Testing the generalizability of the bankruptcy prediction models of Altman, Ohlson and Zmijewski for Dutch listed and large non-listed firms

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Summary

Bankruptcy and bankruptcy prediction is a very actual subject in the news and academic literature. The problem of the bankruptcy prediction models is the generalizability of the models because they there are developed with a specific sample. In the original studies, the sample included firms in a specific industry and a specific time period. The goal of this study is to test the generalizability of bankruptcy prediction models to industries and periods outside of those in the original samples.

In the literature of bankruptcy prediction the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are the most cited ones that are based on accounting variables. These bankruptcy prediction models use different explanatory variables and statistical techniques. Therefore, the predictive power of these bankruptcy prediction models differ.

I re-estimate these bankruptcy prediction models using an estimation sample which covers the period 2008-2010 and validate the models with another sample which covers the period 2011-2012. There are 15 bankrupt and 476 non-bankrupt firm included in the estimation sample. For the validation sample there are 14 bankrupt and 326 non-bankrupt firms included. All these firms are Dutch listed and large non-listed firms. Firstly, I test the bankruptcy prediction models with their original statistical technique. Secondly, to examine the role of the accounting ratios, I test all the bankruptcy prediction models with the logit regression.

When the original statistical techniques are used, the accuracy rates for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are respectively 80.6%, 93.8%, and 95.3%. At first sight it looks like the model of Zmijewski (1984) has the highest predictive power. But the model of Zmijewski (1984) predicted 0% of the bankrupt firms correctly and 99.4% of the non-bankrupt correctly. The accuracy rates for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) models are respectively 49.1%, 93.8%, and 87.7% when the logit regression is used. At first sight it looks like the model of Ohlson (1980) has the highest predictive power. But the same applies for the model of Ohlson (1980) as for the results of the model of Zmijewski (1984). The model of Ohlson (1980) is the most accurate when all the models use the same statistical technique. This implies that the explanatory variables of this model are the best predictors of the likelihood of bankruptcy. In conclusion, practitioners should use the bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) cautiously because the frequency of Type I errors is high (Ohlson [1980] and Zmijewski [1984]) or the accuracy rate is low (Altman [1986]). To use these models in practice, I recommend to re-estimate the coefficients of the bankruptcy prediction models with a specific and bigger sample to improve the predictive power.

Samenvatting

Faillissementen en de voorspelling hiervan zijn zeer actuele onderwerpen in het nieuws en wetenschappelijke literatuur. Het probleem van de faillissement voorspellingsmodellen is de generaliseerbaarheid van de modellen omdat deze ontwikkeld zijn met een specifieke steekproef. In het oorspronkelijke onderzoek van deze faillissement voorspellingsmodellen bevat de steekproef bedrijven in een specifieke sector en een bepaalde periode. Het doel van deze studie is om de generaliseerbaarheid van het deze modellen te testen op industrieën en periodes buiten deze oorspronkelijke steekproeven.

In de literatuur van faillissement voorspelling zijn de modellen van Altman (1968), Ohlson (1980) en Zmijewski (1984) het meest geciteerd en gebaseerd op boekhoudkundige variabelen. Deze faillissement voorspellingsmodellen gebruiken verschillende verklarende variabelen en statistische technieken. Daarom verschilt de voorspellende kracht van deze modellen.

Ik schat de coëfficiënten van deze voorspellingsmodellen met een steekproef die de periode 2008-2010 bestrijkt en daarna valideer ik deze modellen met een steekproef die de periode 2011-2012 bestrijkt. Er zijn 15 failliete en 476 niet-failliete onderneming opgenomen in de steekproef voor de schatting. Voor de steekproef die wordt gebruikt om de schattingen te valideren zijn er 14 failliete en 326 niet-failliete bedrijven opgenomen. Al deze bedrijven zijn Nederlandse beursgenoteerde en grote niet-beursgenoteerde bedrijven. Ik begin met het testen van de faillissement voorspellingsmodellen met hun oorspronkelijke statistische techniek. Daarna ga ik de rol van de boekhoudkundige ratio's onderzoeken. Dit doe ik door alle faillissement voorspellingsmodellen te testen met de logistische regressie.

Wanneer de originele statistische techniek wordt gebruikt is de nauwkeurigheid van de modellen van Altman (1968), Ohlson (1980) en Zmijewski (1984) respectievelijk 80,6% , 93,8% en 95,3%. Op het eerste gezicht lijkt het model van Zmijewski (1984) de hoogst voorspellende kracht te hebben. Maar deze algehele nauwkeurigheid moet met meer aandacht worden geïnterpreteerd. Het model van Ohlson (1980) voorspelde 0% van de failliete bedrijven correct en 99,4% van de niet-failliete bedrijven correct.

Het model van Ohlson (1980) is het meest nauwkeurig (93,8%) wanneer alle modellen dezelfde statistische techniek gebruiken. Dit impliceert dat de verklarende variabelen van dit model de beste voorspellers van de kans op een faillissement zijn. Concluderend moeten de modellen van behoedzaam worden gebruikt omdat het aantal fouten van de eerste soort erg hoog is (Ohlson [1980] en Zmijewski [1984]) en een lage nauwkeurigheid hebben (Altman [1968]). Om deze modellen te gebruiken in de praktijk raad ik aan om op basis van een specifieke steekproef opnieuw een schatting van de coëfficiënten te maken.

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1 Introduction

1.1 Background information

Bankruptcy is a very actual subject in the financial world and the academic literature due to the worldwide financial crisis between 2007 and 2008. This financial crisis started with the collapse of one of the biggest banks of the United States in 2005: Lehman Brothers. In 2009 the Basel Committee presented the additions for Basel II what resulted in Basel III. This accord is a global, voluntary regulatory standard on bank capital adequacy, stress testing and market liquidity risk. The aim of this accord was to increase the quality and the amount of the capital reserves of the banks.

During the financial crisis many organizations filed for bankruptcy. An organization will go through various stages before filing for bankruptcy. One of these stages is financial distress. In this stage, the organization is facing difficulties with paying their invoices and other contractual obligations. When financial distress cannot be relieved, it will lead to bankruptcy. One of the possibilities to relieve financial distress is a capital injection by shareholders or the bank. Since Basel III, banks impose stricter requirements before they provide a loan agreement.

Bankruptcy is a worldwide problem but this research will focus only on the bankruptcies in the Netherlands. According to the *Centraal Bureau voor de Statistiek* the total number of bankruptcies in 2011 for all Dutch legal entities in all industries was 6,175. Table 1 gives an illustration of the number of declared bankruptcies between 2007 and 2011. From the year 2007 until 2011, the number of declared bankruptcies increased. There was a peak in 2009.

Table 1. Declared bankruptcies of legal entities in the Netherlands between 2007 and 2011

Legal entities	Period	**2007**	**2008**	**2009**	**2010**	**2011**
Operating	Number	289,685	318,375	330,280	334,905	343,245
Declared bankruptcies	Number	3,589	3,840	6,995	6,226	6,175
Declared bankruptcies	Percentage	1.24%	1.21%	2.12%	1.86%	1.80%

Note: Centraal Bureau voor de Statistiek: http://statline.cbs.nl

1.2 Problem statement

As mentioned above, the number of declared bankruptcies increased from 2007. These bankruptcies are a major concern for the stakeholders of the organization. The stakeholders can predict the likelihood of bankruptcy in order to respond before they are overtaken by events. The problem is that the prediction models, which are studied in this research, are developed with another methodology and are dated. For example, the Altman model was developed in the year 1968, the model of Ohlson in 1980, and the Zmijewski model in 1984. According to the literature review of Grice and Ingram (2001), the accuracy and structure of the models change over time periods. Furthermore, Grice and Ingram (2001) stated that when the population of firms differs (e.g. country) from the original methodology, it is likely that the accuracy rate of the bankruptcy prediction models change. Boritz, Kennedy and Sun (2007) agree with this and stated that because there have been many changes in business conditions (e.g. decreased tolerance of debt financing, different legal systems) the performance of the models change.

1.3 Objectives

The main objective of this research is to determine if the work of Altman (1968), Ohlson (1980), and Zmijewski (1984) can be applied to listed and large non-listed firms operating in the Netherlands. Specifically, the study explains the differences between the bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984). This objective is achieved through a comparison of the goodness of fit measures of the different bankruptcy prediction models. The results of these tests are interpreted and an explanation is given why a particular model has a higher accuracy rate than another.

1.4 Research question

Given the above objective, this paper seeks to answer the research question:

What is the difference in predictive power between the bankruptcy prediction models of Altman (1968), Ohlson (1980) and Zmijewski (1984) to Dutch listed and large non-listed firms?

Each prediction model uses different explanatory variables and alternative statistical methodologies to estimate the probability of facing bankruptcy. The similarities are that all the three models use accounting based variables. The discussion of the three prediction models will be elaborated in section 2.

1.5 Justification

The focuses of this study are listed and large non-listed firms, because this is consistent with prior research (e.g. Grice & Dugan, 2003; Grice & Ingram, 2001; Imanzadh, Maran-Jouri & Sepehri, 2011). Another reason is the available data for listed and large non-listed firms in the database ORBIS. There are numerous studies outside the Netherlands that compare popular bankruptcy prediction models. For example, Thailand was examined by Pongsatat, Ramage and Lawrence (2004), South Korea by Bae (2012), China by Gang and Xiaomao (2009), Turkey by Canbaş, Önal, Düzakin and Kiliç (2006), and Sweden by Yazdanfar (2008). This study will focus on the Netherlands because there was not any research about the models like in other countries. Specifically the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) are studied because these models are the most cited in the literature and have the highest accuracy rates. The accounting ratios from the different models are shown in Appendix A.

1.6 Main results

Practitioners should use the bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) cautiously when they apply the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) in the Netherlands for listed and large non-listed firms. They should use the models cautiously because the frequency of Type I errors is high (Ohlson [1980] and Zmijewski [1984]) or the accuracy rate is low (Altman [1986]). To use these models in practice, I recommend to re-estimate the coefficients of the bankruptcy prediction models with a specific and bigger sample to improve the predictive power.

1.7 Contribution

This research makes a contribution to the bankruptcy literature and practice. First, numerous studies have been conducted to analyze bankruptcy prediction models. Nevertheless, this study has a contribution to the literature, because Dutch listed and large non-listed firms are analyzed. Some of the recent studies evaluated the models for firms in Thailand (Pongsatat et al., 2004), South Korea (Bae, 2012), China (Gang & Xiaomao, 2009), Turkey (Canbaş et al., 2006), Sweden (Yazdanfar, 2008), but in the Netherlands there was not any research about the models like in other countries. The prediction of bankruptcy in Belgium is studied by Pompe and Bilderbeek (2005). However, they used no prediction models but tested different ratios. Second, these prediction models can be used in a variety of situations when the models are re-estimated by stakeholders. Investors can assess the likelihood of bankruptcy so that this risk can be compensated in the expected return and commercial bank uses the models to assess the credit risk of a firm. The stakeholders will benefit from this research because they will have a better insight how bankruptcy can be predicted.

1.8 Outline

An outline of this paper is as follows. Section 2 reviews the existing literature on bankruptcy prediction models. The original methodology used to estimate the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) are examined. Section 3 presents the research method of this study. Data sources and descriptive statistics of the variables used in the various models are presented. The results and the discussion of these results are reported in section 4. This paper ends with the conclusion. Furthermore, in this section several suggestions are made for further research.

2 Literature review

2.1 Models for financial distress prediction or bankruptcy prediction?

Grice and Dugan (2003) stated that it is not clear whether the prediction models in the literature are specifically useful for identifying firms that are likely to go bankrupt or for identifying firms experiencing financial distress. The studies of McKee (2003) and Grice and Dugan (2003) pay attention to this issue. To simplify the problem, McKee (2003) focused on predicting bankruptcy or non-bankruptcy. Platt and Platt (2002, p. 185) also recognize this problem, "*while there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress*". This lack of research on financial distress is mainly due to hardness of defining objectively the start date of financial distress. Platt and Platt (2002) define financial distress as a late stage of corporate decline that precede the more destructive event bankruptcy. So before bankruptcy there are several events that can be recognized, this is in line with what McKee (2003) stated that a firm goes through various stages of financial distress. McKee (2003) mentioned inadequate income and inadequate liquid asset position as the two stages before bankruptcy.

The bankrupt group of the original study of Altman (1968) included "*manufacturers that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act*" (p. 593). Ohlson (1980) selected firms that must "*filed for bankruptcy in the sense of Chapter X, Chapter XI, or some other notification indicating bankruptcy proceedings*" (p. 114). These Chapters of the National Bankruptcy Act are not applicable in the Netherlands. In the Netherlands there is a Bankruptcy law (art. 1 Fw). A creditor, tax authorities and the prosecution can apply for bankruptcy when a firm stops to pay the invoices. When multiple claims have not been fulfilled, the court may pronounce bankruptcy. Zmijewski (1984) used the following definition of financial distressed firms: "*the act of filing a petition for bankruptcy*" (p. 63). Altman (1968) and Ohlson (1980) used both bankrupt firms. On the other hand, Zmijewski (1984) used financial distressed firms. Nevertheless, several academics used the model of Zmijewski (1984) to predict bankruptcy (e.g. Grice & Dugan, 2003; Pongsatat et al., 2004; Imanzadeh et al., 2011).

The studies who evaluated the prediction models of Altman (1968), Ohlson (1980) and Zmijewski (1984) used different conditions to be selected for the distressed/bankrupt and non-distressed/non-bankrupt group. Wu, Gaunt and Gray (2010) refer to the United States' bankruptcy code. They defined a firm as bankrupt if the firm makes a chapter 11 filing within 1 year. Chapter 11 of the Bankruptcy code stated that: "*When a business is unable to service its debt or pay its creditors, the business or its creditors can file with a federal bankruptcy court for protection.*" Boritz et al. (2007) expanded the definition because otherwise the sample size was restricted. They included also firms that have been liquidated. The difference between liquidation and bankruptcy is that liquidation is voluntary, while bankruptcy is forced.

2.2 Differences between key bankruptcy prediction models

In the 1930's univariate (ratio) analysis was used as an analytical technique in assessing the performance of firms. In 1968, Altman employed a multiple discriminant analysis (MDA) wherein a set of financial and economic ratios were investigated. The result of his study was a bankruptcy prediction model based on accounting data. More recent, academics developed various bankruptcy prediction models. According to Wu et al. (2010) key models that have been developed to predict bankruptcy are: (i) Altman (1968), (ii) Ohlson (1980), (iii) Zmijewski (1984), (iv) Shumway (2001), and (v) Hillegeist, Keating and Cram (2004). The models of Altman (1968), Ohlson (1980) and Zmijewski (1984) are based on accounting variables and the models of Shumway (2001) and Hillegeist et al. (2004) are based on market variables.

The consensus of the first three models is that they all use accounting ratios that measure liquidity, leverage and profitability. In general, when the liquidity is low, profitability is low, and leverage is high, the likelihood of bankruptcy increases. The differences between these accounting-based models are the explanatory variables and statistical techniques that are used to predict bankruptcy.

A brief summary of the models, which are compared in this study, is provided in Appendix A. As can be seen in Appendix A, the Altman (1968) model uses five explanatory variables, the Ohlson (1980) model uses nine explanatory variables and the model of Zmijewski (1984) uses three explanatory variables. For the number of explanatory variables in the model, a trade-off must be made. When there are too few variables the explanatory power of the model can be low or the construct validity of the results are weak. When there are too many variables in the model, multicollinearity can occur.

Hensher and Jones (2007) propose to examine the partial correlations across the covariates. This partial correlation coefficient provides information about the relationship between explanatory variables when another explanatory variable is held constant. When the coefficient is smaller after including the control variable, this variable may explain a part of the observed relationship. If the correlation is weak, this suggests that the explanatory variables are providing unique information.

2.3 Market-based and accounting-based prediction models

As mentioned in the previous section, some well-known bankruptcy prediction models include market variables and accounting variables while other models include only accounting variables. Beaver, McNichols and Rhie (2005) give three reasons why market-based variables are valuable in predicting bankruptcy. First, market prices reflect a rich and comprehensive mix of information. This information is based on the financial statements of the firm. Second, market-based variables can be measured with "*a finer partition of time*" (Beaver et al., 2005, p. 110). Financial statements are available at best on a quarterly basis (for most firms only on yearly basis), market-based variables are daily available. Third, the market-based variables can provide direct measures of volatility (e.g. standard deviation of earnings per share). So, therefore it is assumed that models with market variables have better predictive power in forecasting bankruptcy than models with only accounting variables.

Agarwal and Taffler (2006) compared the performance of market-based and accounting-based bankruptcy prediction models. This study covers all non-finance industry UK firms fully listed on the London Stock Exchange (LSE) during the period 1985-2001. Agarwal and Taffler (2006) mentioned two advantages and four disadvantages of accounting-based bankruptcy prediction models. Agarwal and Taffler (2006) argue that accounting-based models are in favor because: (i) bankruptcy is not a sudden event but the result of several years of adverse performance. This is captured by the financial statements of the firm. (ii) Loan covenants of firms are generally based on accounting numbers and this information is reflected in the financial statements of the firms. Another reason why accounting-based models are popular among practitioners is that the necessary data for the market-based models is not always available.

On the other hand, Agarwal and Taffler (2006) argue that accounting based models casts doubt on their validity because: (i) accounting information present past performance and therefore not useful for predicting, (ii) "*conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values*" (Agarwal & Taffler, 2006, p. 2), (iii) the accounting numbers are subject to manipulation by management, (iv) Hillegeist et al. (2004) and McKee (2003) argue that since financial statements are prepared on a going-concern basis, they are not suitable to predict bankruptcy.

Despite extensive criticism on the accounting-based models, the results of the study of Agarwal and Taffler (2006) showed that the accounting-based approach of Altman produces significant economic benefit over the market-based approach of Hillegeist et al. (2004) and Bharath and Shumway (2004). The accuracy rate of the model of Altman (1968) was 79% and for Hillegeist et al. (2004) and Bharath and Shumway (2004) respectively 68% and 73%.

2.4 The original studies

In this section the original methodologies and conclusions of Altman's (1968), Ohlson's (1980), and Zmijewski's (1984) studies are examined and conclusions of prior studies who evaluated the original methodologies are presented.

2.4.1 Altman (1968)

Altman (1968) used the MDA as a statistical technique to construct his well-known Z-score prediction model. This statistical technique was developed in 1936 by Sir Ronald Fisher. The objective of the MDA technique is to "*classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics*" (Lin, 2009, p. 3509). Altman (1968) argued that the MDA technique has several advantages in comparison with the traditional univariate ratio analysis. First, the statistical MDA technique has the potential to analyze an entire set of explanatory variables simultaneously, as well as the interaction of these variables. Secondly, MDA reduces the number of explanatory variables under consideration. The discriminant function is as follows:

$$Y = C + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (eq. 1)$$

Where x is the discriminant variable, β the discriminant coefficient, and c the constant term (intercept). The objective of discriminant analysis is to construct a boundary line through the graph such that if the firm is to the left of the line it is unlikely to go bankrupt, whereas if it falls to the right it is likely to go bankrupt. This boundary line is called the discriminant function.

Altman (1968) uses 33 bankrupt manufacturing firms and 33 non-bankrupt manufacturing firms as his sample. Altman (1968) used the cross-validation approach to validate the function. This means he used an estimation sample and a hold-out sample. The estimation sample is used to estimate the function and the hold-out sample is used to validate the estimated function. The estimation sample included 66 observations. The mean asset size of these firms is \$6.4 million, with a range of between \$0.7 million and \$25.9 million. This means that small and very large firms are eliminated from the initial sample. The sample period spans from 1946 to 1965. Firms were defined as bankrupt when they filed bankruptcy in the period between 1946 and 1965. Firms were defined as non-bankrupt if they were still in existence in 1966. One point of attention is this definition of non-bankrupt firms. The process of bankruptcy could take several years. When a non-bankrupt firm is still in existence in 1966, the process of bankruptcy can already be initiated. This will lead to biased results because "non-bankrupt firms" can show ratios of bankrupt firms. Altman (1968) stratified and matched the firms in the two groups (bankrupt and non-bankrupt) by the variables industry and size (the proxy asset size is used). The constructed discriminant function with the variables and estimated coefficients from the study of Altman (1968) is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.9X_5 \qquad (eq. 2)$$ [1]

Where $X_1 = working\ capital/total\ assets$

$X_2 = retained\ earnings/\ total\ assets$

$X_3 = earnings\ before\ interest\ and\ taxes/total\ assets$

$X_4 = market\ value\ of\ equity/book\ value\ of\ total\ debt$ [2]

$X_5 = sales/total\ assets$

Altman (1968) evaluated twenty-two variables. These ratios are chosen on the basis of their popularity in the literature and potential relevancy to the study. The five explanatory variables of the constructed discriminant function are not the most significant variables when they are measured independently. The reason for this is that the contribution of the entire variable profile is evaluated by the MDA function (Altman, 1968).

X1-working capital/total assets. The current ratio and quick ratio were two other liquidity ratios that were considered by Altman (1968) but this ratio showed greater statistical significance on univariate and multivariate basis.

X2-retained earnings/total assets. The age of the firm is considered in this ratio, because retained earnings is a component of this explanatory variable. Altman (1968) stated that a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits.

X3-earnings before interest and taxes/total assets. The EBIT are the earnings from the primary operations. Non-operational earnings like tax and interest are excluded from the EBIT.

X4-market value of equity/book value of total debt. This ratio is a measure of leverage.

X5-sales/total assets. This profitability ratio is a measure of the "*sales generating ability of the firm's assets*" (Altman, 1968, p. 595).

The cutoff point selected by Altman (1968) is 2.675. This cutoff point is based on the number of minimal Type I (actual bankrupt but predicted non-bankrupt) and Type II (actual non-bankrupt but predicted bankrupt) errors. If the Z value is higher than 2.675, the firms are classified as non-bankrupt. A firm is classified as bankrupt if the Z value is lower than 2.675.

In Appendix A the categories (liquidity, profitability, or leverage) of the ratios are shown. Altman (1968) uses one liquidity ratio, two profitability ratios and two leverage ratios.

The accuracy rate is computed by dividing the number of correct predictions by the total number of predictions. This accuracy rate is the percent of firms correctly classified. According

[1] Notice that there is no constant term in the discriminant function. The discriminant function does not include a constant term when standardized coefficients are used. Coefficients are standardized to measure the effect of the independent variable on the dependent variable when the independent variables use different measurement units (dollars, minutes, etc.).

[2] The reciprocal of X_4 is familiar debt/equity ratio often used as a measure of financial leverage.

to Altman (1968) this percentage is analogous to the coefficient of determination (R^2) in regression analysis. The accuracy rate of the original study of Altman for the estimation sample was 95% and for the hold-out sample 84%[3] (Altman, 1968). According to Grice and Dugan (2001) the hold-out samples are biased upward because the hold-out samples consisted of firms from the same industries as those in the estimation sample.

Wu et al. (2010) tested the models of Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and Hillegeist et al. (2004). They used listed US firms as the sample of their study and cover the period from 1980 to 2006. One of the conclusions was that the model of Altman (1968) "*performs poorly relative to other models in the literature*" (Wu et al., 2010, p. 45). The estimation sample test showed the following Receiver Operating Characteristics (ROC) scores: 0.861 (Altman), 0.887 (Ohlson), and 0.852 (Zmijewski). The ROC statistic measures "*the ability of a model to discriminate between bankrupt and non-bankrupt firms, with a higher score indicating a better ability*" (Wu et al., 2010, p. 41). The conclusion of Wu et al. (2010) for the Altman (1968) model is supported by Grice and Ingram (2001). They stated that the accuracy of the Altman's (1968) model declined when applied to their samples. The research of Grice and Ingram (2001) was designed to avoid the limitations of the research design of Altman (1968) and to re-estimate the discriminant coefficients. Large and proportional sample sizes were used instead of small and equal sample sizes. Manufacturing as well as non-manufacturing firms with S&P ratings were used as the sample and covers the period from 1985 to 1987. Furthermore, because of the randomly selected firms, the sample contained firms over different industries. The accuracy rates of re-estimated model were significantly improved. The overall[4] accuracy rate with the original coefficients was 57.8% and with the re-estimated coefficients 88.1%. Grice and Ingram (2001) showed that the classification results for the re-estimation sample were significantly (at the 0.05 level) higher for the re-estimation model than for Altman's (1968) original model.

The criticism on the Altman (1968) model, besides the age of the model (Grice and Ingram, 2001) are based on the research design Altman (1968) used for his research. First, the original parameters were estimated with the use of small and equal sample sizes. Namely, 33 bankrupt and 33 non-bankrupt firms (Boritz et al., 2007). Van Dalen (1979) proposes to use proportional samples to improve the representativeness of the samples. Second, only manufacturing firms are used as the sample for the study (Grice & Ingram, 2001). This limits the generalizability of the results because other industries are excluded. Finally, the explanatory variables are selected based on popularity in the literature not on theoretical basis.

[3] The correct number of correct predicted bankrupt (n=24) plus correct predicted non-bankrupt (n=52) firms divided by the total number of predictions (n=91).

[4] The weighted average of the distressed and non-distressed group.

Other weak points of the Altman (1968) model arise from the use of the statistical technique MDA. First, the cut-off point for firms that are classified as bankrupt or non-bankrupt is very arbitrary. Second, Wu, Gaunt and Gray (2010) argue that the logit model of Ohlson (1980) uses less restrictive assumptions than those taken by the MDA of Altman (1968). For the MDA several assumptions must be made about the distribution of the data (see section 2.4.2 for further discussion).

2.4.2 Ohlson (1980)

Another popular bankruptcy prediction model is the logit model of Ohlson (1980). This logit model was introduced by Joseph Berkson in 1944. Ohlson (1980) used the logit model instead of the MDA. The criticism of Ohlson (1980) to the MDA of Altman (1968) are:

1. There are two key assumptions that must be made to use the discriminant function. The first assumption is that the explanatory variables are normally distributed. The second assumption is equal variance and covariance of the explanatory variables for the bankrupt and non-bankrupt firms (Ohlson, 1980).
2. The Z-score is basically an ordinal ranking device. Therefore, the output of the MDA model is a score which has little intuitive interpretation. Ohlson stated that any economic problem "*would typically require a richer state partition*" (1980:112).
3. Bankrupt and non-bankrupt firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. Ohlson (1980) claimed that variables should be included to predict bankruptcy not for matching purposes. This statement is outdated since recent studies use size and industry to make a matched-pair and therefore to control for these variables.

Ohlson (1980) stated that the use of logit analysis, on the other hand, essentially avoids all of the above problems with respect to MDA. The logit function is suitable to model the probability of bankruptcy because the dependent variable has only two categories (bankrupt or non-bankrupt). The logit function maps the value to a probability bounded between 0 and 1.

The cutoff point used by the original study of Ohlson (1980) is 0.38 because it minimizes the Type I and Type II errors. The boundaries for the population of the Ohlson (1980) model were restricted by: (1) the period from 1970 to 1976; (2) the equity of the firm had to be traded on some stock exchange or over-the-counter (OTC) market; (3) the company must be classified as an industrial. The data collection started three years prior the date of bankruptcy. The bankrupt firms must have file for bankruptcy "*in the sense of Chapter X, Chapter XI, or some other notification indicating bankruptcy proceedings*" (Ohlson, 1980, p. 114). The data for the non-bankrupt firms was obtained from the *Compustat* tape. The final estimation sample was made up of 105 bankrupt firms (US industrials) and 2,058 non-bankrupt firms (US industrials).

The constructed logit function with the variables and estimated coefficients from the study of Ohlson (1980) is as follows:

$$Ohlson = -1.3 - 0.4X_1 + 6.0X_2 - 1.4X_3 + 0.8X_4 - 2.4X_5 - 1.8X_6 + 0.3X_7 - 1.7X_8 - 0.5X_9 \qquad (eq. 3)$$

Where $X_1 = log(total\ assets/GNP\ price - level\ index)$ [5]

$X_2 = total\ liabilities/total\ assets$

$X_3 = working\ capital/total\ assets$

$X_4 = current\ liabilities/current\ assets$

$X_5 = 1\ if\ total\ liabilities\ exceeds\ total\ assets, 0\ otherwise$

$X_6 = net\ income/total\ assets$

$X_7 = funds\ provided\ by\ operations/total\ liabilities$

$X_8 = 1\ if\ net\ income\ was\ negative\ for\ last\ two\ years, 0\ otherwise$

$X_9 = (NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)\ where\ NI_t\ is\ net\ income\ for\ the\ most\ recent\ period$

The first six predictors were partially selected simply because they appear to be the ones most frequently mentioned in the literature (Ohlson, 1980). The logit model of Ohlson (1980) includes four liquidity ratios, two profitability ratios and two leverage ratios (see also Appendix A). For the Ohlson (1980) model the overall accuracy rate of the estimation sample was 96%[6] and for the hold-out sample 85%[7].

The logit model of Ohlson is criticized because "*all parameters are fixed and the error structure is treated as white noise, with little behavioral definition*" (Hensher and Jones, 2007, p. 243). Hensher and Jones (2007) propose a mixed logit model instead of a simple logit model. This mixed logit model recognizes "*the substantial amount of heterogeneity that can exist across and within all firms in terms of the role that attributes play in influencing an outcome domain*" (Hensher and Jones, 2007, p. 243). Grice and Dugan (2003) indicated that the accuracy of the models of Ohlson (1980) and Zmijewski (1984) increased when the coefficients are re-estimated. This finding is the result of another research design proposed by Grice and Dugan (2003). Grice and Dugan (2003) evaluated the models with samples of distressed and non-distressed companies from time periods, industries, and financial conditions other than those

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[5] For the first explanatory variable the assumption must be made that a base value of 100 for 2005 applies.

[6] See model 1 of the three tested models. Model 1 means one year prior bankruptcy, model 2 means two years prior bankruptcy and model 3 means three years prior bankruptcy.

[7] With a cutoff point of 0.38, 17.4% of the non-bankrupt (n=306) and 12.4% of the bankrupt (n=13) were misclassified. The accuracy rate for the hold-out sample is the total correct of classified firms (n=1,846) divided by the total of observations (n=2,163)

used to develop the original models. One of the conclusions of Grice and Dugan (2003) is that the relation between financial ratios and bankruptcy appears to change over time.

2.4.3 Zmijewski (1984)

In the study of Zmijewski (1984) two methodological issues are examined that are related to the estimation of bankruptcy prediction models. The two biases are *choice-based sample biases* and *sample selection biases*. The choice based bias is the result of "*over-sampling distressed firms*" (Zmijewski, 1984, p. 59). When a matched-pair (one-to-one match) design is for a study to predict bankruptcy, the potential of bankruptcy is overstated. This lead to biased probabilities in the models. The sample selection biases occur when "*the probability of distress given complete data is significantly different from the probability of distress given incomplete data*" (Zmijewski, 1984, p. 74).

The model of Zmijewski (1984) based on the 40 bankrupt and 800 non-bankrupt firms is the most commonly used model by accounting researchers (Grice & Dugan, 2003). Zmijewski (1984) used the probit technique to construct his bankruptcy prediction model. The accuracy rate of the Zmijewski (1984) model for the estimation sample was 99%[8].

The population of firms for the study of Zmijewski (1984) consists of all firms listed on the American and New York Stock Exchanges during the period 1972 through 1978 which have SIC-codes of less than 6000. This means that the finance, service and public administration industries are excluded from the research. Zmijewski (1984) defined bankrupt firms as the act of filing petition for bankruptcy. Bankrupt firms are identified as bankrupt if it filed a bankruptcy petition during this period and non-bankrupt if it did not. The final estimation sample of the study of Zmijewski (1984) contained 40 bankrupt and 800 non-bankrupt firms, and a hold-out sample containing 41 bankrupt and 800 non-bankrupt firms. The constructed probit function with the variables and estimated coefficients from the study of Zmijewski (1984) is as follows:

$$Zmijewski = -4.3 - 4.5X_1 + 5.7X_2 + 0.004X_3 \qquad (eq. 4)$$

Where $X_1 = net\ income/total\ assets$

$X_2 = total\ liabilities/\ total\ assets$

$X_3 = current\ assets/\ current\ liabilities$

While Altman used the ratio earnings before interest and taxes/total assets (EBIT/TA) for profitability, Zmijewski (1984) used the ratio net income/total assets (NI/TA). The difference between these two ratios are that the financial profits/losses (e.g. interest and/or taxes)

[8] Zmijewski (1984) did not report the accuracy rate for the hold-out sample.

included in the net income and not in EBIT. These profits/losses are not from the operations of the firm. EBIT eliminates the effect of different capital structures and therefore EBIT makes it easier to compare the profitability of the firm[9]. One factor that influences net income is the capital structure of the firm, which already is measured by the ratio total liabilities/total assets (TL/TA) of the Zmijewski (1984) model. This is consistent with the results of the research from Shumway (2001). He argues that the model of Zmijewski (1984) is in fact only a one variable model. This is because the variables TL/TA is strongly correlated (p = 0.40) with NI/TA. Shumway (2001) stated that the model of Zmijewski (1984) does not have strong predictive power for bankruptcy.

Grice and Dugan (2003) stated that one of the limitations of the study of Zmijewski (1984) is that the ratios were not selected on a theoretical basis, but rather on the basis of their performance in prior studies. The models of Altman (1968) and Ohlson (1980) have the same limitation. Furthermore, it is criticized because the original study used "*financial ratios that discriminated among industrial firms*" (Grice and Dugan, p. 85, 2003).

Like the logit function, the probit function maps the value between 0 and 1. Zmijewski (1984) classified the correct hits on another way than Ohlson (1980) did. Firms with probabilities greater than or equal to 0.5 were classified as bankrupt or having complete data. Firms with probabilities less than 0.5 were classified as non-bankrupt or having incomplete data.

The probit model of Zmijewski is preferred in comparison with MDA because the probit function maps the value to a probability bounded between 0 and 1, this value is easily to interpret. This is also the case for the logit model.

As mentioned earlier, Zmijewski (1984) tried to avoid the choice-based sample bias. He observed that most of the early models of predicting bankruptcy suffered from this bias. Zmijewski (1984) argues that unless one builds a model based on the entire population, the estimated coefficients will be biased, and the resulting predictions will over-estimate the proportion of bankrupt firms that are correctly classified as such.

Platt and Platt (2002) argue that although he tried to avoid choice-based sample bias his empirical test was weak. "*Because he [Zmijewski (1984)] ran only one regression for each sample size, he could not test the individual estimated coefficients for bias against the population parameter, a more direct test of bias*" (Platt & Platt, 2002, p. 186). By contrast, Platt and Platt (2002) used more standard tests of bias, comparing the mean estimated coefficient to the population parameter.

[9] To measure the profitability from operations; Earnings before interest taxes amortization and depreciation (EBITDA) is frequently used by practitioners.

2.5 Review of the original studies

Based on the previous literature the three studies are reviewed. Table 2 showed the ranking of the methodology and the statistical technique.

Table 2. Ranking of the methodology and statistical technique used in the original studies

Study	Method	Statistical technique	Explanatory variables	Remarks
Altman (1968)	-	-	+	Method: Small matched pair sample -> 30:30 Statistical technique: Result of MDA is not bounded and to use MDA several assumptions about the distribution must be made. Explanatory variables: Altman (1968) evaluated twenty-two variables. From these variables, this set of five variables were the most significant.
Ohlson (1980)	+	+	-/+	Method: Large proportional sample -> 105:2,058 Statistical technique: The logit function maps the value between 0 and 1. Furthermore, it uses less restrictive assumptions in comparison with the MDA. Explanatory variables: Nine explanatory variables.
Zmijewski (1984)	-/+	-/+	-	Method: Small proportional sample -> 40:800 Statistical technique: The probit function maps the value between 0 and 1. Secondly, it uses less restrictive assumptions in comparison with the MDA. Explanatory variables: Only three explanatory variables. And where two (TL/TA and NI/TA) of the three variables are strongly correlated.

3 Methodology

3.1 Research question

In this study de following research question will be answered:

What is the difference in predictive power between the bankruptcy prediction models of Altman (1968), Ohlson (1980) and Zmijewski (1984) to Dutch listed and large non-listed firms?

3.2 Sample selection

To answer this research question the data on firm bankruptcies is obtained from ORBIS. This is a database of the University of Twente. Another source of data for this study are the annual reports (balance sheet, profit and loss statement, and cash flow statement) of the listed and large non-listed firms.

The population of this research includes all listed and large non-listed firms in the Netherlands. Prior research (e.g. Grice & Dugan, 2003; Grice & Ingram, 2001) questioned the generalizability of the prediction models because they stated that it is unlikely that the models perform equally in all industries. Therefore, this study identifies the population from all industries. Only financial and insurance firms are excluded from the dataset because their capital structure are likely to be significantly different from non-financial and non-insurance firms. If the financial institutions will be included this will lead to biased results. The industries are selected by the *SBI-code*. This Dutch classification code is the same as the well-known Standard Industrial Classification (SIC) code. The firms with SBI-codes 64 and 65 (financial service activities and insurance activities) are excluded. Thus, to be selected for study, the bankrupt firms must have the following conditions:

Table 3. Population for the study

Condition	Value
Status	Bankruptcy, Dissolved (bankruptcy)
Size	Listed and large non-listed firms
SBI-code	All (except: 64 - Financial service activities and 65 – Insurance activities)[a]
Country	Netherlands

[a] SBI-code 64 and 65 are excluded because the ratios of this industry are likely to be significantly different from other industries.

For this research I use an estimation sample and a validation sample. The accounting information for the estimation and validation samples are collected three, two and one year before the observed event (bankruptcy/non-bankruptcy). Figure 1 gives an illustration of the time periods and data collection.

Figure 1. Estimation and validation sample

	2005	2006	2007	2008	2009	2010	2011	2012
	x	x	x	y				
Estimation sample		x	x	x	y			
			x	x	x	y		
Validation sample				x	x	x	y	
					x	x	x	y

Note: the year where the firm filed for bankruptcy is t=0.

Both samples contain two subsets. The first subset includes firms that filed for bankruptcy in t=0 and the second subsets include firms who are not bankrupt in t=0. A firm is defined as bankrupt if the firm has the status "Bankruptcy" or "Dissolved (bankruptcy)" in the database ORBIS. The criteria for the non-bankrupt firms is that they are operating in the years t=1 and t=2. This means that for this study I use a different definition for non-bankrupt firms than Altman (1968) does. Altman (1968) defines non-bankrupt firms as firms who are operating only one year after the data collection. I use two years because the process of bankruptcy can take several years.

I use proportional sampling to avoid the choice based sample bias. According to Grice and Ingram (2001) limitations of prior studies were that the test samples were not proportional to actual bankruptcy rates. Proportional sampling provides the researcher a way to achieve even greater representativeness in the sample of the population (Van Dalen, 1979). Therefore, the proportional sampling method is used for this study. The actual bankruptcy rate of the Dutch corporations can be found in table 1.

After the elimination of missing values, double entries and holding companies the final estimation sample contained 476 non-bankrupt firms and 15 bankrupt firms. The proportion of bankrupt to non-bankrupt firms in the estimation sample 3.15%.

The results are validated with a validation sample. The same procedures are followed for the estimation sample and validation sample to gather a complete set of financial data for the bankrupt and non-bankrupt firms. The final estimation sample contained 326 non-bankrupt firms and 14 bankrupt firms. The proportion of bankrupt to non-bankrupt firms in the validation sample is 4.29%.

3.3 Hypotheses

The following hypotheses will be tested to extract necessary answers to the main research question of this study:

$H1_0$: There is no difference in the predictive power between the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) when the original statistical techniques are used.

$H2_0$: There is no difference in the predictive power between the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) when the logit regression is used.

For the first hypothesis, the bankruptcy prediction models will be estimated with the original statistical technique. These three estimated models will be tested with the validation sample. For the second hypothesis, all the three the bankruptcy prediction models will be estimated with the logit regression. These three estimated models will be tested with the validation sample. Based on table 2 in the literature review the alternative hypothesis is that the bankruptcy model of Ohlson (1980) has the highest predictive power.

3.4 Bankruptcy prediction models

3.4.1 Dependent variable

As stated earlier in Section 2.1, it is not clear whether the prediction models in the literature are specifically useful for identifying firms that are likely to go bankrupt or for identifying firms experiencing financial distress. Because of the selected statuses “Bankruptcy” and “Bankruptcy (dissolved)” in the database ORBIS, the terms bankrupt firms and non-bankrupt firms is used in this paper. The dependent variable “bankruptcy” is dichotomous (binary) variable and can have the values non-bankrupt or bankrupt (0 or 1).

3.4.2 Independent variables

The independent variables in this study are different accounting ratios used by the models of Altman (1968), Ohlson (1980) and Zmijewski (1984). For the model of Altman (1968) I use the ratio DET/EQUITY instead of the ratio market value of equity/book value of total debt as a measure of financial leverage. The reason for this is there are no market values available for the listed and large non-listed firms.

3.5 Statistical techniques for bankruptcy predicting models

In the literature different statistical techniques are used to predict bankruptcy. The techniques used by Altman (1968), Ohlson (1980) and Zmijewski (1984) are: (i) multiple discriminant analysis, (ii) logit regression, and (iii) probit regression.

3.5.1 Multiple discriminant analysis

The well-known MDA is used by Altman (1968) for his function to predict bankruptcy (see equation 1). MDA is appropriate statistical technique when the dependent variable (y) is qualitative and the independent variables (x) are quantitative. MDA can be used to test hypotheses that the group means of a set of independent variables for two or more groups are equal. This group mean is referred to as a centroid.

The goal of an ordinary regression model is to estimate the parameters that minimize the *residual* sums of squares. Discriminant analysis uses (ordinary least squares) OLS to estimate the constant and product terms to minimize the *within group* sums of squares. The within group sums of squares measures the variation around the centroid.

Discriminant coefficients are chosen that maximize the eigenvalue for the composite variable, that is, the ratio of *between-group* to *within-group* sums of squares. A critical feature of these composite sums of squares is that they encapsulate the variability of each variable and also their covariability. This means that the coefficients are partial, so each indicates the contribution of a particular variable while statistically controlling for all of the others.

The key assumptions for deriving the discriminant function are multivariate normality of the independent variables and unknown (but equal) dispersion and covariance matrices for the groups.

3.5.2 Logit regression

Ohlson (1980) used logit regression for his bankruptcy prediction model. Like MDA, the logit regression is suitable when dependent variable (y) is qualitative and the independent variables (x) are quantitative. Unlike the MDA, the logit regression does assume linearity of relationship between the independent and dependent variable. The logistic curve comes closer to the y=0 and y=1 points on the y-axis. Therefore, the logit regression is better for modeling binary dependent variables. Even more, the logistic function is bounded by 0 and 1, whereas the OLS regression function may predict values above 1 and below 0. The success or failure likelihood of this regression is computed by the following formula:

$$p(z) = \frac{1}{1+e^{z}} = \frac{1}{1+e^{-(C+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \qquad (eq. 5)$$

The logit regression owes his name to the adjustment of the independent variable. Instead of using proportions, log odds (logits) are used. This cumulative logistic distribution function transforms the latent variable Z (using a linear model) into a predicted value between 0 and 1. Since the logit regression equation is non-linear, OLS is not applicable. The logit model uses maximum likelihood estimation (MLE) to construct the model. So, while the objective of OLS is to minimize the within group of squares, the objective of MLE is to produce logit coefficients that maximizes the likelihood of classifying the cases in the observed category.

One disadvantage of the logit model is the interpretation of the coefficients. Note that logistic regression calculates the changes in the log odds and not the changes in the latent variable itself as OLS regression does.

3.5.3 Probit regression

Zmijewski (1984) used the probit regression for his bankruptcy prediction model. Probit is an abbreviation for probability unit. Like MDA and logit regression, the probit regression is suitable when dependent variable (y) is qualitative and the independent variables (x) are quantitative.
Like the logit regression, the probit regression uses also MLE to estimate the coefficients of the function. The difference between these two regressions is that the curve of the probit regression approaches the axes more quickly than the curve of the logit regression.
Probit models use a latent variable Y* that ranges from negative infinity to positive infinity. The *cumulative standard normal function G* transforms the latent variable Y* into a predicted Y value between 0 and 1:

$$\Pr(Y) = G(Y^*) = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) \qquad (eq. 7)$$

The estimated coefficients from the probit regression are difficult to interpret because they measure the change in the latent variable, not Y itself. The marginal effects is a more useful way to measure the magnitude of the estimated coefficients.

3.6 Evaluation approach for bankruptcy prediction models

To evaluate and compare the different prediction models, the following goodness of fit measures are used in the literature: Pseudo R^2 and the accuracy rate.

3.6.1 Pseudo R²

A common goodness of fit measure is the Pseudo R^2 and is proposed by McFadden in 1974:

$$Pseudo\ R^2 = 1 - \frac{L_{ur}}{L_o} \qquad (eq. 8)$$

Where $L_{ur} = log\ likelihood\ value\ from\ the\ regression\ (proposed\ model)$

$L_o = log\ likelihood\ value\ from\ the\ regression\ with\ only\ the\ intercept\ (base\ model)$

The proposed model is the model with the estimated coefficients and the base model includes only the intercept. The goodness of fit would be close to 0 if the regression has no explanatory power, and if good, would be close to 1.

3.6.2 Accuracy rate

A classification matrix is a matrix containing numbers that reveal the predictive ability. The overall accuracy rate is the percentage of correct classification to total classifications. This overall accuracy rate can be separated into the accuracy rate of good predicted bankrupt firms and good predicted non-bankrupt firms.

3.7 Univariate analysis

Table 4 en 5 reports the descriptive statistics of the bankrupt and non-bankrupt firms in the estimation and validation sample. A comparison of the accounting variables is made between the bankrupt and non-bankrupt groups. A t-test (with a confidence level of 95%) of differences in variable means between the bankrupt and non-bankrupt firms was conducted.

A comparison of the bankrupt and non-bankrupt firms in the estimation sample indicated that non-bankrupt firms show a higher volatility of the leverage ratio. This is shown in the standard deviation of the DEBT/EQUITY ratio. The standard deviation for the non-bankrupt firms (6.829) is much higher than for the bankrupt firms (0.337). The *p*-value for the test of mean differences between bankrupt and non-bankrupt firms is significant for the ratios EBIT/TA, NI/TA, and FU/TL at 0.10 level. Furthermore, the ratios WC/TA and RE/TA are significant at 0.05 level. Finally, the ratio SIZE is significant at 0.01 level. This significance means that that the null hypothesis for these ratios can be rejected. This implies that there is a difference between the means of these ratios between the bankrupt and non-bankrupt firms in the estimation sample.

This comparison is also made for the validation sample. For the bankrupt firms in the validation sample the standard deviation for the DEBT/EQUITY, SALES/TA, and CHIN ratios are higher than for the non-bankrupt firms. The *p*-value for the test of mean differences between bankrupt and non-bankrupt firms is significant for the ratios WC/TA and NI/TA, at 0.10 significance level. This significance means that that the null hypotheses for these ratios can be rejected. This implies that there is a difference between the means of these ratios between the bankrupt and non-bankrupt firms in the validation sample.

The statistics of the estimation sample are very similar to those of the validation sample. The ratios in the estimation sample have a similar standard deviation. In the estimation sample there are more significant *p*-values for the test of mean differences. The ratio's that differ significant are the same.

Table 4. Descriptive statistics for the estimation sample

Accounting variable	Bankrupt firms (N=15)		Non-bankrupt firms (N=476)		
	Mean	**St. dev.**	**Mean**	**St. dev.**	***p*-value**[a]
A: Altman					
WC/TA	0.267	0.238	0.411	0.267	**0.04****
RE/TA	-0.047	0.211	0.079	0.201	**0.02****
EBIT/TA	-0.032	0.184	0.071	0.210	**0.06***
DEBT/EQUITY	0.258	0.337	1.802	6.829	0.38
SALES/TA	2.970	2.261	2.186	2.775	0.28
B: Ohlson					
SIZE	2.704	0.878	3.198	0.501	**0.00*****
TL/TA	0.762	0.300	0.635	0.318	0.13
WC/TA	0.245	0.247	0.411	0.267	**0.02****
CL/CA	1.052	0.491	0.908	0.828	0.51
OENEG	0.133	0.352	0.042	0.201	0.33[b]
NI/TA	-0.039	0.181	0.048	0.177	**0.06***
FU/TL	0.074	0.210	0.363	0.618	**0.07***
INTWO	0.267	0.458	0.120	0.325	0.24[b]
CHIN	0.076	0.757	0.183	4.046	0.92
C: Zmijewski					
NI/TA	-0.039	0.181	0.048	0.177	**0.06***
TL/TA	0.762	0.298	0.635	0.318	0.13
CA/CL	0.933	0.440	1.844	2.642	0.18

Note: The independent variables used for this test are from the year t-1.

[a] *p*-Value of pooled *t*-test (with a confidence level of 95%) of differences in variable means between the bankrupt and non-bankrupt groups. Because the *p*-value of the Levene's test is greater (for exceptions see b) than the α-level of 0.05, the null hypothesis is accepted. This means that I will assume that the variances between the bankrupt and non-bankrupt group are equal.

[b] The *p*-value of the Levene's test is lower than the α-level of 0.05.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.001 level

Table 5. Descriptive statistics for the validation sample

Accounting variable	Bankrupt firms (N=14)		Non-bankrupt firms (N=326)		
	Mean	**St. dev.**	**Mean**	**St. dev.**	***p*-value[a]**
A: Altman					
WC/TA	0.508	0.307	0.393	0.240	**0.08***
RE/TA	-0.261	0.118	0.043	0.636	0.69
EBIT/TA	-0.010	0.049	0.069	0.209	0.16
DEBT/EQUITY	0.353	0.346	1.279	5.987	0.56
SALES/TA	1.320	1.521	2.494	4.079	0.28
B: Ohlson					
SIZE	3.356	0.511	3.180	0.700	0.35
TL/TA	0.774	0.187	0.694	0.666	0.65
WC/TA	0.508	0.307	0.393	0.240	**0.08***
CL/CA	1.326	2.221	1.024	2.270	0.63
OENEG	0.071	0.267	0.061	0.240	0.88
NI/TA	-0.037	0.060	0.054	0.200	**0.09***
FU/TL	0.066	0.065	0.334	0.650	0.13
INTWO	0.214	0.426	0.141	0.349	0.45
CHIN	-0.366	1.063	0.162	3.672	0.59
C: Zmijewski					
NI/TA	-0.037	0.060	0.054	0.200	**0.09***
TL/TA	0.775	0.187	0.694	0.666	0.65
CA/CL	3.061	3.957	1.737	1.964	0.23[b]

Note: The independent variables used for this test are from the year t-1.

[a] *p*-Value of pooled *t*-test (with a confidence level of 95%) of differences in variable means between the bankrupt and non-bankrupt groups. Because the *p*-value of the Levene's test is greater (for exceptions see b) than the α-level of 0.05, the null hypothesis is accepted. This means that I will assume that the variances between the bankrupt and non-bankrupt group are equal.

[b] The *p*-value of the Levene's test is lower than the α-level of 0.05.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.001 level

The basic information regarding size and year for the estimation sample is given in table 6. Regarding the financial crisis between 2007 and 2008, it is worth mentioning that nine of the fifteen bankrupt firms filed for bankruptcy in the year 2008. The minority (six) of the bankrupt firms filed later (2009 and 2010) after the financial crisis for bankruptcy. Furthermore, table 6 indicates that the book value of the total assets of nine of the fifteen bankrupt firms are not higher than € 100,000.

The number of observations of the non-bankrupt firms are almost equally distributed among the years. There is a negative relation between the size of the firm and the number of observations in the estimation sample: when the size of the firm increases, the number observations decreases.

Table 6. Number of observations for the estimation sample in each year by size

Size	**2008**	**2009**	**2010**	**Total**
A: Bankrupt firms				
< € 100,000	6	1	2	9
€ 100,000 - € 500,000	2	1	1	4
> € 500,000	1	1	0	2
Total	**9**	**3**	**3**	**15**
B: Non-bankrupt firms				
< € 100,000	79	53	59	191
€ 100,000 - € 500,000	65	63	61	189
> € 500,000	36	24	36	96
Total	**180**	**140**	**156**	**476**

Note: The size of the firms is measured by the amount of total assets.

Table 7 reports the distribution of the validation sample. This sample is used to validate the estimated models. The number of observations for the bankrupt firms was in 2011 higher than in 2010. Furthermore, the non-bankrupt firms with a book value of the total assets higher than € 500,000 were in 2012 less than in 2011.

The distribution of the estimation sample and the distribution of the validation sample look very similar except for the size of the bankrupt firms. The relationship between the size and number of observations for the validation sample is positive. While, the relationship between size and the number of observations for the estimation sample is negative.

Table 7. Number of observations for the validation sample in each year by size

Size	2011	2012	Total
A: Bankrupt firms			
< € 100,000	2	2	4
€ 100,000 - € 500,000	4	1	5
> € 500,000	4	1	5
Total	**10**	**4**	**14**
B: Non-bankrupt firms			
< € 100,000	54	65	119
€ 100,000 - € 500,000	64	77	141
> € 500,000	45	21	66
Total	**163**	**163**	**326**

Note: The size of the firms is measured by the amount of total assets.

4 Empirical results and discussion

This section reports the findings of the tests[10] used to evaluate the bankruptcy prediction models. In general, when the liquidity is low, profitability is low, and leverage is high, the likelihood of bankruptcy increases. Therefore, the expected signs for the re-estimated coefficients for the liquidity and profitability ratios are negative. And for the leverage ratios the expected sign is positive.

4.1 Testing partial correlation

Before the hypotheses will be tested, multicollinearity is examined. As mentioned earlier, Hensher and Jones (2007) propose to examine multicollinearity by testing the partial correlation of the explanatory variables. The control variables are the book value of total assets and industry. The reason for this is that these firm characteristics may be potential predictors of the likelihood of bankruptcy (e.g. Beaver et al., 2005; Lin, 2009; Donker, Santen & Zahir, 2009). And statistically, the variable book value of total assets shows significant relationship to explanatory variables of the prediction models. The bivariate correlation is compared with the partial correlation. The control variables may explain a part of the observed relationship when the partial correlation is significant weaker than the bivariate correlation.

The results of these tests for the estimation sample show that the partial correlation of the relationship between the ratios WC/TA and SALES/TA of the Altman (1968) model is significant weaker (r = 0.130, $p < 0.05$) than the bivariate correlation. This is also true for three relationships between ratios of the model of Ohlson (1980). Namely, SIZE and CL/CA (r = 0.113, $p < 0.05$), WC/TA and CL/CA (r = -0.296, $p < 0.01$), and CL/CA and NI/TA (r = -0.150, $p < 0.05$). There are no correlations that are significant weaker when the controlling variables are entered for the model of Zmijewski (1984).

For the validation sample, the partial correlations between the ratios RE/TA and EBIT/TA (r = 0.610, $p < 0.01$) and WC/TA and SALES/TA (r = 0.175, $p < 0.01$) of Altman (1968) is significant weaker than the bivariate correlation. The partial correlations between the ratios TL/TA and FU/TL (r = -0.191, $p < 0.01$), TL/ TA and INTWO (r = 0.257, $p < 0.01$), and CL/CA and INTWO (r = 0.170, $p < 0.01$) of the model of Ohlson (1980) are significant weaker when the controlling variables are entered in the regression. And for the model of Zmijewski (1984) only the partial correlation between the ratios TL/TA and CA/CL (r = -0.212, $p < 0.01$) is significant weaker than the bivariate correlation.

[10] The dependent variable is set to 1 for bankrupt firms and 0 for non-bankrupt firms, so a positive (negative) coefficient indicates that the relevant independent variable is associated with an increase (decrease) in the likelihood of bankruptcy.

These results imply that the control variables book value of total assets and industry explain a part of the relationship between the several ratios and the likelihood of bankruptcy.

4.2 Testing hypothesis 1

In this section I re-estimate the coefficients of the bankruptcy prediction models with their original statistical technique. For each bankruptcy prediction model, three sets of estimated models were computed. Model 1 predicts bankruptcy within one year; Model 2 predicts bankruptcy within two years; Model 3 predicts bankruptcy within three years. The results for each prediction model are reported in table 8, 9, and 10.

4.2.1 In-sample results

Table 8 shows the estimated coefficients of the MDA model of Altman (1968). The negative coefficient of SALES/TA implies that if profitability increases the likelihood of bankruptcy decreases. This result is consistent with general theory.

Table 8. In-sample analysis for MDA model of Altman (1968)

	Altman (1968)	**Model 1** **Estimate**	**Model 2** **Estimate**	**Model 3** **Estimate**
Intercept		-1.009	-0.471	-0.526
WC/TA	1.200	2.487	2.330	2.509
RE/TA	1.400	2.450	0.159	-0.003
EBIT/TA	3.300	0.967	3.711	4.067
DEBT/EQUITY	0.600	0.041	0.017	0.005
SALES/TA	0.900	-0.146	-0.397	-0.385
Eigenvalue		0.026	0.022	0.032
Accuracy rate		0.697	0.758	0.786

Notes: Coefficients estimated using full estimation sample (N=491, 15 bankrupt and 476 non-bankrupt firms).

Because the independent variables use the same measurement units (euro), unstandardized coefficients are used. Therefore the intercept is included in the function.

EBIT/TA of Model 3 has an estimated coefficient of 4.067 and decrease to 0.967 (Model 1). From this it can be derived that when the years within the prediction of bankruptcy decline, the ratio EBIT/TA becomes a less good predictor of the likelihood of bankruptcy. On the contrary, table 8 shows that the ratio RE/TA becomes a better predictor of the likelihood of bankruptcy when the years within the prediction of bankruptcy decline.

The estimated coefficients of the MDA model are easily to interpret. The ratios WC/TA and RE/TA in Model 1 have the highest coefficients. These ratios tend to be good predictors because the weight is large.

In accordance with the original function of Altman (1968), the estimated coefficients indicate that WC/TA and RE/TA are good explanatory variables for bankruptcy prediction.

The estimated model has an very low eigenvalue of 0.026. As mentioned earlier, the eigenvalue is the ratio between variances between groups and variances within groups. This means that the predictive power of the model is very low because the variance between groups is low and the variance within groups is high. The overall accuracy of the MDA model of Altman (1968) range from 69.7% to 78.6%. It is remarkable that Model 3 is more accurate than Model 1 because the general assumption is that predicting bankruptcy within one year is much easier than predicting bankruptcy within three years.

Table 9. In-sample analysis for logit model of Ohlson (1980)

	Ohlson (1980)	Model 1		Model 2		Model 3	
		Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	-1.300	-4.821	0.07	-3.697	0.18	**-4.902**	**0.05***
SIZE	-0.400	**-2.130**	**0.01****	**-2.137**	**0.01*****	**-2.536**	**0.00*****
TL/TA	6.000	-0.067	0.96	3.090	0.13	**3.485**	**0.05****
WC/TA	-1.400	**-3.594**	**0.01****	**-3.272**	**0.01****	**-4.514**	**0.00*****
CL/CA	0.800	0.079	0.81	-1.029	0.20	-1.977	**0.04****
OENEG	-2.400	0.792	0.48	-1.582	0.29	-0.916	0.53
NI/TA	-1.800	1.559	0.43	4.904	0.41	-5.076	0.26
FU/TL	0.300	**-5.302**	**0.02****	**-6.233**	**0.09***	-0.392	0.86
INTWO	-1.700	0.356	0.65	0.666	0.39	0.718	0.44
CHIN	-0.500	0.013	0.81	-0.010	0.80	0.015	0.70
Pseudo R^2		0.245		0.220		0.238	
Accuracy rate		0.974		0.967		0.969	

Notes: Coefficients estimated using full estimation sample (N=491, 15 bankrupt and 476 non-bankrupt firms).

Because the independent variables use the same measurement units (euro), unstandardized coefficients are used. Therefore the intercept is included in the function.

A cutoff point of 0.5 is selected for Model 1, 2, and 3.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.01 level

Table 9 indicates that the direction of the relationship between several ratios and the likelihood of bankruptcy changed between Model 1, 2 and 3. Also, several re-estimated coefficients have not the same sign as the original function of Ohlson (1980). This finding suggests that the predictors of the original Ohlson (1980) model are not stable across time periods.

Furthermore, the table reports that the coefficients are significant for the ratios: (1) SIZE, (2) WC/TA, and (3) FU/TL. This small *p*-value indicates that a slope this large would be very unlikely to occur by chance if, in fact, there was no linear relationship between the variables. The overall accuracy rate of the model of Ohlson (1980) for Model 1 is 97.4%. The Pseudo R^2 and the accuracy rate for Model 1 indicate that the model of Ohlson (1980) is the most accurate when predicting bankruptcy within one year. The Pseudo R^2 is bounded between 0 and 1, how larger this score how better the fit of the model. The Pseudo R^2 of the estimated Ohlson (1980) model is very low.

The analysis for the probit model of Zmijewski (1984) in table 10 indicates that the intercepts are in all three models significant at 0.01 level. There are no slopes that are significant in Model 1. The directions of the relationships do not change over time for the ratios of the Zmijewski (1984) model. The sign of the re-estimated coefficients of the ratio CA/CL is not the same as the original function of Zmijewski (1984). The Pseudo R^2 range from 0.042 to 0.089. The Pseudo R^2 (0.089) of the model of Zmijewski (1980) indicate that Model 1 is the most accurate.

Table 10. In-sample analysis for probit model of Zmijewski (1984)

	Zmijewski (1984)	**Model 1**		**Model 2**		**Model 3**	
		Estimate	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**
Intercept	-4.300	**2.114**	**0.00*****	**2.512**	**0.00*****	**2.114**	**0.00*****
NI/TL	-4.500	-1.719	0.17	-0.582	0.60	-1.719	0.17
TL/TA	5.700	0.513	0.32	**0.956**	**0.06***	0.513	0.32
CA/CL	0.004	-0.046	0.71	-0.010	0.92	-0.046	0.71
Pseudo R^2		0.089		0.045		0.042	

Notes: Coefficients estimated using full estimation sample (N=491, 15 bankrupt and 476 non-bankrupt firms).

Because the independent variables use the same measurement units (euro), unstandardized coefficients are used. Therefore the intercept is included in the function.

A cutoff point of 0.5 is selected for Model 1, 2, and 3.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.01 level

4.2.2 Out-of-sample results

The validation sample is used to perform the generalizability test for the three bankruptcy prediction models. Table 11 reports the accuracy rates using coefficients estimated from the estimation sample. The three panels represent the three different bankruptcy prediction models.

Table 11. Classification matrix for the bankruptcy models with original statistical technique

	Observed	Predicted Bankrupt	Non-bankrupt	Good predictions
A: Altman (1968)	**Bankrupt**	5 (1.47%)	9 (2.65%)[a]	5 (35.71%)
	Non-bankrupt	57 (16.76%)[b]	269 (79.12%)	269 (82.52%)
	Overall			274 (80.59%)
B: Ohlson (1980)	**Bankrupt**	0 (0%)	14 (4.12%)[a]	0 (0.00%)
	Non-bankrupt	7 (2.06%)[b]	319 (93.82%)	319 (97.85%)
	Overall			319 (93.82%)
C: Zmijewski (1984)	**Bankrupt**	0 (0.00%)	14 (4.12%)[a]	0 (0.00%)
	Non-bankrupt	2 (0.59%)[b]	324 (95.29%)	324 (99.39%)
	Overall			324 (95.29%)

Note: For the model of Altman (1968), Ohlson (1980), and Zmijewski (1984) the cutoff points are respectively 2.675, 0.5, and 0.5.

[a] Type I error occurs when the observed firm is bankrupt but predicted non-bankrupt.
[b] Type II error occurs when the observed firm is non-bankrupt but predicted bankrupt.

Table 11 reports that the model of Altman (1968) has an overall accuracy rate of 80.59%. The overall accuracy rate of this model is (compared to the others) low, but the accuracy rate for predicting bankrupt firms is high.

Furthermore, table 11 reports that the model of Ohlson (1980) has an overall accuracy rate of 97.14%. The model of Ohlson (1980) predicted 0% of the bankrupt firms correctly. Therefore the frequency of Type I errors for the model of Ohlson (1980) is very high. All the observed bankrupt firms are misclassified. It is likely that when the proportion bankrupt:non-bankrupt firms of the validation sample was different, the accuracy rate of the model was also different. The model of Zmijewski (1984) has the highest overall accuracy rate (95.29%). However, the model of Zmijewski (1984) has also a high frequency of Type I errors; all the bankrupt firms are misclassified. Therefore, the model of Zmijewski (1984) has an accuracy rate for predicting bankrupt firms of 0% and for predicting non-bankrupt firms 99.39%.

4.3 Testing hypothesis 2

In this section I use the logit model to test the prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984). This statistical technique is used in the original study of Ohlson (1980). While holding the statistical technique constant, the explanatory variables can be examined. The same procedure is followed as for the logit model in hypothesis 1. I evaluate the prediction models with the Pseudo R^2 and the accuracy rate.

4.3.1 In-sample results

Table 12 reports the estimated coefficients for the model of Altman (1968) with the logit model. The results indicate that the intercepts for all the models are significant at 0.01 level. Furthermore, the WC/TA is significant for all the three models, EBIT/TA is significant for Model 3, DEBT/EQUITY is significant for Model 1, and SALES/TA is significant for Model 2 and 3. The null hypothesis for these slopes can be rejected. This means that these slopes are likely to be a meaningful addition to the model because changes in these slopes are related to the changes in the dependent variable. The results show that the prediction model of Altman (1968) is the most accurate when predicting bankruptcy within one year. The accuracy rate is higher when the logit model is used (96.9%) than when the original MDA is used (69.7%). The Altman (1968) has more differences when the logit model instead of the MDA model. First, different ratios are significant. Secondly, a different model is the most accurate.

Table 12. In-sample analysis for logit model of Altman (1968)

	Model 1		**Model 2**		**Model 3**	
	Estimate	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**
Intercept	**-1.946**	**0.00*** **	**-2.333**	**0.00*** **	**-2.397**	**0.00*** **
WC/TA	**-2.589**	**0.03** **	**-2.116**	**0.06* **	**-2.952**	**0.02** **
RE/TA	-0.757	0.56	-1.579	0.62	0.003	0.88
EBIT/TA	-0.002	1.00	-1.191	0.73	**-5.803**	**0.03** **
DEBT/EQUITY	**-1.635**	**0.06* **	-1.234	0.11	-0.378	0.36
SALES/TA	0.065	0.23	**0.153**	**0.09* **	**0.163**	**0.05*** **
Pseudo R^2	0.134		0.115		0.119	
Accuracy rate	0.969		0.969		0.969	

Notes: Coefficients estimated using full estimation sample (N=491, 15 bankrupt and 476 non-bankrupt firms).

Because the independent variables use the same measurement units (euro), unstandardized coefficients are used. Therefore the intercept is included in the function.

A cutoff point of 0.5 is selected for Model 1, 2, and 3.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.01 level

The results for the model of Ohlson (1980) when the logit model is used can be found in table 9 because he used the logit model in his original study.

Table 13 reports the estimated coefficients for the explanatory variables of the model of Zmijewski (1984). In Model 1, only the ratio CA/CL is significant. The Pseudo R^2 for the logit model of Zmijewski (1984) ranges from 0.040 to 0.089. Model 1 has the highest Pseudo R^2. When the probit model of Zmijewski (1984) is used, the Pseudo R^2 ranges from 0.042 to 0.089. This finding suggest that the explanatory variables of Zmijewski (1984) are more accurate when the logit model is used.

Table 13. In-sample analysis for logit model of Zmijewski (1984)

	Model 1		**Model 2**		**Model 3**	
	Estimate	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**
Intercept	-1.398	0.10	**-4.717**	**0.00*** **	**-3.933**	**0.00*** **
NI/TL	-1.513	0.39	-1.018	0.67	-3.709	0.18
TL/TA	-0.445	0.64	**1.941**	**0.08***	1.053	0.35
CA/CL	**-1.465**	**0.01****	-0.058	0.83	-0.113	0.71
Pseudo R^2	0.089		0.041		0.040	
Accuracy rate	0.969		0.969		0.969	

Notes: Coefficients estimated using full estimation sample (N=491, 15 bankrupt and 476 non-bankrupt firms).

Because the independent variables use the same measurement units (euro), unstandardized coefficients are used. Therefore the intercept is included in the function.

A cutoff point of 0.5 is selected for Model 1, 2, and 3.

* Statistical significance at 0.10 level
** Statistical significance at 0.05 level
*** Statistical significance at 0.01 level

4.3.2 Out-of-sample results

The validation sample is used to perform the generalizability test for the three bankruptcy prediction models. Table 14 reports the accuracy rates using coefficients estimated from the estimation sample. The three panels represent the three different bankruptcy prediction models.

Table 14. Classification matrix for the bankruptcy models with logit regression

	Observed	*Predicted* Bankrupt	Non-bankrupt	Correct classifications
A: Altman (1968)	**Bankrupt**	7 (2.06%)	7 (2.06%)[a]	7 (50.00%)
	Non-bankrupt	166 (48.82%)[b]	160 (47.06%)	160 (49.08%)
	Overall			167 (49.12%)
B: Ohlson (1980)	**Bankrupt**	0 (0%)	14 (4.12%)[a]	0 (0.00%)
	Non-bankrupt	7 (2.06%)[b]	319 (93.82%)	319 (97.85%)
	Overall			319 (93.82%)
C: Zmijewski (1984)	**Bankrupt**	4 (1.18%)	10 (2.94%)[a]	4 (28.57%)
	Non-bankrupt	32 (9.41%)[b]	294 (86.47%)	294 (90.18%)
	Overall			298 (87.65%)

Note: A cutoff point of 0.5 is selected for Model 1, 2, and 3.

[a] Type I error occurs when the observed firm is bankrupt but predicted non-bankrupt.
[b] Type II error occurs when the observed firm is non-bankrupt but predicted bankrupt.

Table 14 reports that the model of Altman (1968) has an overall accuracy rate of 49.12%. As mentioned earlier, this rate can be split into the rate of correct predicted bankrupt and non-bankrupt firms. Both accuracy rates are near 50%. This means that the frequency of Type I and Type II errors is almost the half of the total observations.

Furthermore, table 14 reports that the model of Ohlson (1980) has the highest overall accuracy rate (93.82%). This means that the model of Ohlson (1980) has the highest accuracy rate when all the prediction models use the logit model. This may imply that the explanatory variables of the model of Ohlson (1980) are the best predictors of the likelihood of bankruptcy. This is in contrast with the assumption which was derived from the literature review (see table 2). But there is a pitfall, the model of Ohlson (1980) predicted 0% of the bankrupt firms and 97.85% of the non-bankrupt frims correctly.

The overall accuracy rate for the model of Zmijewski (1984) is 87.65%. The percentage of correctly predicted bankrupt firms is 28.57% and for the non-bankrupt firms 90.18%.

5 Conclusions

5.1 Research question

This study examined the predictive power of bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984). These bankruptcy prediction models use profitability, leverage and liquidity ratios to predict bankruptcy. The differences between these models are the statistical technique (multiple discriminant analysis, logit regression, and probit regression) and the explanatory variables. The following research question is answered:

What is the difference in predictive power between the bankruptcy prediction models of Altman (1968), Ohlson (1980) and Zmijewski (1984) to Dutch listed and large non-listed firms?

5.2 Main results

Two hypotheses were tested in order to assess the predictive power of these bankruptcy prediction models. The first hypothesis stated that there is no difference in accuracy between the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) when the original statistical techniques are used. The results showed that there is a difference between the predictive power of the prediction models. When the original statistical techniques are used, the accuracy rates for the validation sample for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) models are respectively 80.6%, 93.8%, and 95.3%. At first sight it looks like the model of Zmijewski (1984) has the highest predictive power. But this overall accuracy rate should be interpreted with more attention. The model of Zmijewski (1984) predicted 0% of the bankrupt firms correctly and 99.4% of the non-bankrupt correctly. This means that the model is not able to discriminate between bankrupt and non-bankrupt firms. The result is a high frequency of Type I errors. Because of the proportional sample the overall accuracy rate of the model of Zmijewski (1980) is 95.3%. The accuracy rates for the validation samples in the original study of the Altman (1968) and Ohlson (1980) models are respectively 84% and 85%. This means that the accuracy rate in this study for the model of Altman (1968) is lower and for the model of Ohlson (1980) higher.

The second hypothesis stated that there is no difference in accuracy between the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) when the logit model is used. Because the original study of Ohlson (1984) used the logit model, the accuracy rate did not change for hypothesis two. Therefore, the model of Ohlson (1984) has an accuracy rate of 93.8%. The models of Altman (1968) and Zmijewski (1984) had a lower accuracy rate, respectively 49.1% and 87.7%. First, these results indicates that there is a difference between the models when the same statistical technique is used. The model of Ohlson (1980) is the most accurate when all the models use the same statistical technique. This implies that the explanatory variables of this model are the best predictors of the likelihood of bankruptcy. This is in contrast with the assumption which was derived from the literature review (see table 2). Second, the results showed that the accuracy rate of the models changed when another statistical technique is used. The accuracy of the model of Altman (1968) decreased from 80.6% to 49.1%. This implies that the statistical technique has an effect on the predictive power of the models. Finally, the results suggest that the model of Ohlson (1980) has the highest predictive power when the model is evaluated with the accuracy rate. But as mentioned earlier, this overall accuracy rate should be interpreted cautiously.

In conclusion, practitioners should use the bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) cautiously when they apply the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) in the Netherlands for listed and large non-listed firms. They should use the models cautiously because the frequency of Type I errors is high (Ohlson [1980] and Zmijewski [1984]) or the accuracy rate is low (Altman [1986]). To use these models in practice, I recommend to re-estimate the coefficients of the bankruptcy prediction models with a specific and bigger sample to improve the predictive power.

5.3 Limitations

The reader should be aware that this study has several limitations. Firstly, because of time limitations the study is elementary. This is expressed in the research methodology; the sample sizes is are not big and the window of time is short. Secondly, this study focuses only on accounting variables. This has three implications (i) accounting variables can be distorted (e.g. by the use of a different depreciation method), (ii) accounting variables are aimed at the past, and (iii) the accounting variables are available on yearly basis.

5.4 Suggestions for future research

First, the results of this study suggest that the statistical technique has an effect on the predictive power of the models. Therefore, an area for future research would be to extend the analysis to other statistical techniques. A study with one bankruptcy prediction model and multiple statistical techniques would allow to a more detailed analysis about the effects of these statistical techniques.

Secondly, a major contribution can be made when an identical study can be conducted in another economic period. The results of both studies can be compared when the methodology of this future research and this research are identical. Differences between the accuracy may imply that a specific bankruptcy prediction model is preferred in a specific economic period.

At last, this study used the book value of total assets and the size of the firm as control variables. It is likely that there are more variables that influence the ratios of the firms. It can be considered that the corporate strategy and the competition in the industry are other control variables.

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Appendix A: Brief summary of bankruptcy prediction models

Model	Econometric technique	Explanatory variables	Profitability	Liquidity	Leverage
Altman	Multiple discriminant analysis (MDA)	WC/TA = Net working capital/total assets		x	
		RE/TA = Retained earnings/total assets			x
		EBIT/TA = Earnings before interest and taxes/total assets	x		
		DEBT/EQUITY = Debt/equity			x
		SALES/TA = Sales/total assets	x		
Ohlson	Logit regression	SIZE = Log(total assets/GNP price-level index)			
		TL/TA = Total liabilities/ total assets			x
		WC/TA = Working capital/total assets		x	
		CL/CA = Current liabilities/current assets		x	
		OENEG = 1 If total liabilities exceed total assets, 0 otherwise			x
		NI/TA = Net income/total assets	x		
		FU/TL = Funds provided by operations (income from operation after depreciation)/total liabilities		x	
		INTWO = 1 If net income was negative for the last 2 years, 0 otherwise		x	
		CHIN = $(NIt\ \ NIt1)/(\lvert NIt\rvert + \lvert NIt1\rvert)$, where NIt is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure the relative change in net income.	x		

Zmijewski	Probit regression	NI/TL = Net income/total liabilities	**x**		
		TL/TA = Total liabilities/total assets			**x**
		CA/CL = Current assets/current liabilities		**x**	