977). Financiële ratio-analyse: kengetallen ten behoeve van de ondernemingsbeoordeling. *Stenfert Kroese*.

Blazy, R., Chopard, B., & Fimayer, A. (2008). Bankruptcy law: a mechanism of governance for financially distressed firms. *European Journal of Law and Economics*, *25*(3), 253-267.

Boot, A. W., & Ligterink, J. E. (2000). Faillissementswetgeving in internationaal perspectief. *Maandblad voor Accountancy en Bedrijfseconomie*, 74(11), 492-499.

Van Elswijk, D.A., Jansen, J.P., Duijkers, R.P.R., & Moerman, M.P. (2016). Faillissementen oorzaken en schulden 2015. *Centraal Bureau voor de Statistiek*, WODC *(Dutch report)*

Couwenberg, O. (2001). Survival rates in bankruptcy systems: overlooking the evidence. *European Journal of Law and Economics*, 12(3), 253-273.

Couwenberg, O., & De Jong, A. (2006). It takes two to tango: an empirical tale of distressed firms and assisting banks. *International Review of Law and Economics*, 26(4), 429-454.

Couwenberg, O., & De Jong, A. (2008). Costs and recovery rates in the Dutch liquidation-based bankruptcy system. *European Journal of Law and Economics*, 26(2), 105-127.

Davydenko, S. A., & Franks, J. R. (2008). Do bankruptcy codes matter? A study of defaults in France, Germany, and the UK. *The Journal of Finance*, 63(2), 565-608.

El Khoury, R., & Al Beaïno, R. (2014). Classifying Manufacturing Firms in Lebanon: An Application of Altman's Model. *Procedia-Social and Behavioral Sciences*, 109, 11-18.

Geng, R., Bose, I., & Chen, X. (2015). Prediction of financial distress: an empirical study of listed Chinese companies using data mining. *European Journal of Operational Research*, 241(1), 236-247.

Grice, J. S., & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research*, 54(1), 53-61

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, 9(1), 5-34.

Hillier, D., I., Ross, S., Westerfield, R., Jaffe, J., & Jordan, B. (2010). Corporate Finance. *McGraw Hill education.*

Hummelen, J. M. (2014). Efficient bankruptcy law in the US and the Netherlands. *European Journal of Comparative Law and Governance*, 1(2), 148-211.

Karas, M., Reznakova, M., Bartos, V., & Zinecker, M. (2014). Possibilities for the application of the Altman model within the Czech Republic. *Recent Researches in Law Science and Finances*, 203-208.

Kim, Y. H., & Choi, I. S. (2013). The usefulness of z-score model on bankruptcy forecast. *Korea International Accounting Review*, 52(12), 465-478.

Machek, O. (2014). Long-term predictive ability of bankruptcy models in the Czech Republic: evidence from 2007-2012. *Central European Business Review*, 3(2), 14-17.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109-131.

Pompe, P. P. M. (2001). New developments in bankruptcy prediction. *Proefschrift University of Twente. (Book)*

Pompe, P. P., & Bilderbeek, J. (2005). The prediction of bankruptcy of small-and medium-sized industrial firms. *Journal of Business Venturing*, 20(6), 847-868.

Pompe, P. P. M., & J. Bilderbeek (2000), Prestaties van modellen en ratio's bij het voorspellen van faillissementen. *Maandblad voor Accountancy en Bedrijfseconomie*, 73(10), 465-472.

Ravi-Kumar, P., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques–a review. *European Journal of Operational Research*, 180(1), 1-28.

Siddiqui, S. A. (2012). Business bankruptcy prediction models: a significant study of the Altman's z-score model. *Asian Journal of Management Research*, 3(1), 212-219.

Singh, B. P., & Mishra, A. K. (2016). Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies. *Financial Innovation*, 2(1), 1-28.

Van Frederikslust, R. A. I. (1978). Predictability of corporate failure: models for prediction of corporate failure and for evaluation of debt capacity. *Martinus Nijhoff Social Sciences Division*.

Wang, Y., & Campbell, M. (2010). Do bankruptcy models really have predictive ability? Evidence using China publicly listed companies. *International Management Review*, 6(2), 77.

Woudt, J.(2014). 'Enkele reis Holten' Opkomst & ondergang van familiebedrijf Oad. *Financieel Dagblad, uitgave 26 april, 2014.*

Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics*, 6(1), 34-45.

Xu, M., & Zhang, C. (2009). Bankruptcy prediction: the case of Japanese listed companies. *Review of Accounting Studies*, 14(4), 534-558.