

Master Thesis

Business Administration – Financial Management



Comparison of accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) to German and Belgian listed companies during 2008 - 2013

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25th July 2014

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Management Summary

Companies in all kind of fields are interested in the performance of their business. The prediction of financial soundness of a business has led to presence in many academic work and newspaper; especially in times of financial crises and economic downturns. As financial ratios are key indicators of a business performance, different bankruptcy prediction models have been created to forecast the likelihood of bankruptcy. However, a bankruptcy prediction model with high accuracy rate remains a challenge since bankruptcy prediction models are based on industries and specific samples. Therefore, the aim of this Master Thesis is to assess the accuracy rate of accounting-based bankruptcy prediction models to industries and periods outside those of original studies. The accuracy rate of three accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) were tested on German and Belgium listed companies between 2008- 2013. The sample on Belgium listed companies implies 5646 active and 140 bankrupt companies. The sample on German listed companies implies 1432 active and 21 bankrupt companies. The Master Thesis assumed that there is a difference of accuracy rate between the three accounting-based bankruptcy prediction models since they imply different financial ratios and; therefore provide different information about a companies' status of health. Further, since the models are tested on two different countries, the Master Thesis seeks to analyze differences of accuracy rates in both countries. Results of this study confirmed those assumptions. The accuracy rates for Belgian listed companies on Altman (1968), Ohlson (1980), and Zmijewski (1984) are 68.3 %, 68.0 % and 67.9 % whereas the accuracy rates for German listed companies on Altman (1968), Ohlson (1980), and Zmijewski (1984) are 52.1 %, 53.1 % and 52.0 %. Overall, Ohlson's logit model (1980) performed most accurate on German and Belgium listed companies within the three years of investigation. That means that the financial ratios of Ohlson's model (1980) are most predictive for bankruptcy likelihood. However, the accuracy rates for German and Belgian listed companies highly differ from each other. In sum, the accuracy rate of Altman (1968), Ohlson (1980); and Zmijewski (1984) on German listed companies are lower than on Belgium listed companies which can be explained due to the low ratio of bankrupt to non-bankrupt companies. As consistent to general theory the accuracy rate of the three accounting-based bankruptcy prediction models decline towards the year of bankruptcy. Therefore, results should be set into perspective and studied cautiously.

Table of Content

Management Summary	2
1. Introduction	6
1.1 Background Information	6
1.2 Problem Statement	7
1.3 Objectives.....	7
1.4 Research Objective.....	8
1.5 Justification	8
2. Conceptualization	9
2.1 Bankruptcy, financial distress, insolvency- naming the concept.....	9
2.2 Bankruptcy prediction models.....	10
2.2.1 Accounting-based bankruptcy prediction models	10
2.2.2 Altman (1968)	11
2.2.3 Ohlson (1980).....	14
2.2.4 Zmijewski (1984)	16
2.2.5 Conclusion.....	17
2.3 Market-based bankruptcy prediction models	18
2.4 Comparing accounting-based and market-based bankruptcy prediction models	20
3. Operationalization	23
3.1 Research Question.....	23
3.2 Research Methodology	23
3.3 Sample Selection	25
3.4 Sample Description	26
3.5 Derivation of Hypotheses.....	26
4. Data Analysis	32
4.1 Univariate analysis of the sample.....	32
4.2 Testing hypotheses	34
4.3 Analysis of Altman´s model (1968)	34
4.3.1 Results of Altman´s model (1968) on Belgian listed companies	35
4.3.2 Results of Altman´s model (1968) on German listed companies	36

4.3.3 Conclusion on the model of Altman (1968)	37
4.4 Analysis of Ohlson model (1980).....	38
4.4.1 Results of Ohlson's model (1980) on Belgian listed companies	39
4.4.2 Results of Ohlson's model (1980) on German listed companies	40
4.4.3 Conclusion on model of Ohlson (1980)	41
4.5 Analysis of Zmijewski's model (1984).....	41
4.5.1 Results of Zmijewski's model (1984) on Belgian listed companies	42
4.5.2 Results of Zmijewski's model (1984) on German listed companies	43
4.5.3 Conclusion on the model of Zmijewski (1984)	44
4.6 Discussion	45
5. Conclusion	46
5.1 Conclusion of Findings	46
5.2 Limitations.....	49
5.3 Outlook for Future Research	50
Appendices	60
Appendix A: Classification of financial variables.....	60
Appendix B: Overview of Hypotheses and Research Question	61

Table of Tables

<i>Table 1: Overview of common accounting-based bankruptcy prediction models (based on own assessment)</i>	18
<i>Table 2: Overview of market-based bankruptcy prediction models (based on own assessment)</i>	20
<i>Table 3: Population for the study (based on own assessment)</i>	26
<i>Table 4: Categorization if hypotheses are rejected or not (based on own assessment)</i>	29
<i>Table 5: Summary on studies analysing the three accounting-based bankruptcy prediction models (based on own assessment)</i>	30
<i>Table 6: Descriptive statistics for the sample (based on own assessment)</i>	33
<i>Table 7: Results for Belgian listed companies (based on own assessment)</i>	35
<i>Table 8: Results for German listed companies (based on own assessment)</i>	36
<i>Table 9: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)</i>	38
<i>Table 10: Results for Belgian listed companies (based on own assessment)</i>	39
<i>Table 11: Results for German listed companies (based on own assessment)</i>	40
<i>Table 12: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)</i>	41
<i>Table 13: Results for Belgian listed companies (based on own assessment)</i>	42
<i>Table 14: Results for German listed companies (based on own assessment)</i>	43
<i>Table 15: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)</i>	44
<i>Table 16: Comparison of the accuracy rate of Belgian listed companies (based on own assessment)</i>	47
<i>Table 17: Comparison of the accuracy rate of German listed companies (based on own assessment)</i>	48

1. Introduction

1.1 Background Information

In times where firms disappear from the marketplace due to different reasons such as running out of liquidity or facing economic downturns, it has become crucial for companies to forecast the failure of their business as this “is an event which can produce substantial losses to creditors and stockholders” (Deakin, 1972). The phenomenon of bankruptcy became again evident in media in the last few years due to the financial crises period between 2007 and 2009. For example, when in 2008 23 534 companies declared bankruptcy in Germany in 2009 27875 companies went bankrupt (Federal Statistical Office Germany, 2013). This increase by 5.3 % of bankruptcy stresses the importance, that events like financial crisis has an effect on the likelihood of bankruptcy. However, the unforeseen event of a financial crises can not only lead to bankruptcy; there are many different factors leading to it as high interests rates, recession-squeezed profits and heavy debt burdens (Charitou *et al.*, 2004). In that manner, bankruptcies seem to be unexpected although signs may have been evidence that years ago the filing took place. Past studies have shown that the phenomenon of going bankrupt takes place over a period of time and a company runs through different stages before it declares bankruptcy; so a company is possible to take appropriate actions well ahead (Hambrick and D'Aveni, 1988). Before a company faces bankruptcy the company will be headed as “financially distressed”. Here, the company is not able to pay their debt, invoices or other obligations.

To deduce, “Bankruptcies are devastating” (Bhagarva *et al.*, 1998) and therefore it is important to systematically study bankruptcies so as to minimize the impact; especially since the economic costs of business failure is significant because market value of distressed firms decline substantially before ultimate collapse (Werner, 1977; Charalambous *et al.*, 2000). Since the process of bankruptcy is a non-exclusive event for any company, the prediction of business bankruptcy is crucial and highly beneficial because it tends to reduce future costs. Naturally, stakeholders such as investors of a company are interested in finding a reliable method to predict a possible bankruptcy. Hence, there are a number of well-established and worldwide-known bankruptcy prediction models. Two approaches, accounting-based bankruptcy prediction models and market-based bankruptcy prediction models, imply different views of a company and use financial ratios to estimate the possibility of bankruptcy. The goal of this Master Thesis is to examine the accuracy rate of the original Altman (1968) and Ohlson (1980) and Zmijewski (1984) models on German and Belgian listed companies.

1.2 Problem Statement

A major concern for stakeholder is to predict the likelihood of financial bankruptcy in order to respond before the events take place. Hence, different bankruptcy prediction models that are able to forecast corporate failure have been developed after Beaver's pioneering work in 1966. Beaver (1966) came up with an univariate approach to analyse bankruptcy and it was Altman (1968) who based his work (the z- score model) on him. The univariate analysis is the analysis of one single variable and its attributes. However, until now a bankruptcy prediction model with high predictive power still remains a challenge since no model performs with 100% accuracy rate.

The majority of bankruptcy prediction studies have mainly analysed one single method or a combination of two. However, only a few studies have paid attention to multiple models regarding bankruptcy prediction.

According to Xiao *et al.* (2012), the existing literature showed that a single bankruptcy prediction model faces limitations and multiple bankruptcy prediction models improved the prediction of accuracy in bankruptcy prediction. A limitation of a single model is that due to the fact it is based on some variables will not be able to give a full explanation of bankruptcy prediction. As Sun and Li (2008), for example, analysed different models for bankruptcy prediction, they found out that this mix improves the average prediction accuracy and stability by giving an empirical experiment with listed companies in China. Furthermore, Kim *et al.* (2002) and Cho *et al.* (1995) also demonstrated that a combination of multiple bankruptcy models reduce the variance of estimated error and also improves the whole recognition performance. That is why this Master Thesis will study three accounting-based bankruptcy prediction model namely Altman (1968), Ohlson (1980) and Zmijewski (1984).

1.3 Objectives

The objective of this Master Thesis is to apply the work of Altman (1968), Ohlson (1980), and Zmijewski (1984) to listed companies in Germany and Belgian. In more depth, this paper has the aim to assess the accuracy rate of the three accounting-based bankruptcy prediction models in order to find out whether or not there are differences between the different accounting-based bankruptcy prediction models.

1.4 Research Objective

The leading general question of this Master Thesis is:

What is the difference between the accuracy rate of accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), Zmijewski (1984) to listed German and Belgian companies between 2008 - 2013?

1.5 Justification

This topic of this Master Thesis about predicting bankruptcy was chosen because it allows analyzing the development and stages of a company might run through ending with the state of bankruptcy.

Since this topic become recently in literature and newspaper, it seems important to draw attention to bankruptcy prediction models. Moreover, this topic seems to be interesting in that aspect in how far accounting-based bankruptcy prediction models can predict the likelihood of bankruptcy. This is going to be measured with their accuracy rate. Moreover; the topic seems also to be challenging in aspect in how far different accounting-based prediction models can be applied in other countries outside original settings and periods.

Concluding, this Master Thesis adds value to existing literature since it covers two countries which has not been studied by accounting-based bankruptcy prediction models. The aim of this study is to find out the accuracy rate of thee accounting-based bankruptcy models using listed companies in Germany and Belgium during 2008 - 2013; because this is consistent with existing studies (e.g. Grice & Ingram, 2001; Grice & Dugan, 2001). Further, this Master Thesis will focus on German and Belgian listed companies since most studies has been undertaken outside the European Union (EU). For example, Pongsat *et al.* (2004) undertook a study in Thailand and Bae (2012) in South Korea, Canbas *et al.* (2006) in Turkey. Additionally, this thesis will focus on three most common accounting-based bankruptcy prediction models since a combination of multiple bankruptcy models increases the overall prediction accuracy and reduces the variances of estimated errors. As outlined by Wu *et al.* (2010) there have been a number of key bankruptcy models but the most cited one are : Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2000) and Hillegeist (2004). Since the database ORBIS does not report market variables, I will stick to the accounting-based bankruptcy prediction models.

2. Conceptualization

The following section outlines the important concept of this Master Thesis namely the concept of bankruptcy. Since this Master Thesis deals with bankruptcy prediction models a definition of this concept is provided in order to understand what this term means and how it is applied in the Master Thesis also to regards to the analysis of the results of bankruptcy prediction models. After this, a review of common bankruptcy prediction models follows and ends with a discussion about them.

2.1 Bankruptcy, financial distress, insolvency- naming the concept

In existing literature, one will find different terms describing the term of business failure. McKee (2003) highlights this problem as: “while there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress”. For example, as Balcan and Ooghe (2004) describe that recent studies define the term of bankruptcy in “legal” matters. Karles and Prakash (1987) clarify that “bankruptcy is a process which begins financially and is consummated legally”. However, the reason why the legal interpretation is mostly cited is because it is an objective criterion allowing researchers to classify a specific population. For example, in a study about corporate failure in the United Kingdom by Charitou *et al.* (2004) the authors used the definition of failure according to the UK Insolvency Act of 1986. A similar legal definition of bankruptcy can be also found in the studies of Altman (1986) and McNichols and Rhie (2005) or Ohlson (1980).

On the other hand there are further terms for describing business failure. Firstly, failure, in terms of economic criteria is defined as: “the realized rate of return on invested capital is significantly and continually lower than prevailing rates on similar investments. It includes insufficient revenues to cover the costs and where the average return on investment is below the firm’s cost of capital” (Altman & Hotchkiss, 2006). A second term is insolvency and is defined as “one that is not able to service its current debts due to the lack of liquidity and often culminates in a declaration of bankruptcy” (Altman & Hotchkiss, 2006). Thirdly, the last term “default” occurs when a debtor is unable to meet the legal obligation of debt repayment (Altman & Hotchkiss, 2006)

When reviewing literature about bankruptcy models either the legal definition or the term of financial distress occurs. However, the term “financial distress” is hard to define as there is no common definition of the term financial distress since studies used different meanings and conditions to define so. Platt and Platt (2002) define financial distress as the late stage of

corporate decline, which implies the result of bankruptcy. Compared to that, McKee (2003) mentions that financial distress is a process a firm undertakes before it goes bankrupt.

Concluding, when reviewing studies about the five selected bankruptcy prediction models (explained below), one can say that different conditions were applied to define a company as bankrupt/distressed or non-bankrupt/non-distressed. This Master Thesis will stick to the assumption that the term “bankruptcy” is applied to firms that are not operating at least two years. As Altman (1968) has titled firms being bankrupt when they do not operate one year, this master thesis will assume that the bankruptcy will not happen within one year.

2.2 Bankruptcy prediction models

In exiting literature, there are two major groups of models for evaluating bankruptcy: accounting-based bankruptcy prediction models and market-based bankruptcy prediction models. For the first group the models can be used to predict business failure empirically based on accounting data of companies; whereas the market-based models includes data from market and do not only rely on accounting data. Examples for market variables are interest rates, stock shares and, macroeconomic variables.

2.2.1 Accounting-based bankruptcy prediction models

Accounting-based bankruptcy prediction models use financial statement information and therefore take into account the firm's past performance as a base to predict future performance (Xu and Zhang, 2000). Therefore, the advantage of considering financial statement is that “financial statement analysis identifies aspects that are relevant to investment decisions since the goal of the analysis is to assess firm value from financial statements” (Penman, 1996).

The use of financial statement data in investigating the relationship between failed and non-failed firms started in the early 30's, when Fritzpack (1931) and Merwin (1942) studied the phenomenon of bankruptcy. In the late 1960's it was Beaver who developed a univariate method for predicting bankruptcy based on accounting data (Dambolena & Khoury, 1980; He & Kamath, 2006 and Ugurlu & Aksoy, 2006). The use of financial ratios to predict failure has been a topic of much interest in accounting and finance since 1960's.

Many financial bankruptcy models rely on financial ratios such as Altman MDA model (1968) or Zmijewski probit model (1984) (Poston *et al.*, 1994). According to Yadav (1986) “financial

ratios as a predictor variables for the prediction of company failure are primarily selected on their basis of their ex- hypothetical capability to indicate the financial soundness or sickness of a company and on the basis of their proven in earlier studies”. Beaver (1966) analysed thirty financial ratios among bankrupt and non-bankrupt companies and found out that three financial ratios were significant in predicting bankruptcy of a company. Those ratios namely are: total assets / total debt; net income / total assets and cash flow / total debt.

2.2.2 Altman (1968)

In 1968 Altman built a statistical technique upon Beavers work which later became known as the multivariate discriminate analysis (MDA). Altman (1968) extended the univariate analysis by enlarging it with more financial ratios.

In general, the “MDA is a statistical technique used to classify an observation into one of several a priori groupings dependent upon the observation’s individual characteristics” (Altman 1968, p. 591). Altman (1968) criticises the univariate approach by Beaver (1966): “a firm with a poor profitability and/or solvency may be regarded as a potential bankrupt. However, because of its above average liquidity, the situation may not be considered serious”. So, according to Elliott & Elliott (2006, p.703) the z-score has the advantage that it “can be employed to rise above some of the limitations of traditional ratio analysis as it assess corporate stability and more significantly predicts potential case of corporate failures”.

Altman (1968) undertook a study with the objective to find out which combinations of financial ratios predict the bankruptcy at best. He collected data from 66 publicly held manufacturing companies in the USA between 1946 and 1965. He excluded very small and very large companies due to the fact that they could lead to wrong conclusions. This means that Altman (1968) included companies with a mean asset size of firm’s dollar 6.4 million. After having found a combination of five most important ratios, Altman (1968) started different tests in order to be sure that his model can correctly differentiate between bankrupt and non-bankrupt companies. Altman (1968) stated that the process of bankruptcy can take several years and that there are different stages a company has to run through to become bankrupt. The linear function according to Altman (1968) is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (eq.1)$$

Where

X_1 = is the working capital / total assets,

X_2 = retained earnings / total assets,

X_3 = earnings before interest and taxes / total assets,

X_4 = market value equity / book value of total debt,

X_5 = sales / total assets

To note in this regard is that X_1 is categorized as a liquidity ratio and that it shows a greater statistical significance on the univariate and multivariate basis compared to other statistical bankruptcy prediction models. Concerning X_2 Altman (1968) made the observation that this ratio will be low for young companies since those companies did not have time to build up its cumulative profits in the past. When coming to variable X_3 , one have to note that EBIT (earnings before interest and taxes) include only primary operations.

The cut-off point (z-score) selected by Altman (1968) is 2.675. In case with a higher z-score than the cut-off value is a non-bankrupt company whereas a z-value lower than the cut-off value can be classified so. Appendix A categorizes the different financial ratios into three financial ratios (liquidity, leverage and profitability).

Frydman, Altman and Kao (1985) explain that the MDA approach (1968) is one of the most appropriate models for detecting bankruptcy since it includes a wide range of financial ratios. Especially in the time before 1980's many bankruptcy models built on Altman z-score model (1968) (Balcaen and Ooghe, 2004); for example, the linear multiple approach by Deakan (1972) and Oohse (1974), Wilcox's model (1971) or Edmister (1972) and Libby (1975).

Still, over the last 30 years the MDA approach was employed to a variety of different industries and periods worldwide. Khalid Al-Rawi *et al.* (2008) state that the MDA approach (1968) can well integrate financial ratios and therefore determine the likelihood of bankruptcy. In conclusion, Lifschutz and Jacobi (2010) described that the MDA approach (1968) is able to forecast bankruptcy of publicly traded companies in Israel. They observed that Altman's z-score is a well-established model to show up early warnings of a possible bankruptcy.

Moreover, Res (2013) compared the MDA approach to Ohlson's logit model (1980) on Iranian listed companies. For the first year of observation Res (2013) reported a 74.4 % accuracy of MDA approach, for the second year of observation he reported a 64.4 % accuracy rate and for the third year of observation an accuracy of 50.0 %. In comparison to the accuracy rate of Ohlson's model (1980) Res (2013) concluded: "in all three situations the Altman works better and it could be suggested to investors in order to predict bankruptcy of companies". Furthermore, Ponsatat *et al.* (2004) undertook a study on 60 failed and 60 non-failed Thai listed firms and found out that the accuracy rate of the MDA approach was between 59 % - 75 %. Puagwatana and Gunawardana (2005) analysed 24 non-listed companies consisting of 12 failed and 12 non-failed technology firms in Thailand and their findings indicated that the accuracy rate of MDA approach in all three observation years was higher than 77.8 %. Grice (2001) who analysed 972 companies from 1950 to 1960 came to the same conclusion as Puagwatana and Gunawardana (2005). Grice (2001) and Grice & Ingram (2003) reported that for the first year of observation the accuracy rate of MDA was at highest (83.5%) and declined in the following years.

That is why the decline of accuracy rate is a common criticism to Altman's model (e.g Joy and Tollefson (1975), Dimitras, Slowinski, Susmaga and Zopounidis (1999)). A further criticism of Altman's model concerns the sample on which the MDA approach is based: Eisenbeis (1977), Ohlson (1980) and Jones (1987) criticized Altman's approach regarding its assumptions of normality and group distribution. Altman observed 33 bankrupt and 33 non-bankrupt companies which accordingly to Abdullah *et al.* (2008) lead to bias and error rates due to the equal distribution of sample sizes (estimation and validation sample). In this aspect, van Dalen (1979) as other authors recommend as well one should use proportional sampling since this improves representativeness of results. Another point of critics is, besides the age of the MDA model, that Altman's model is limited since it was only applied on the manufacturing industry (Grice and Ingram, 2001).

2.2.3 Ohlson (1980)

Another accounting-based bankruptcy prediction model is the logit approach by Ohlson (1980). In a study, Ohlson (1980) analysed 105 bankrupt companies to 2058 non-bankrupt companies in a time period from 1970 to 1976. The overall accuracy rate for the estimation sample was 96% and for the hold-out sample 85%. Overall, his results showed that the factors “size“ of a company and the “financial structure of a company” as well as the “current liquidity” play a crucial role in detecting bankruptcy (Ohlson, 1980). The model of Ohlson (1980) is as follows:

$$\text{Ohlson} = -1.3 - 0.4X_1 + 6.0X_2 - 1.4X_3 + 0.8X_4 - 2.4X_5 - 1.8X_6 + 0.3X_7 - 1.7X_8 - 0.5X_9 \quad (eq.2)$$

Where

$X_1 = \log (\text{Total assets} / \text{GNP price-level index})$

$X_2 = \text{total liabilities} / \text{total assets}$

$X_3 = \text{Working capital} / \text{total assets}$

$X_4 = \text{current liabilities} / \text{current assets}$

$X_5 = 1 = \text{if total liabilities} > \text{total assets}, 0 \text{ otherwise}$

$X_6 = \text{net income} / \text{total assets}$

$X_7 = \text{funds provided by operations} / \text{total liabilities}$

$X_8 = 1 [1 \text{ if net income is negative for last two years}, 0 \text{ otherwise}]$

$X_9 = (NI_t - NI_{t-1}) / (NI_t + NI_{t-1})$, where NI_t = net income for recent period and t is the number of years

All in all, this formula depicts the six important financial ratios being consistent with existing literature (see for comparison Altman (1968)). The approach by Ohlson (1980) maps the value to a probability bounded between 0 and 1; hereby the cut-off point is 0.38. A company facing a cut-off point below 0.38 is said to be bankrupt whereas a cut-off point above it tells a firm that it does not face bankruptcy.

When comparing the model of Altman (1968) to Ohlson's model (1980), Ohlson (1980) critics to the MDA approach in the following points: At first, Ohlson (1980) argues that Altman's model (1968) is based on the assumption that the explanatory variable is normally distributed. Further, a point of critic is that the bankrupt and non-bankrupt firms are matched according to criteria such as size and industry. Therefore, he argues the model is restricted in terms of

generalizability. In Ohlson's point of view variables should not be included for matching reasons but rather for predicting bankruptcy. Ohlson (1980) states that his models (the logit approach) avoids the aforementioned critics because it is not based on those strict assumptions (Ohlson, 1980)

A study by Wang and Campbell (2005) found out that the Ohlson (1980) model is "an applicable measure for predicting firm delisting in China". The authors studied listed Chinese companies during a period of 2000-2008 and reported that the accuracy rate of Ohlson's model was by 95%. Pongsgat *et al.* (2004) analysed a matched pair sample of 60 bankrupt and 60 non-bankrupt firms over the years 1998 to 2003. Their study concludes that while each of the two methods have predictive ability when applied to Thai firms. They state that the Ohlson model (1980) has a higher predictive ability in all three years preceding bankruptcy than that of Altman's MDA (1968) model: "The overall difference between Ohlson's model and Altman's model respectively was 69.6 % to 58.9 % for the first year prior to bankruptcy, 69.6 % and 62.5 % for the second year prior to bankruptcy and 69.6 % to 62.5 % for the third year to bankruptcy" (Pongsgat *et al.*, 2004). Further, Begley *et al.* (1997) applied Ohlson's model to 1365 industrial firms and reported an overall 98 % classification accuracy.

However some critics are left on Ohlson's model. The logit approach averages data whereby a healthy firm is given the value of 0 and a non-healthy company the value of 1 (Abdullah *et al.*, 2008). Thereof, the logit approach treats non-healthy companies as if they were bankrupt from the beginning onwards. Studies by Collins and Green (1982) or Ingram and Frazier (1988) came to similar results, saying that generally the logit model (1980) is superior to the multi-discriminant approach by Altman (1968). Chen, Huang and Lin (2009) state: "Logit Regression would have a better theoretical jurisdiction and more diversity and breadth for the independent variables selected". Further, Hillegeist (2004) adds that there are "two econometric problems with the single period logit model": Firstly, the sample selection bias that arises from only using one and non-randomly selected observation. Secondly, Ohlson's model (1980) fails by not including time varying changes. Especially, the second point of critics is crucial since Grice and Dugan (2001) emphasizes that the relation between financial ratios, as those mentioned above, and its effect on bankruptcy changes over industries and time. As Hensher and Jones (2007) point it out: "all parameters are fixed and the error structure is treated as white noise, with little behavioural definition". To conclude, the critics suggest that Ohlson's model (1980) seems to be inefficient and biased although the results of his model suggests a high accuracy rate compared to MDA (1968).

2.2.4 Zmijewski (1984)

Based on Ohlson's work (1980), Zmijewski (1984) created another bankruptcy prediction model: the probit model. His model takes into account accounting data as well as on a set of independent variables. That independent variables are crucial factors needed to be considered has been pointed out by Lennox (1999). Zmijewski (1984) observed that external factors like industry sector, size of a company and economic cycle are crucial factors influencing bankruptcy likelihood. Therefore, he used all non-financial, non-service and non-public administration firms listed on the American and New York Stock Exchanges during the period 1972 till 1978. The estimation sample of the study of Zmijewski (1984) contained 40 bankrupt and 800 non-bankrupt companies, and the hold-out sample consisted of 41 bankrupt and 800 non bankrupt companies. With his probit function Zmijewski (1984) tried to avoid the choice-based sample bias since this was a major point of critic: the MDA model (1968), so Zmijewski (1984), is based on the entire population and therefore the estimated coefficients will be biased and as a result companies will be over-estimated which has the effect that bankrupt companies are wrongly classified.

The probit function including variables and estimated coefficient from the study of Zmijewski (1984) is:

$$\text{Zmijewski} = - 4.3 - 4.5X_1 + 5.7X_2 + 0.004X_3 \quad (eq.3)$$

Where

X_1 = net income / total assets

X_2 = total liabilities / total assets

X_3 = current assets / current liabilities

When comparing the model of Altman (1960) and Zmijewski (1984) in more depth, a difference between both is that Altman used the ratio "earnings before interest and taxes / total assets" whereas Zmijewski (1984) used the ratio "net income / total assets" for profitability. Hereby is to note that profit or losses of a company is part of the net income (Zmijewski's model) whereas not in the EBIT (Altman's model (1968)). Therefore, one can conclude that EBIT does not take into account the effects of different capital structure; which on the other side effects the net income. This is, however, measured by the financial ratio "total liabilities/total assets" (Zmijewski, 1984).

When comparing Ohlson's model (1980) to the probit regression is how Zmijewski (1984) classified bankrupt companies. Zmijewski (1984) defines a bankrupt company when it requests a bankrupt petition during a specific period of time. In statistical matters, Zmijewski (1984) defines it as follows: In case of a p-value that is equal or greater than 0.5 is classified as bankrupt and companies having a p-value that is lower than 0.5 are classified as non-bankrupt.

Mehrani *et al.* (2005) applied Zmijewski's probit model on firms listed at the Tehran Stock Exchange and presented that his model has the ability to divide firms into bankrupt and non-bankrupt firms. Further, Grice and Dugan (2001) applied Zmijewski model to 1988 - 1991 firms and reported an accuracy rate of 81.3 %. Although the accuracy rate of Zmijewski's probit model seems to be high, there are some critics left.

The probit model is a "one-variable model" and as a result variables are highly correlated to each other (Shumway, 2001). Shumway (2001) argues that the variable TL/TA is strongly correlated ($p = 0.40$) to the variable NI/TA and concludes that due to this high correlation the model of Zmijewski (1984) does not have strong predictive power for bankruptcy. Additionally, Platt and Platt (2002) argue: "Because Zmijewski ran only one regression for each sample size, he [Zmijewski (1984)] could not test the individual estimated coefficients for bias against the population parameter, a more direct test of bias".

However, studies of Grice (2001) and Shumway (2004) emphasizes the probit model over the preferred MDA approach by Altman (1968) due to the reason that the probit function maps the value to a probability bounded between 0 and 1 and therefore, results are more easily to analyse. Shumway (2001) concludes that the model of Zmijewski (1984) does not have strong predictive.

2.2.5 Conclusion

The aforementioned bankruptcy prediction model are at the same time beneficial and limited. Nevertheless, Collins and Green (1972) state that "no technique is superior to other techniques". In more depth, there have been many critics to the work of Altman's MDA approach. However, when reviewing existing articles, most studies still use this approach since the work of Altman is the most famous when it comes to accounting-based bankruptcy prediction models. However, with the work of Ohlson (1980) and Zmijewski (1984) the literature about accounting-based bankruptcy prediction models was enlarged upon. Factors as size and the financial structure of a company became crucial factors in detecting the likelihood of bankruptcy. That is why in existing literature the models of Ohlson (1980) and Zmijewski (1984) are said to be more

advantageous compared to Altman's work (1968). For example, Collins and Green (1972) and Harrell and Lee (1985) undertook several studies where they found out that the logit approach is superior to MDA (1968). The table below summarizes important findings of the three common accounting-based bankruptcy prediction models:

Table 1: Overview of common accounting-based bankruptcy prediction models (based on own assessment)

Researcher	Statistical Technique	Period of Study	Sample size	Advantages/disadvantages
Altman (1968)	Z-score model, multi-discriminant analysis	1946-65	Estimation Sample: 33/33 Validation Sample : 25/66	+ Most common method - many assumptions
Ohlson (1980)	Logit Model	1970-76	Estimation sample: 105/ 2058 Validation sample: no	+ uses value (0 to 1) + less restrictive assumptions compared to Altman (1960) - bias
Zmijewski (1984)	Probit model	1972-1978	Estimation sample: 40/800 Validation sample: 41/800	+ external factors are taken into account - variables are highly correlated

2.3 Market-based bankruptcy prediction models

The second stream of prediction models focuses on market based variables. According to Agarwal *et al.* (2007) market-based bankruptcy prediction models “provide a sound theoretical model for firm bankruptcy; in efficient markets, stock process will reflect all information contained in accounting statements and will also contain information not in the accounting statements; market variables are unlikely to be influenced by firm accounting policies; market prices reflect future expected cash flows, and hence should be more appropriate for prediction purposes; the output of such models is not time or sample dependent”. However since the Merton model also relies on assumptions, Saunders and Allen (2002, p.58 - 61) criticizes that the underlying theoretical model is dependent on assumptions about stock market and that this

model cannot distinguish between different types of debt (e.g. short-term debt, long-term debt) neither it can differ between the asset value nor volatility.

In common literature, there are two common market-based bankruptcy prediction models which are Shumway's hazard model (2001) and Hillegeist *et al.* (2004) Black-Scholes pricing model. However, studies are limited on validating the quality of market-based bankruptcy prediction models.

One common market-based bankruptcy prediction model is Shumway's (2001) discrete-time hazard model to predict bankruptcy by using accounting but also market variables. The model is based on a previous study by Shumway (2001) where he found out that many accounting-based variables employed in previous studies are not significant in predicting failures. Shumway (2001) includes market-based data, such as firm's market size, firm's previous returns, and the idiosyncratic standard deviation of these returns are better predictors of bankruptcy. In a study where Abdullah *et al.* (2008) observed 26 bankrupt and 26 non-bankrupt companies registered on the Malaysian stock exchange compared the MDA, logistic regression and the hazard models to each other and came to the following results: The MDA model provided an overall accuracy of 80.8 % and 85 %, the logit model predicted 82.7 % and 80 % accurate and the hazard model 94.8 % and 63.9 % (Abdullah *et al.*, 2008, p.215). To turn it around, one can say the hazard model "provides a higher accuracy rate in the estimation model, but when the estimated equation is applied in the holdout sample, the MDA gives a higher accuracy" (Abdullah *et al.*, 2008, p. 215). Consistent with other studies, also Chava and Jarrow (2004) found out that the relative performance of Shumway's hazard model against accounting models of Altman and Ohlson (1980) is outperforming.

The second common market-based bankruptcy prediction model is the model of Hillegeist *et al.* (2004). The model by Hillegeist *et al.* (2004) is based on the Black-Scholes-Merton option-pricing model. The BSM option-pricing model is used to price European options and was developed in 1973 by Fischer Black, Myron Scholes and Robert Merton. Based on this model, Hillegeist *et al.* (2004) have developed their BSM-prob bankruptcy prediction model. A sample of 65960 firms was included whereas 516 went bankrupt in a period from 1979-1997. In a paper by Wu *et al.* (2010) the authors compare Altman's model (1968) to Ohlson's model (1980) to the Hillegeist *et al.* (2004) model and come to the conclusion that "the BSM-prob model outperforms the other models". However, comparing Hillegeist *et al.* (2004) towards Shumway (2001) model, Wu *et al.* (2010) comes to the conclusion that the "Hillegeist *et al.* (2004)

performs adequately but is generally inferior to Shumway model”. Charitou *et al.* (2004) also supported this argument. Here, the authors explain that due to the fact that Hillegeist *et al.* (2004) do not examine the probability of default at an intermediate stage, their results would be more a consequence of bad performance of the accounting-based models they are taking into account. A further point of critics comes from Hillegeist *et al.* (2004) stating that those models “do not provide time series prediction rates in the years prior to the default year of a company” (Charitou *et al.*, 2004).

Table 2: Overview of market-based bankruptcy prediction models (based on own assessment)

Researcher	Statistical Technique	Period of study	Sample size	Advantages/disadvantages
Shumway (2001)	Hazard model	1962-1992	300	+ accuracy
Hillegeist <i>et al.</i> (2004)	BSM prob model	1979-1997	65960/516	+ based on a famous and well-applicable method

2.4 Comparing accounting-based and market-based bankruptcy prediction models

As outlined above, there are differences between accounting- and market-based bankruptcy prediction models. When comparing both in more detail, one faces some points of critics to both streams of models. For example, a common critique is that market-based bankruptcy prediction models are said to outperform the accounting-based models (Hillegeist *et al.*, 2004).

Wu *et al.* (2010) undertook a study where they compared the most relevant accounting-based and market-based bankruptcy models with each other. They found out that the MDA model of Altman (1968) “performs poorly relative to other models” since other models such as the hazard model of Shumway (2001) takes into account market data, firm characteristics and key accounting information. Agarwal *et al.* (2008) and Begley *et al.* (1996) add that Altman’s model (1968) suffer from high misclassification rates.

Furthermore, Agarwal *et al.* (2008) state that those accounting-based bankruptcy prediction models are built upon large number of accounting ratios estimating a sample of failed and non-failed firms. Since the financial ratios and weightings are derived from a sample analysis a

disadvantage of accounting-based prediction models is that they are too sample specific and as a result generalizations are difficult to make.

When it comes to the methodological implications, accounting-based bankruptcy prediction models doubt on their validity (Agarwal *et al.*, 2008): “accounting statements present past performance of a firm and may or may not be informative in predicting the future; conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values; accounting numbers are subject of manipulation by management”; and as Hillegeist *et al.* (2004) argue that since “accounting statements are prepared on a going concern basis, they are, by design, of limited utility in predicting bankruptcy” (Agarwal *et al.*, 2008). An additional point of criticism has been that accounting models ignore economic idiosyncrasies and that data are collected over many years while leaving out market changes (Mensah, 1984).

On the other hand Agarwal and Taffler (2007) found out that accounting-based bankruptcy prediction models such as Altman’s approach (1968) implies significant economic benefit over market-based bankruptcy prediction models (Hillegeist *et al.*, 2004). Agarwal and Taffler (2006) mention two advantages: firstly, since accounting-based bankruptcy prediction models rely on information of financial statements, the event of bankruptcy is not sudden because performance can be observed over a longer period.

Secondly, since in accounting data record loan covenants one can more easily take into account a possible bankruptcy likelihood. However, there are still some critics left for market-based bankruptcy models. For example, according to Campbell (2010) market-based bankruptcy prediction models have little forecasting power after controlling for other variables and moreover Reisz and Perlich (2007) state that Altman z-score model is a better bankruptcy predictor over one-year period than market-based bankruptcy prediction models since they need a longer time horizon.

To conclude, when comparing the conclusions on accounting-based models towards market-based bankruptcy prediction models one can say that both streams of models imply advantages and disadvantages. In common literature, the arguments why market-based bankruptcy models are more valuable in predicting bankruptcy are firstly market-based bankruptcy models reflect market prices and as a result they reflect a rich and comprehensive bound of information.

A second argument is that they are direct measure of volatility since standard deviation is taken into account. Thirdly, market-variables takes into account the partition of time (Beaver *et al.*, 2005, p.10; Beaver, McNicholas and Rhie, 2005).

However, the aforementioned market-based bankruptcy prediction models implies some disadvantages: they are time-consuming; little forecasting power and events are still hardly to be taken into account.

3. Operationalization

3.1 Research Question

In order to assess the performance of different accounting-based bankruptcy prediction models, measuring of accuracy rate power of bankruptcy models is crucial. The higher the accuracy rate of a bankruptcy prediction model, the better the forecast of bankrupt likelihood. As outlined above, most studies have analysed one bankruptcy models and only few reviewed the accuracy rate of several bankruptcy prediction models.

The focus of this study is to apply the three most common accounting-based bankruptcy prediction models. As each of the bankruptcy model employs different statistical technique to predict bankruptcy, each model captures slightly different aspects of corporate financial health. The underlying problem leads to the following research question:

What is the difference between the accuracy rate of accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), Zmijewski (1984) to German and Belgian listed companies?

The following sub-questions shall help to tackle the underlying problem:

1. Are and what are the advantages and disadvantages of accounting-based bankruptcy prediction models?
2. What is the accuracy rate of accounting-based bankruptcy prediction models used in this Master Thesis?
3. Are there differences of accuracy rates between accounting-based bankruptcy prediction models and how, if there are any, can they be explained?

3.2 Research Methodology

Before discussing the sample selection and statistical methods that will be applied in this thesis it is useful to discuss some important methodological concepts. The following chapters compare the accuracy rate of three accounting-based bankruptcy prediction models towards German and Belgian listed companies. The accuracy rate is the percentage of correct classification (bankrupt or non- bankrupt) to the total classification. Another method to observe if models are able to classify correctly companies is the Pseudo R^2 . “Many different R^2 statistics have been proposed in the past three decades (see, e.g., McFadden (1973), McKelvey and Zavoina (1975), Maddala

(1983), Agresti (1986), Nagelkerke (1991), Cox and Wermuch (1992), Ash and Shwartz (1999), Zheng and Agresti (2000)“ (Hu *et al.*, 2006). Most common is the McFadden R^2 which is also known as the ratio of likelihood: $Pseudo R^2 = 1 - \frac{Lur}{Lo}$ where $Lur = log$ is the likelihood value from the regression model and the $lo = log$ is the likelihood value of the regression intercept (McFadden, 1972). Both measures will be used to evaluate the accuracy rate of the three accounting-based bankruptcy prediction models.

The sub-questions will be answered by the outcome of the data analysis and the literature review (especially sub-question 3).

According to Sadvnik (2007) a comparative case study is a holistic in-depth examination of a topic (in this case bankruptcies) that can be investigated quantitatively but also qualitatively. Yin (2009) explain that an advantage of a case study is “that it investigates a contemporary phenomenon in depth and within its real-life context, (...)” (Yin, 2009). The study is of quantitative nature and examines two different cases, bankruptcy models assessed to two different datasets, namely the German and Belgian listed companies. Further, this thesis uses proportional sampling in order to avoid the choice based sample bias since previous studies pointed out that test samples were not proportional to the actual rate of bankruptcies (Grice and Ingram, 2001). According to Babbie (2004) proportional sampling provides a useful description of the sample is efficient to reflect variations that exist in the sample. Further since the bankruptcy models’ formula imply multivariate analysis, one have to discuss the advantages and disadvantages of this analysis. For example, the multivariate analysis (1968) examines simultaneously the effects of different variables, in this case the financial ratios. “Instead of explaining the dependent variable on the basis of a single variable, we’ll seek an explanation through the use of more than one independent variable” (Babbie, 2004). According to Rencher (2002) the multivariate analysis is a powerful tool due of its mathematical tractability and they often perform well in practice. However, there are some critics left to the MDA: at first the MDA may result in less clear understanding of data since group differences are reported on a linear combination. Secondly, multivariate analysis are always held under specific rules and assumptions (Rencher, 2002). In this thesis the dependent variable is “bankruptcy”. Since bankruptcy is a dichotomous variable (bankrupt or non-bankrupt) the status whether a company is bankrupt or not is reported by the database ORBIS. Moreover, the independent variable of the hypotheses are the different financial accounting ratios used by the three accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984). To note hereby is, that for the model of Altman (1968) I will make use the ratio DEBT/EQUITY instead

of the ratio market value of equity/book value of total debt. That is due to the fact that ORBIS does not report market values for the German and Belgian listed companies.

3.3 Sample Selection

To answer these research questions and sub-questions the data on firm bankruptcies are collected from the database ORBIS. This is a database relying on the data of the Bureau van Dijk (BvD). From this database all other relevant information will be collected as well, such as the status of firms, industrial classification codes, size and name etc. Additionally, the financial ratios are calculated from companies' financial statements (annual reports). The advantages of using annual reports data are the savings of time and money saving and the open tractability by third parties. The calculation of the different financial bankruptcy prediction models is done by SPSS and EXCEL. Since previous research mainly focused on Asian countries or the United States of America (e.g.: Pongat *et al.* (2001); Grice and Ingram (2001); Sarlija & Jeger (2011)) this study likes to test the accuracy rate of accounting-based bankruptcy prediction models in Germany and Belgium since no previous study focused on this country.

Only financial companies and insurance companies as well as very small companies are excluded. This has the reason that those might lead to biased results since for example insurance companies have a different structure of capital. Further, the industries are obtained by the industry code called Standard Industrial Classification (SIC). Companies having a SIC code of 64 or 65 (financial services and insurance activities) are excluded. To sum up, the sample of this Master Thesis includes all listed companies and large companies in Belgium and Germany. As other studies do it similar, the sample are analysed in two years before the event of non-bankruptcy. That means that I will collect data in 2008 in order to find out if the event of bankruptcy/non-bankruptcy happens in 2010. Therefore, I will test the selected firms' accounting data with the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) in each year of investigation. The accounting-based bankruptcy prediction models will report if the company is distressed/bankrupt in each investigation year.

As Altman (1968) has titled firms being bankrupt when they do not operate one year, this Master Thesis will assume that the bankruptcy will not happen within one year. That is due to the reason that the process of bankruptcy might take several years (as outlined above).

Therefore, the investigation period will be from 2008 to 2013 since it is consistent with studies as Hossari (2006) or Al- Khabib, H.Z & Al- Horahi, A. (2005). "The objective of any collapse prediction model is to signal collapse before it happens. If the reporting period were too short,

it would be too late to take corrective action and try to turn the company around. Likewise, if the reporting period were too long, then the prediction model might not detect any signs of impending collapse” (Hossari, 2006, p. 222).

3.4 Sample Description

After having deleted double, missing values and error rates the final sample consists of 5646 active Belgian listed companies and 140 bankrupt Belgium listed companies. The sample of German listed companies that are active is 1432 companies and 21 bankrupt.

Table 3: Population for the study (based on own assessment)

Criteria	Value
Status	Active, Bankrupt or Dissolved
Country	Belgian, Germany
Size	Listed companies
Investigation period	2008 - 2013
SBI code	All (except code 64 and 65)

3.5 Derivation of Hypotheses

Comparing the variety and the differences of financial ratios and the advances in presenting accounting-based bankruptcy prediction models, the question that arises is whether there is a significant difference towards the results of the accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980) and Zmijewski (1984). Components and results of each model have been extensively analysed in existing literature; but since environment is always in change it becomes interesting how the models of Altman (1968), Ohlson (1980), Zmijewski (1984) perform in different economic conditions and in different industries. For example, Grice and Dugan (2003) assessed the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) with samples of distressed and non-distresses companies from different time periods and industries other than those used in original studies and concluded that the relation between bankruptcy occurrence and financial ratios changes over time.

Existing literature has pointed out that the accuracy rate of Altman (1968), Ohlson (1980), and Zmijewski (1984) are all high and all models perform equally meaning that all results of

accuracy rate lie close to each other. For example a study of Wu *et al.* (2010) reported that accuracy rate of all three models are between 86.1 % (Altman), 88.7 % (Ohlson), and 85.2 % (Zmijewski). Similar results were reported by Grice and Ingram (2001) or Grice and Dugan (2003).

However, there are some differences in performance of the accuracy rates in three models: Studies by Grice and Ingram (2011) came to the conclusion that the accuracy rate of Altman's model (1968) declines over the years of observation. Reasons why the Altman z-score (1968) decreases in accuracy during the investigation period is explained by the fact that the relation between financial ratios and financial distress changes over time (Grice, 2001). According to Grice (2001), the MDA model (1968) is sensitive towards industry classification because the original model was only applied to manufacturing factories. Therefore, it is suggested that the z-score model should be re-estimated by the model's coefficients. Another reason why the accuracy rate during investigation period might decline is that Altman's model (1968) possibly underestimates the Type I error and overestimates the Type II error that results from using non-proportional samples of bankrupt and non-bankrupt companies. Under the Type I error the null hypothesis is rejected although it is true and under the Type II error the other way round. Meaning in the context of this Master thesis, the Type I error would classify bankrupt companies as not bankrupt as healthy.

Studies by Grice and Ingram (2001) reports that the models of Ohlson (1980) and Zmijewski (1984) have a high accuracy rate on all years of observation; but in common literature it is not clear which model performs better. Some studies as Shumway (2001) reports a higher accuracy rate of the Ohlson model (1980) but studies like Mehrani *et al.* (2005) report that the accuracy rate for Zmijewski (1984) is higher when compared to Ohlson (1980).

To sum up one can say that the accounting-based bankruptcy prediction models perform differently due to the fact that they are based on different financial ratios. Studies having studied on how the three mentioned models perform differently were applied only to one country and therefore did not explain whether or not there might be differences country wise. This Master Thesis observes two countries since the study of bankruptcy models were not that often applied to European countries. It seeks to find out whether or not there are differences between the accuracy rates of the three models. A common critic to the Altman model (1968) was that the accuracy rate declines over the investigation years.

From the discussion above, the following hypothesis were derived and will be tested:

Hypothesis 1 (null hypothesis)

H₀: There is a difference in the accuracy rate between accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984).

Hypothesis 2 (alternative hypothesis)

H_A: There is no difference in the accuracy rate between accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984).

Since literature on the accounting-based bankruptcy prediction models is broad, it is possible to make some assumptions about the results of the four hypotheses outlined above. Therefore, the following section deals with possible outcomes of the four hypothesis. In general, “Hypothesis testing or significance testing is a method for testing a claim or hypothesis about a parameter in a population, using data measured in a sample. In this method, we test some hypothesis by determining the likelihood that a sample statistic could have been selected, if the hypothesis regarding the population parameter were true“(Coolidge, 2012). There are four steps to test a hypothesis:

1. State the hypotheses: Firstly, a hypothesis needs to be created where a claim is made about a population. The hypothesis is called the null hypothesis and is assumed to be true. In this thesis, I assume that there is no difference between the accuracy rates of bankruptcy between the accounting-based prediction models. Contrary to null hypothesis, the alternative hypothesis is set up which “is a statement that directly contradicts a null hypothesis by stating that that the actual value of a population parameter is less than, greater than, or not equal to the value stated in the null hypothesis” (Coolidge, 2012). In this thesis, I assume that there is a difference in the accuracy rate of bankruptcy between the three models.

2. Criteria for testing. In order to set the criteria, a level of significance is set. Mostly, for the level of significance is set at 5%. In case that the probability of obtaining a sample mean is less than 5% if the null hypothesis were true, one rejects the null hypothesis.

3. The test statistic. The test statistic tells how many standard deviations, a sample mean is from the population mean. As a result, the larger the value of the test statistic, the further the distance a sample mean is from the population mean.

4. Decide. The test statistic is used to make a decision about the null hypothesis. Either the probability is below $p = 0.05$ %, we reject the null hypothesis or not. In sum, there are four

possible outcomes in hypothesis testing (Table 4). Therefore, table 4 illustrates the relationship between the type of errors and the decision concluding from it. The Type I error is the false rejection of a true null hypothesis. In this Master Thesis, one would falsely state that there is no difference between the accuracy rate of bankruptcy prediction models although there is one. The type II error represents therefore a false negative.

Table 4: Categorization if hypotheses are rejected or not (based on own assessment)

	The null hypothesis is true	The null hypothesis is false
Fail to reject the null hypothesis	Type A error	Type II Error (false negative)
Reject the null hypothesis	Type I error (false positive)	Type B error

In more depth, coming to

Hypothesis 1: I assume that hypothesis 1 will be rejected due to the fact that common literature comes to the same conclusion that there are differences between the accuracy rates of bankruptcy prediction models. This assumption is explained by the discussions above in chapter 2. Several studies pointed out that the accuracy rate of all three models are different from each other; e.g. the accuracy rate of bankruptcy prediction of Altman's model (1968) declines over the investigation years while Ohlson (1980) and Zmijewski (1984) perform constantly.

Hypothesis 2: I assume that this hypothesis will not be rejected since literature came to the same results that the accuracy rates of models perform differently. The following table supports this assumption since it reviews on some most important papers discussing the three accounting-based bankruptcy prediction models and points out remarks.

Table 5: Summary on studies analysing the three accounting-based bankruptcy prediction models (based on own assessment)

Author	Model analysed	Findings	Remarks
Sarlija & Jeger (2011)	MDA (1986)	financial ratios are constant but compared to market-based models perform less accurate	macroeconomic variables need to be considered
Grice & Ingram (2001)	MDA (1968)	Accuracy rate declines over investigation period; accuracy rate for manufacturing rates higher than the total sample, Altman's model is sensitive to industry classification	results should be cautiously studied; re-estimation of samples
Wu <i>et al.</i> (2010)	MDA (1968), Ohlson logit regression (1980), and Zmijewski probit regression (1984)	if lower earnings before interest and tax; decline in net income → higher probability to face bankruptcy; MDA performs poorly compared to the other models; small companies with small business segments → larger probability to face bankruptcy	a comprehensive model consists of market data, accounting data and company characteristics
Charitou <i>et al.</i> (2004)	MDA (1968), Ohlson logit regression (1980)	performed less well compared to market-based models or cash flow models	lack of theoretical framework that guide the selection of variables when calculating bankruptcy likelihood
Hayes <i>et al.</i> (2010)	MDA (1968)	"may be employed to indicate financial distress"	Altman's model is sensitive to small companies and industries → a different formula is required for them

Agarwal & Taffler (2008)	MDA (1968)	<p>Three advantages of the model:</p> <p>1) corporate failure as no sudden event</p> <p>2) accounting policies changing no effect on accounting data</p> <p>3) loan covenants are reflected</p>	<p>accounting-based bankruptcy prediction models have an economic benefit but lack of theoretical grounding</p>
Begley <i>et al.</i> (1997)	MDA (1968) and Ohlson's logit model (1980)	<p>changes in bankruptcy laws have an effect on bankruptcy likelihood</p> <p>→ macroeconomic changes need to be considered;</p> <p>Ohlson's model (1980) outperforms Altman's model with a lower combined error rate;</p> <p>liquidity ratio plays a crucial role</p>	<p>macroeconomic variables need to be considered</p>

4. Data Analysis

The following section deals with the analysis of the data and reports the findings of the statistical tests being conducted. It starts with a descriptive analysis of the data; afterwards the two hypotheses will be tested with statistical techniques.

4.1 Univariate analysis of the sample

As other studies (e.g. Beaver *et. al*, 2005) do it similar, the analysis of the data will start with some descriptive statistics. Therefore, the following table reports the descriptive statistics of bankrupt and non-bankrupt companies in Germany and Belgium. The aim of table 6 is to compare accounting variables and to observe mean differences between the bankrupt and non-bankrupt companies. A t-test with a confidence level of 95% of differences in variable means between the bankrupt and non-bankrupt firms in both countries is conducted as this is proven to show the performance of financial ratios. The p-value of the Levene's test is $\alpha = 0.05$ %. Financial accounting variables are used one year before bankruptcy in order to show the group means of bankrupt and non-bankrupt companies performing before bankruptcy. This is consistent with other studies such as Nilsson (2008) and Mohammed (2013) and Allah (2014). In general, the standard deviation for the non-bankrupt and bankrupt companies are quite big. That is due to including small, large and very large companies in this sample. When comparing bankrupt and non-bankrupt firms in the sample in more depth one can say that non-bankrupt firms show a higher volatility to the financial ratios of RE/TA-1. The mean for non-bankrupt companies is 3.88 whereas the mean for bankrupt companies is negative (here the mean is = - 2.93). The standard deviation for bankrupt companies is also higher and the p-value for the test of mean differences between bankrupt and non-bankrupt firms is significant (p- value = 0.016). Identically to that the ratio of NI/TA-1 is higher for bankrupt companies than non-bankrupt companies. That this financial ratio shows same results as RE/TA-1 can be led back to the fact that retained earnings is the sum of beginning retained earnings plus net income minus dividends. Significance means that that the null hypothesis for these accounting ratios can be rejected; to turn around it means that there is a difference between the means of financial ratios between the bankrupt and non-bankrupt firms. Further, change in net income; WC/TA-1, SALES /TA-1 are also higher for bankrupt companies; however only EBIT/TA-1, DE/EQ-1, CL/CA-1 shows statistical significance in the group means of bankrupt and non-bankrupt companies. Furthermore, the table below also highlights that the funds from operations are is significantly higher for non-bankrupt companies than bankrupt companies.

This indicates that a company is more likely to go bankrupt if the cash flow from operations is low and volatility for leverage ratios increases.

Table 6: Descriptive statistics for the sample (based on own assessment)

A. Altman			bankrupt companies		
	active companies				
	mean	st. dev.		mean	st. dev. p-value
WC/TA-1	0.2359	0.2334	WC/TA-1	0.2408	0.2446 0.135
RE/TA (%) -1	3.88	9.578	RE/TA (%) -1	-2.9313	16.8362 0.016*
EBIT/TA-1	0.0635	0.1063	EBIT/TA-1	0.0099	0.1497 0.03*
DE/EQ-1	14.193	588.6019	DE/EQ-1	8.8179	21.8999 0.08*
SALES/TA-1	1.9544	2.2269	SALES/TA-1	2.1590	2.2885 0.00
B. Ohlson			bankrupt companies		
	active companies				
	mean	st. dev.		mean	st. dev. p-value
TL/TA-1	0.6243	0.2562	TL/TA-1	0.8134	0.2355 0.00*
WC/TA-1	0.2362	0.2337	WC/TA-1	0.2429	0.2524 0.07*
CL/CA-1	3.3549	186.9995	CL/CA-1	1.0532	0.7659 0.08*
NI/TA (%) -1	3.9419	9.5614	NI/TA (%) -1	-3.5352	16.5929 0.00*
FUNDS from OPERATIONS/TL -1	0.2965	2.0250	FUNDS from OPERATIONS/TL -1	0.13553019	0.9827 0.604
1 if NI<0; 0 if NI>0	0.09	0.291	1 if NI<0; 0 if NI>0	0.28	0.451 0.00*
Change in Net Income [(NI-Nit-1)/(NI+Nit-1)]	0.0786	8.1718	Change in Net Income [(NI-Nit-1)/(NI+Nit-1)]	-0.8218	12.8716 0.158
Adjusted size	4.4003	0.6925	Adjusted Size	4.14826	0.4904 0.00*
C. Zmijewski			bankrupt companies		
	active companies				
	mean	st. dev.		mean	st. dev. p-value
NI/TA (%) -1	3.8706	9.5777	NI/TA (%) -1	-2.5759	16.7943 0.00*
TL/TA-1	0.6239	0.2562	TL/TA-1	0.7921	0.2540 0.00*
CA/CL-1	4.6351	76.1614	CA/CL-1	2.4133	10.2981 0.70

4.2 Testing hypotheses

The following tables 7-14 present how the different financial ratios of the three accounting-based bankruptcy prediction model perform during the years of investigation. Therefore the original statistical models were used: Altman (1968) is going to be analyzed with a multivariate discriminant analysis; Ohlson (1980) with a logit model and Zmijewski (1984) with a probit model. For each of the three models the accuracy rate is calculated via SPSS and EXCEL since this is the main objective of this Master Thesis. In order to get a bigger picture of how the models perform, the eigenvalue (for the Altman model) and the R^2 is calculated. The eigenvalue is the ratio between variances between groups and variances within groups. The higher it is, the better the model can differentiate variances between groups (being bankrupt or non-bankrupt). The R^2 is another statistical method reporting how accurate bankruptcy prediction models perform and is widely used in common literature. Additionally, the estimated coefficient of all models for all investigation periods will be reported. This aims at showing how the financial ratios of each model perform (increase or decrease) which facilitates interpreting the results of accuracy rates.

4.3 Analysis of Altman's model (1968)

The two table 7 and 8 below summarize the estimated coefficients of the MDA model of Altman (1968) for Belgian and German listed companies. The MDA statistical technique is to differentiate between a dependent categorical variable and independent quantitative variables. In this case the dependent categorical variable is being bankrupt or non-bankrupt and the independent variable are the five financial ratios.

As Bramhandkar (2011) state, the MDA has the advantage that it is simple to implement and performs adequately. However, compared to the logistic regression, the discriminant analysis relies on meeting the assumptions of multivariate normality and equal variance and covariance matrices across groups. However, since each model is analyzed by its original statistical technique, the following tables will report the outcome of the MDA technique. For each year of investigation one estimation model was calculated. Estimation model 1 shows bankruptcy within one year, estimation model 2 for bankruptcy within two years and estimation model 3 bankruptcy within three years.

4.3.1 Results of Altman's model (1968) on Belgian listed companies

Table 7: Results for Belgian listed companies (based on own assessment)

Altman (1968)			Estimation model 1	Estimation model 2	Estimation model 3
	Intercept		-0.213	-0.267	0.013
	WC/TA	1.2	0.57	-0.42	-1.009
	RE/TA	1.4	8.926	11.032	2.144
	EBIT/TA	3.3	0.481	-0.779	7.722
	DE/EQ	0.6	0.00	0.00	0.00
	Sales/TA	0.9	-0.032	-0.047	-0.187
	Eigenvalue		0.26	0.18	0.006
	Accuracy Rate in %		68.3	68.0	67.9

The coefficient for EBIT/TA decreases from 7.722 to 0.481 when the years within prediction of the bankruptcy decline. This indicates that this financial ratio becomes a less good predictor for estimating bankruptcy likelihood during the three years of investigation. Contrary to that is the performance of the coefficient of RE/TA: the estimated coefficient increased from 2.0144 to 8.926. Therefore, one can conclude that RE/TA is a better predictor for the likelihood of bankruptcy when the investigation years decline. Further, the negative coefficient of SALES/TA shows that if profitability increases, the likelihood of bankruptcy decreases which is consistent to general theory about bankruptcy likelihood. It needs to be mentioned is that the financial ratio DE/EQ is not a good predictor for the likelihood of bankruptcy because it does not show any changes within the investigation period.

Coming to the overall performance, one can say that estimation model 1 performs at best. The accuracy rate is at 68.3 % and the eigenvalue is 0.26. The eigenvalue indicates in this respect that the variance between groups is high (bankrupt or non-bankrupt) and the variance within groups is low; meaning that that Altman's model (1968) is able to distinguish between group mean variances of bankrupt and non-bankrupt companies. Additionally, that the eigenvalue declines significantly from estimation model 2 to 3, although the accuracy rate declines less steep.

It can be argued that Altman's model makes less precise distinctions between bankrupt and non-bankrupt companies and therefore the classification rate is almost similar in the investigation year 2 and 3.

4.3.2 Results of Altman's model (1968) on German listed companies

Table 8: Results for German listed companies (based on own assessment)

Altman (1968)			Estimation model 1	Estimation model 2	Estimation model 3
	Intercept		0.420	-0.427	-0.489
	WC/TA	1.2	-1.267	0.388	1.680
	RE/TA	1.4	13.340	-4.954	7.499
	EBIT/TA	3.3	-8.153	-10.880	-0.423
	DE/EQ	0.6	0.00	-0.131	0.00
	Sales/TA	0.9	-0.022	-0.427	-0.050
	Eigenvalue		0.04	0.01	0.01
	Accuracy rate in %		52.1	53.1	52.0

Similar to the results of German listed companies one can say, that the RE/TA is a better predictor for the likelihood of bankruptcy when the years of investigation declines. Another similarity to the results on German listed companies is that the financial ratio SALES/TA indicates that if profitability increases the likelihood of bankruptcy decreases. In contrast to the results on Belgian listed companies, the financial ratio of DE/EQ shows that it has an effect on the likelihood of bankruptcy. In estimation model 2 it shows a negative coefficient of -0.131. In difference to the results of German listed companies, the results of Belgian companies suggest that the estimation model 1 performs at best when only analyzing the classification rate. Model 1 has a higher eigenvalue meaning that, it can better distinguish variances between group means. However the accuracy rate is lower than in estimation model 2; although the estimation model 2 is performing less accurate in distinguishing group mean variances. Looking at the results of the three estimation models on German listed companies together, one has to mention that the eigenvalue of the estimation models two and three do not change; although the financial ratios coefficients and accuracy rate do so.

That can mean that in the estimation models two and three the model performed less good in classifying the variance between groups (bankrupt and non-bankrupt). This is evident with the results on the German listed companies.

4.3.3 Conclusion on the model of Altman (1968)

Concluding the results on Altman's model (1968) one can say, that the accuracy rate of both samples (Belgian and German listed companies) perform consistent with general theory. The ratio of RE/TA has the highest coefficients and therefore it tends to be a good predictor since its weight is large. Comparing to the results to Altman's original model, the financial ratios RE/TA and EBIT/TA performs with a higher significance than in the original study. This is consistent with results of a study undertaken by Grice *et al.* (2001) where the author states: "the retained earnings/total assets and earnings before interest and taxes / total assets exhibit higher significance levels in the 1985-1987 model than in the Altman's original model". The overall performance of accuracy rate of Altman's model (1968) ranges between 67.9 % and 68.3 % for Belgian listed companies and 52.0 % and 53.1 % for German listed companies. Similar to general theory, the more the investigation period declines, the more accurate the MDA model performs. However, it is interesting to note, that the estimation models on German listed companies performed less well (lower accuracy rate and eigenvalue) than the estimation models on Belgian listed companies. It can be reasoned that Altman's model underestimate the Type I error and overestimates the Type II error; meaning that although companies being bankrupt are classified as healthy. This argument is supported by Grice (2001). Further, the sample consists of very small and big firms and only double entries, errors have been deleted. As Al-Rawi (2008) explains, the model was primarily designed for manufacturing firms and hence, in common literature it was shown that accuracy rate performs less good when applied to all industry sectors. Further the author argues that "the bankruptcies studied by Altman were for the period between 1946 to 1965. As most large firms operate in several industries, matching can be difficult. It is not clear if past experience will always be transferable to future situations given the dynamic environment in which business operates" (Al- Rawi, 2008). Grice *et al.* (2001) come to same conclusions after they compared the accuracy rate of Altman's model (1968) between the time periods 1985-1987 and 1988-1991.

The table 9 below puts the results of Belgian and German listed companies into perspective with results of other studies. This has the aim to show in how far the findings of this Master

This can be put into perspective. Comparing the findings on the Altman's model (1968) model in existing literature to the results in this Master Thesis, one can say that the results found on Belgian and German listed companies perform lower to findings in literature. It can be concluded that the accuracy rate ranges from 74.4 % and 83.5 % in model t-1. The accuracy rate on Belgian listed companies, for example, scored 86.3 % whereas the accuracy rate on German listed companies in estimation model t-1 is 52.1 %.

Table 9: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)

Author	Accuracy rate observed in t-1
Res (2013)	74.4 %
Ponstat <i>et al.</i> (2004)	75.0 %
Puagwatana & Gunawardana (2005)	77.8 %
Grice (2001)	83.5 %

4.4 Analysis of Ohlson model (1980)

The logistic regression is part of the broad class of linear models including models such as ordinary regression and ANOVA. Similar to the multivariate discriminant analysis, the logit regression analyzes the effects of independent variables on the dependent variable. However, the logit regression does assume linearity of the relationship between both variables and estimates the probability of an event occurring coded as 0 (for event not occurring) or 1 (event occurring) and are defined as the ratio of odds of the event occurring to it not occurring.

As the logit model is a non-linear one, it uses maximum likelihood estimation (MLE) to construct the model. Consequently it produces logit coefficients that maximizes the likelihood of classifying cases correctly. The logit regression (1980) has the advantage that results can be easily interpreted and as Flagg *et al.* (1991) states: "has less rigorous constraints". Another advantage of this statistical method is the assumption of no linear relationship between the two variables and therefore it can handle nonlinear interaction effects. However, a disadvantage of this model is however that it calculates the changes of log odds and not the change itself.

4.4.1 Results of Ohlson's model (1980) on Belgian listed companies

The table below shows the estimated coefficients of the logit regression of Ohlson (1980) on Belgian listed companies. The results suggest that the coefficients are significant for the financial ratios: SIZE, NI Binary, TL-TA binary meaning that the p-value tells that the slope of the regression this large would be unlikely to occur by chance if there was no relationship between the financial ratios. Furthermore, the overall accuracy rate is at highest in estimation model 1 and declines when the year of investigation increases. This is in accordance to general theory that the accuracy rate attains its maximum when the investigation year is low. That is why the accuracy rate ranges from 0.974 to 0.970. Contrary to that is the performance of the Pseudo R² which is bounded between 0 and 1. The larger the Pseudo R² the better the fit of the logit model. However, although the accuracy rate is at highest in estimation model 1, the Pseudo R² is at largest at estimation model 3. That means that the fit of model does not perform adequately. It needs to be mentioned, that generally the Pseudo R² is very low which in contradiction to the original study of Ohlson (1980). It might be reasoned that this is due to the fact of sample size and the ratio of bankrupt to non-bankrupt companies.

Table 10: Results for Belgian listed companies (based on own assessment)

Ohlson (1980)		Estimation Model 1		Estimation Model 2		Estimation Model 3	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
intercept	-1.300	-2.435	0.003	-3.197	0.000	-1.501	0.074
ADJ SIZE	-0.400	-0.414	0.018*	-0.454	0.009*	-0.585	0.002*
TL/TA	6.000	0.481	0.121	1.989	0.000	-0.428	0.188
WC/TA	-1.400	0.455	0.153	0.398	0.221	0.819	0.011*
CL/CA	0.800	-0.011	0.719	-0.035	0.530	-0.055	0.456
NI/TA	-1.800	-1.956	0.003*	-3.521	0.000	0.912	0.292
FU/TL	0.300	-0.532	0.172	0.004	0.816	-0.184	0.067
NI binary	-1.700	0.548	0.011*	0.678	0.001*	0.798	0.001*
Change NI	-0.500	-0.017	0.037*	-0.013	0.104	-0.011	0.227
TL-TA binary	-2.400	1.232	0.000*	-0.860	0.034*	2.932	0.000*
Pseudo R²			0.117		0.100		0.155
Accuracy rate			97.4		97.2		97.0

4.4.2 Results of Ohlson's model (1980) on German listed companies

The table 11 below indicates the direction and performance of estimated coefficients for the financial ratios in Ohlson's logit (1980) regression. From the performance of the p-values of estimated coefficient of financial ratios, one can analyze that they do not perform constantly over investigation time. Especially the estimated coefficients for NI Binary and TL-TA binary performs in estimation model 1, 2, 3 highly negative. Furthermore, the estimated coefficients on financial ratios are less significant as in findings on Belgian listed companies. Only the intercepts in all three estimation model is significant. Looking at the Pseudo R² and the accuracy rate one has to say that the models on German listed companies perform not accurate. The accuracy rate is in all three years of investigation at 0.985 whereas the Pseudo R² ranges from 0.028 to 0.045. As the Pseudo R² is a measure of goodness-of-fit of a model and therefore one can conclude that the model of Ohlson (1980) performs poorly. It can be argued that the performance is poor since the estimated coefficients of financial ratios perform unstable and contrary to the original study of Ohlson (1980)

Table 11: Results for German listed companies (based on own assessment)

Ohlson (1980)							
		Estimation Model 1		Estimation Model 2		Estimation Model 3	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
intercept	-1.300	-3.152	0.039*	-3.206	0,038*	-3.263	0,047*
ADJ SIZE	-0.400	-0.203	0.473	-0.222	0,433	-0.159	0,578
TL/TA	6.000	-0.090	0.936	0.552	0,636	-0.244	0,833
WC/TA	-1.400	-0.895	0.458	-0.264	0,823	-0.385	0,748
CL/CA	0.800	0.076	0.700	-0.292	0,564	-0.285	0,538
NI/TA	-1.800	3.740	0.069*	2.333	0,413	2.677	0,253
FU/TL	0.300	-0.218	0.153	-0.332	0,312	-0.097	0,872
NI binary	-1.700	-16.760	0.803	0.375	0,674	0.190	0,833
Change NI	-0.500	-0.001	0.978	0.000	0,996	-0,003	0.957
TL-TA binary	-2.400	-16.760	0.998	-17.237	0.998	2.374	0.015*
Pseudo R²			0.028		0.017		0.045
Accuracy rate			98.5		98.5		98.5

4.4.3 Conclusion on model of Ohlson (1980)

Comparing the estimated coefficient of the financial ratios and the overall performance and findings on Belgian and German listed companies' one can conduct that both tables suggest different performances. The findings of the estimated coefficients of financial ratios, the Pseudo R^2 and the accuracy rate vary enormous. Although, as outlined above, the performance of estimated coefficients of financial ratios (NI binary or change NI) is in both models similar; however the overall findings (accuracy rate and Pseudo R^2) differ from each other: Whereas the Pseudo R^2 is 0.028 and the accuracy rate is 98.5 % on German listed companies (estimation model 1), the Pseudo R^2 is 0.117 and the accuracy rate 97.4 % on Belgian listed companies (estimation model 1).

The table below wraps up the findings of accuracy rate of the common literature on the model of Ohlson (1980).

Table 12: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)

Author	Accuracy rate observed in estimation model t-1
Ohlson (1980)	96.0 %
Wang & Campbell (2010)	95.0 %
Ponggat <i>et al.</i> (2004)	69.6 %
Begley <i>et al.</i> (1997)	98.0 %

4.5 Analysis of Zmijewski' model (1984)

The probit analysis is a statistical specialized regression model of binominal response variable. Originally, probit models were introduced by Chester Bliss in 1934 and laid down the foundation for computing maximum likelihood estimates.

Similar to the MDA (1968) and logit model (1980), the probit model (1984) studies the relationship between a binary dependent variable (y) and the independent variables (x) being titled as a binary classification model.

In contrast, however, to the other models the probit model uses a maximum likelihood procedure which is called the probit regression.

It includes a latent variable to estimate the coefficients of the function. The predicted variable Y ranges from negative infinity to positive infinity. The standard normal function G is set up to

transform the latent variable Y^* into a predicted value called Y . The predicted value Y ranges between 0 and 1; the closer the estimated value to 1 the higher the fit of the model. The formula is $\Pr(Y) = G(Y^*) = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)$. A disadvantage of this method is that the change in the latent variable is studied and not the variable Y itself.

4.5.1 Results of Zmijewski's model (1984) on Belgian listed companies

Table 13: Results for Belgian listed companies (based on own assessment)

Zmijewski (1984)							
	Estimation Model 1			Estimation Model 2		Estimation Model 3	
	Estimate	p-value		Estimate	p-value	Estimate	p-value
intercept	-4.300	2.354	0.000*	2.454	0.000*	2.317	0.000*
NI/TA	-4.500	-1.416	0.000	-1.776	0.000*	-0.881	0.011
TL/TA	5.700	0.721	0.000*	0.883	0.000*	0.717	0.000*
CA/CL	0.004	-0.012	0.542	-0.005	0.708	-0.008	0.635
Pseudo R²			0.86		0.79		0.38

The above table 13 shows that the estimated intercepts in all three estimation models are significant. Further, the estimated coefficient of the financial ratio NI/TA is in all three estimation models is negative and significant. That means that it has an effect on the slope of the probit model of Zmijewski (1984). From that one can say, that the financial ratio TL/TA as a measure for leverage has a significant effect on the likelihood of bankruptcy in the estimation model 1, 2 and 3. This is consistent with the original study by Zmijewski (1984). Further, the estimated coefficient of the ratio CA/CL increases while the years of investigation period declines. It means that while liquidity decreases, the likelihood of bankruptcy increases which is consistent to general theory in finance. In the three years of investigation the Pseudo R² ranges from 0.038 and 0.068. To general theory, the Pseudo R² ranges from 0 and 1 meaning the higher the Pseudo R² in a model scores, the better the model performs. Turning around, estimation model 1 performs most accurate. This is also estimated by the accuracy rate which is at highest in estimation model 1 (0.086).

4.5.2 Results of Zmijewski's model (1984) on German listed companies

The table below shows the results for the three estimation models on German listed companies. Compared to estimation models on Belgian listed companies one can argue that the estimated coefficients of all three financial ratios perform differently during the investigation period. At first, none of them is of statistical significance. This is contrary to the results on Belgian listed companies. Here, the estimated coefficients on TL/TA and NI/TA were statistically significant. It needs to mention that the estimated coefficient of the financial ratio CA/CL in estimation model 1 is 0 while the p-value is 0.936; however not significant. This means that the financial ratio is not a good measure for bankruptcy likelihood in estimation model 1. One can conclude that none of the estimated coefficients on the three different financial ratio performs stable since none of them decreases or increases constantly. Since none of them is significant, one has to state that these results indicate that the performance of financial ratios on the model of Zmijewski (1984) is less informative when it comes to bankruptcy prediction. Additionally, the performance of the Pseudo R² suggest a similar conclusion. Estimation model 1 performs most accurately followed by the estimation model 3. It is remarkable that estimation model 3 is almost as accurate as estimation model 1. The general assumption is that predicting bankruptcy likelihood within one year is much easier and therefore scores a higher Pseudo R² than predicting bankruptcy model within three years.

Table 14: Results for German listed companies (based on own assessment)

Zmijewski (1984)							
		Estimation Model 1		Estimation Model 2		Estimation Model 3	
		Estimate	p- value	Estimate	p- value	Estimate	p- value
intercept	-4.300	4.053	0.000*	3.738	0.000*	4.828	0.000*
NI/TA	-4.500	2.935	0.105	1.325	0.528	2.742	0.163
TL/TA	5.700	-0.283	0.760	-0.721	0.458	1.056	0.221
CA/CL	0.004	0.000	0.936	0.001	0.746	-0.005	0.821
Pseudo R²			0.12		0.06		0.11

4.5.3 Conclusion on the model of Zmijewski (1984)

The results on the model of Zmijewski (1984) suggest that the accuracy rate of the estimation model 1 is in both samples most accurate. However, the Pseudo R^2 on Belgian listed companies is much higher than on German listed companies. The analysis of probit model indicates that the intercepts are significant at 0.05 level and only estimated coefficient on CL/CA and NL/TA on Belgian listed companies are significant.

To conclude, it becomes clear that the probit model is a “one- variable model” since the variables are highly correlated to each other (Shumway, 2001). Shumway (2001) argues that the variable TL/TA is strongly correlated ($p = 0.40$) to the variable NI/TA and concludes that due to this high correlation the model of Zmijewski (1984) does not have strong predictive power for bankruptcy. This argument becomes clear in the findings on German listed companies where the accuracy rate is 12.0 %. Additionally, Platt and Platt (2002) argue: “Because Zmijewski ran only one regression for each sample size, he [Zmijewski (1984)] could not test the individual estimated coefficients for bias against the population parameter”. This argument is supported when one compares the different findings on German and Belgian listed companies. We can argue that the model of Zmijewski (1984) on different sample sizes and different ratio of bankrupt to non- bankrupt companies perform differently. Therefore, the results might be biased.to be analyzed with cautious. The table below depicts the findings on Zmijewski’s model (1984) on accuracy rate. This aims at putting findings on German and Belgian listed companies into perspective.

Table 15: Overview of accuracy rate observed in t-1 before bankruptcy in common literature (based on own assessment)

Author	Accuracy rate in model t-1
Grice & Dugan (2001)	81.3 %
Hodgin & Marchesinin (2001)	71.2 %
Waquas <i>et al.</i> (2014)	61.0 %

4.6 Discussion

The results on the three different accounting-based bankruptcy prediction model were evaluated to answer the two hypotheses of the Master Thesis. Therefore, the accuracy rate of the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) were studied. The first hypothesis stated that there is no difference between the accuracy rates of the three accounting-based bankruptcy prediction model whereas the second hypothesis claimed that there is a difference. The findings on the model indicated clearly that the accuracy rate of the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) perform differently. The accuracy rate for the Belgian listed companies for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) models are respectively 68.3 %, 97.4 %, and 86.0 %. That means that the model of Ohlson (1980) performs at best.

The accuracy rate for German listed companies for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are respectively 53.1 %, 98.5 % and 12.0 %. Also here the model of Ohlson (1980) performs best. However, it needs to be mentioned that the accuracy rate in all three investigation years is at 98.5 %. Contrary to that performs the Pseudo R^2 . According to the performance of the Pseudo R^2 the estimation model 3 performs at best since the Pseudo R^2 is at 0.045. To conclude, the model of Ohlson (1980) is most accurate on German and Belgian listed companies. This means that the financial ratios used in Ohlson's model are most likely to predict the bankruptcy likelihood. However, as mentioned above the results on accuracy rate should be interpreted cautiously. This can be deducted when analysing the results of German listed companies. When only observing the accuracy rate, it does not become clear which estimation model performs at best since the accuracy rate is the same in all estimation models. However, the Pseudo R^2 suggests that estimation model 3 performs at best.

Concluding, the accuracy rate of the three accounting-based bankruptcy prediction models on German listed companies is much lower than on Belgian listed companies. A reason for it might be the low ratio of bankrupt and non-bankrupt companies on German listed companies. Additionally, there might be the possibility that the statistical methods falsely categorize bankrupt companies as non-bankrupt companies and the other way round. Therefore one can conclude that the financial ratios selected for the bankruptcy prediction models work are less good predictors for bankruptcy likelihood on German listed companies.

5. Conclusion

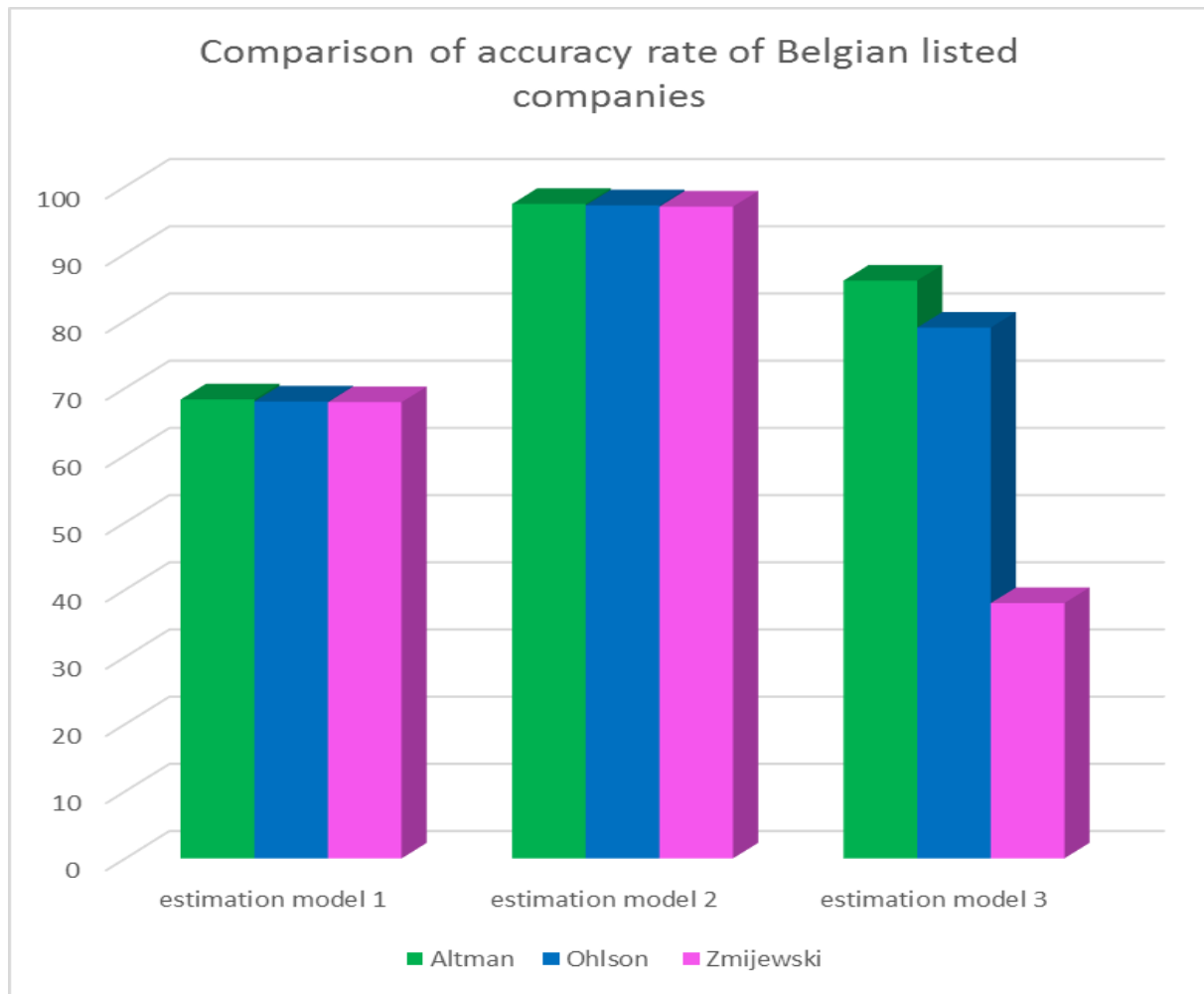
5.1 Conclusion of Findings

This paper compares the performances of three accounting-based bankruptcy prediction models namely Altman (1968), Ohlson (1980) and Zmijewski (1984) on Belgian and German listed companies. Two hypotheses were established to answer the underlying question of this Master Thesis whether or not there is a difference between accuracy rates of Altman (1968), Ohlson (1980) and Zmijewski (1984). The two tables below summarize the findings of accuracy rate on Belgian and German listed companies. Overall, the results show clearly that in the timeframe from 2008 - 2013 Ohlson (1980) logit model performed most accurate; meaning that the selected financial ratios of the Ohlson model (1980) is most accurate in predicting bankruptcy likelihood.

As expected by common literature, the accounting-based bankruptcy prediction models perform highly different in their accuracy rate. As observed in common literature, e.g. Grice (2001) and Grice & Ingram (2003) the accuracy rate of the Altman model (1968) declines during the investigation period. (see results on Belgian listed companies). In more depth, Hayes *et al.* (2010) studied the Altman model (1968) and came to the conclusion that although Altman's model (1968) is a reliable method for bankruptcy prediction, Altman's model (1968) is sensitive to small companies and industries. Grice (2001), Agarwal (2008) and Hays *et al.* (2001) therefore suggest that this problem can be overcome by re-estimating the coefficients of the models using "a sample of firms approximated the proportion of distressed and non-distressed companies in the population" (Grice, 2001).

Additionally, differences between accuracy rates of the three bankruptcy prediction models can be studied especially when comparing the results on the model of Zmijewski (1984) and Ohlson (1980) on German listed companies. The Zmijewski model (1984) is sensitive since the estimated coefficient of financial ratios are not stable due to the fact that the sample on German listed companies has a low ratio of bankrupt to non-bankrupt companies. Moreover, the findings on the German listed companies suggest that the models perform less accurate than on Belgian listed companies. One explanation is the low ratio between bankrupt and non-bankrupt companies.

Table 16: Comparison of the accuracy rate of Belgian listed companies (based on own assessment)

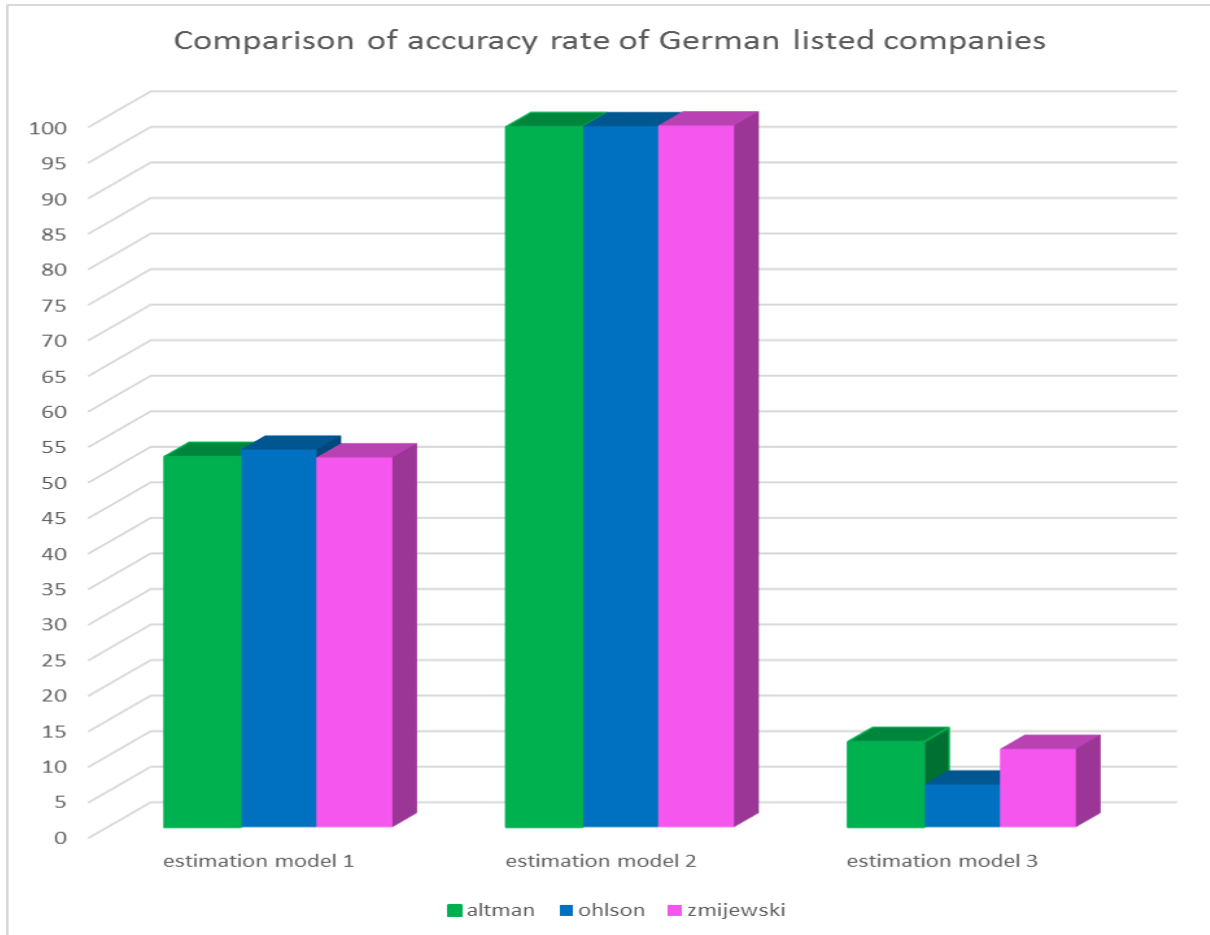


To conclude, Ohlson's model (1980) performed most accurate. However, the results of performance and accuracy rate of the three accounting-based bankruptcy prediction models should be studied carefully.

In more depth, when comparing the accuracy rate of Altman (1968), Ohlson (1980), and Zmijewski (1984) in the estimation model 2 (one year before bankruptcy) to results found in common literature, one can say that the results of accuracy rate of this Master Thesis is overall high. For example, the accuracy rate of Altman model (1968) in t-1 performs, higher than observed in common literature. Whereas common literature indicate that the accuracy rate is between 74.4 % and 83.5 % the results on accuracy rate of the Altman model (1968) suggest an accuracy rate above 94.4 %. As Grice (2001) explains that is due to the reason that the relation between financial ratios and financial distress changes over time. Wu *et al.* (2010) come to similar conclusions stating that the performance of models has deteriorated over the more recent years. As external factors like national economic environments, political affairs, industry

changes have an additional effect on the performance of models, those external factors should be studied intensively as well.

Table 17: Comparison of the accuracy rate of German listed companies (based on own assessment)



In conclusion, the findings in this Master Thesis are similar to general theory about accounting-based bankruptcy prediction models. Ohlson's model (1980) perform most accurate on German and Belgian listed companies during the three years of investigation. Overall results as outlined by table 16 and 17 indicate that there is a difference between accuracy rates of the three accounting-based bankruptcy models and therefore hypothesis II can be rejected. Further, as expected the accuracy rates of all three models namely Altman (1968), Ohlson (1980), and Zmijewski (1984) decline towards the year of bankruptcy (estimation model 2 compared to estimation model 1). Therefore, findings of accuracy rate on accounting-based bankruptcy prediction models should also be set into perspective.

5.2 Limitations

The Master Thesis analysed three different accounting-based bankruptcy prediction models that are common in literature about the current topic. Since each of them depicts different financial accounting variables, they explain bankruptcy accuracy at different levels and stages; however none of them can explain bankruptcy likelihood completely.

From the literature discussion one can conclude that neither model is sufficient statistic for failure prediction since all of them imply advantages and disadvantages. When directly compared to other bankruptcy prediction models, market-based bankruptcy prediction models outperform accounting-based prediction models since they take into account macroeconomic variables.

Data are based on historical information and influenced by future trends. Those trends are not included in the accounting-based bankruptcy models and therefore accounting-based bankruptcy prediction models are limited by themselves. As company's performance is hardly affected by macroeconomic variables and changes, results have to interpret also in respect to those variables. A study by Rose, Andrews and Giroux (1982) describes that macroeconomic conditions are significant factors influencing the probability of bankruptcy ($R^2 = 0.912$). Another common limitation of accounting-based bankruptcy prediction models is that accounting variables in those models can be manipulated (e.g. depreciation method or going concern principle) as companies are motivated by the benefits of concealing failure. This critic has to be taken into account when interpreting accuracy rate results. Moreover, data of this Master Thesis are retrieved from a national and small database and therefore this Master thesis was confronted with a limitation on data availability. The sample is therefore limited in its size and time. A larger sample size would be more beneficial as it would give a clearer and more defined picture to verify the validity of the accounting-based bankruptcy prediction models.

5.3 Outlook for Future Research

In this Master Thesis, the empirical performance of the three prediction models can be used for stakeholders such as investors to evaluate bankruptcy likelihood. However, the Master Thesis implied some limitations. Therefore, this section deals with suggestions for a future research.

First, as the literature discussion pointed out that the market-based bankruptcy prediction models outperform accounting-based bankruptcy prediction models; however those could have not been applied to the limitations from the database being used. Therefore, I suggest that a follow-up study could be conducted comparing the performance and accuracy rate of the three accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), Zmijewski (1984) to the market-based bankruptcy prediction models of Shumway (2004) and Hillegeist *et al.* (2000). This could add value to existing literature because a comparison of both streams of models have not been applied to European listed companies yet. As a follow up study, a further suggestion is to investigate the study to different economic periods in order observe how the models perform in different environments and time periods. That would mean that a cross-sectional study would be applied.

Secondly, a major contribution to this study could also be to study cash flow variables as an “early warning” of potential financial difficulties. This idea is suggested by Mossmann *et al.* (1998) who found out that a firm with insufficient amount of cash available to service debt, the probability that a firm faces bankruptcy likelihood is higher. Further, they found out that the group means of bankrupt and non-bankrupt companies differ significantly in all five years prior to bankruptcy. Especially, this could add significant value when it comes to the study of financial ratio performance during the investigation period. Therefore, a follow-up study could be undertaken including an in-depth analysis of cash flow variables to analyse whether or not there is a significant relation between financial ratios used in the three models. A study by Aziz, Emanuel and Lawson (1999) tested the accuracy rate of cash flow models and compared results to the MDA model of Altman (1968). They came to the conclusion that the cash flow model is superior to the MDA model due to the fact that they give better early warning signals.

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Appendices

Appendix A: Classification of financial variables

Bankruptcy Model	Author	Explanatory Variables	Ratio classification
MDA	Altman (1968)	WC/TA	Liquidity
		DEBT/ EQUITY	everage
		RE/TA	Leverage
		SALES/ TA	Profitability
		EBIT/TA	Profitability
Logit regression	Ohlson (1980)	SIZE= LOG(total assets/GNP price-level)	none
		TL/TA	Leverage
		NI/TA	Profitability
		WC/TA	Liquidity
		CHIN	Profitability
		CL/CA	Liquidity
		INTWO	Liquidity
		FU/TL	Liquidity
		OENEG	Leverage
Probit regression	Zmijewski (1984)	NI/TL	Profitability
		CA/CL	Liquidity
		TL/TA	Leverage
Hazard model	Shumway (2000)	NITL	Profitability
		TLTA	Leverage

Appendix B: Overview of Hypotheses and Research Question

Hypothesis I	<i>H₀: There is a difference in accuracy rate of bankruptcy rate between accounting- based models of Altman (1968), Ohlson (1980), and Zmijewski (1984).</i>
Hypothesis II	<i>H_A: There is no difference in accuracy rate of bankruptcy rate between accounting- based models of Altman (1968), Ohlson (1980), and Zmijewski (1984)</i>
Research Question I	Are and what are the advantages and disadvantages of accounting- based prediction models?
Research Question II	What is the accuracy rate of accounting based prediction models?
Research Question III	If there are differences in the accuracy rate of the accounting- based prediction models, how can they be explained?