MASTER THESIS

Prediction power of accounting-based bankruptcy prediction models: Evidence from Dutch and Belgian public and large private firms

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Abstract

This study examined the prediction power of the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) for Dutch and Belgian public and large private firms. These bankruptcy prediction models include different financial ratios as independent variables and are developed using different econometric methods: multiple discriminant analysis, logistic regression, and probit regression, respectively. It is tested if one of the prediction models outperforms the others, which econometric method is best for developing the models, if the coefficients of the models are non-stationary, and what the optimal time horizon for predicting bankruptcy is. The performance of the three models is assessed using two different estimation samples with firm observations from 2007 – 2010, and 2012 – 2015, and a hold-out sample with firm observations from 2016 – 2019. These different time periods for the estimation samples are chosen because of the different economic environments. During the first time period (2007 – 2010), several important events occurred such as the financial crisis in 2007 and the European debt crisis in 2010. Firms from all industries, except the financial and insurance industry, were included in the samples. The results show that the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) predicted respectively 32.39%, 47.89%, and 38.03% of the bankrupt firms and 99.58%, 99.72%, and 100.00% of the non-bankrupt firms correctly. No statistical significant difference was found between the three prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984), and between the three econometric methods multiple discriminant analysis, logit regression, and probit regression. Additionally, no evidence was found for the non-stationarity of the coefficients. Finally, this study concludes that the optimal time horizon for predicting bankruptcy is one fiscal year before the event.

Keywords: *bankruptcy prediction, Altman Z-score, Ohlson O-score, Zmijewski score, multiple discriminant analysis, logistic regression, probit regression, the Netherlands, Belgium, public firms, private firms*

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1 Introduction

Since the 1960s an increasing number of corporate bankruptcy prediction models have emerged (Adnan Aziz & Dar, 2006). Corporate bankruptcy prediction is of great interest to various stakeholders including shareholders, managers, employees, creditors, suppliers, clients, and the government (Dimitras, Zanakis, & Zopounidis, 1996; Fejér-Király, 2015). Bankruptcy prediction models can be helpful in two different ways. First, bankruptcy prediction can be used as an early warning system to prevent bankruptcy. If the model is able to predict a potential bankruptcy a few years in advance, actions like reorganization or merger of the firm can be undertaken (Dimitras et al, 1996; Pompe & Bilderbeek, 2005; Fejér-Király, 2015). Second, predicting the possibility of bankruptcy can help investors evaluate and select firms to invest in, in order to prevent the risk of losing their investment (Dimitras et al., 1996; Karamzadeh, 2013). Bankruptcy might have a contagious effect within an industry, where one firm's bankruptcy leads to another firm's bankruptcy if their activities depend on one another (Lang & Stulz, 1992; Fejér-Király, 2015).

Two of the most widely used methods for predicting corporate bankruptcy are analysis of financial ratios and analysis of market risk (Karamzadeh, 2013), also known as accounting-based bankruptcy prediction models and market-based bankruptcy prediction models, respectively. This thesis will focus on accounting-based bankruptcy prediction models, because these models do not rely on market data. Accounting-based models estimate the possibility of bankruptcy by using a group of financial ratios (Karamzadeh, 2013). The majority of firms are private firms and for privately held firms only accounting data and no market data are available. The banking industry is the main provider of loans in the economy and for private firms, and is therefore especially interested in reducing the amount of non-performing loans. In order to reduce their own risk of default, banks need to predict the possibility of default of a potential borrower (Atiya, 2001; Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2017). Therefore, it is important to test the accounting-based bankruptcy prediction models. The key accounting-based bankruptcy prediction models are the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) (Wu, Gaunt, & Gray, 2010).

This master thesis will test the accounting-based bankruptcy prediction models on Dutch and Belgian public and large private firms. The number of bankruptcies in the Netherlands decreased since 2013 until 2017 and since then the trend has been relatively stable (Statistics Netherlands, 2019). The number of Belgian bankruptcies also decreased since 2013, and the trend has been relatively stable since 2015 (Statbel, 2020). Despite this current trend of bankruptcies in the Netherlands and Belgium, it will still be important to examine if the bankruptcy prediction models are generalizable to Dutch and Belgian public and large private firms because bankruptcies will always occur. The main goal of this master thesis is to examine the prediction power of the accounting-based bankruptcy prediction models of

Altman (1968), Ohlson (1980), and Zmijewski (1984) when applied to Dutch and Belgian public and large private firms. Given the above, this thesis will answer the following research question:
How accurate are the accounting-based bankruptcy prediction models for Dutch and Belgian public and large private firms?

The literature provides contradictory empirical results concerning the best performing bankruptcy prediction model (e.g. Begley, Ming, & Watts, 1996; Grice & Ingram, 2001; Grice Jr. & Dugan, 2003; Wu et al., 2010). This master thesis will therefore test if one of the models of Altman (1968), Ohlson (1980) or Zmijewski (1984) outperforms the others regarding their prediction power when applied to Dutch and Belgian public and large private firms. Since the three prediction models are developed using different econometric methods, it will also be tested if one of these econometric methods outperforms the others regarding their prediction power. It appears that all three models are sensitive to time periods and that the relation between financial ratios and financial distress changes over time. This can lead to a decline of the accuracy rate of the models when applied to time periods that differ from the time periods used to develop the models (Grice & Dugan, 2001; Grice & Ingram, 2001). In addition to different time periods, different economic environments also affects the accuracy and structure of bankruptcy prediction models, suggesting that the coefficients of the accounting-based bankruptcy prediction models are non-stationary (Mensah, 1984). It will be tested if the accounting-based bankruptcy prediction models retain their accuracy over time, and if re-estimating the coefficients of the prediction models improves the predictive accuracy. Finally, the optimal time horizon for predicting bankruptcy will be assessed.

The sample of this master thesis includes Dutch and Belgian public and large private and non-financial firms across all industries. Studies of bankruptcy prediction mainly focus on publicly listed companies outside the European Union, mostly in the United States (U.S.) (e.g. Altman, 1968; Ohlson, 1980, Zmijewski, 1984; Grice & Ingram, 2001; Shumway, 2001; Grice Jr. & Dugan, 2003; Chava & Jarrow, 2004; Hillegeist, Keating, Cram, & Lundstedt, 2004). However, bankruptcy prediction for private firms is also important since private firms play a critical role in most economies (Filipe, Grammatikos, & Michala, 2016), but have much higher failure rates on average than public companies (Jones & Wang, 2019). According to Jones and Wang (2019), the following factors might be the reason that most studies focus on publicly listed firms instead of private firms. First, the available data for private firms tend to be less complete and reliable since most private firms are not subject to mandatory external auditing requirements or compliance with accounting standards. Second, as already mentioned, bankruptcy prediction for private firms is limited to financial ratios, in contrast to bankruptcy prediction for public firms, where market data can be included. Last, most private firms have heterogeneous business and legal structures, which makes it more difficult to predict bankruptcy. Additionally, a Dutch and Belgian context is chosen because firms in these two countries were affected by the financial crisis in 2007, the European debt crisis in 2010, and the regulatory response to the financial crisis, Basel III. This provides an interesting economic environment to test the predictive accuracy of the three models.

This master thesis therefore contributes to the existing literature by including private firms in the sample and by assessing the usability of the three accounting-based bankruptcy prediction models in a Dutch and Belgian setting, and by providing which model performs best in this setting. Additionally, another contribution of this master thesis is that it tests the accounting-based bankruptcy prediction models in two different periods (2007-2010 and 2016-2019) with different economic environments.

Other students from the University of Twente also conducted research on bankruptcy prediction. Boekhorst (2018) evaluated the predictive ability of the Altman Z-score model (1983) for Dutch private firms. A critic is that the sample consisted of bankrupt and active firms in the time period 2007 – 2015, which is a quite large time period and during this time period the economic environment has changed a lot. This may have biased the results. Additionally, firms from all industries, including the financial and insurance industry, were included in the sample. Most studies about bankruptcy prediction exclude firms from the financial and insurance industries because of their different structure of capital compared to firms in other industries. A strength of the study of Boekhorst (2018) is the use of a large sample size, which makes the results more reliable. However, the high ratio active firms/bankrupt firms in the sample is not proportional to the actual bankruptcy rate and this ratio is not constant per sample, which potentially biased the results. He also did not partition the data into an estimation sample and hold-out sample to verify the predictive performance of the Z-score model.

Elferink (2018) adjusted existing prediction models to achieve an accuracy higher than 80% in an exclusively Dutch setting. He only tested and re-estimated the Z-score model of Altman (1968), and did not include other accounting-based bankruptcy prediction models. However, he did investigated additional ratios that could increase the performance of the prediction model. Another strength of his research is that he tested and re-estimated the Z-score model of Altman (1968) using several econometric methods: multiple discriminant analysis, logistic regression, and neural network. The sample consisted of 125 matched pairs of bankrupt and non-bankrupt firms. However, the actual amount of non-bankrupt firms is much higher than the actual amount of bankrupt firms, meaning that, just as the sample of Boekhorst (2018), the sample is not proportional to the actual bankruptcy rate, leading to potential bias of the results.

Machielsen (2015) assessed the predictive accuracy and information content of the bankruptcy prediction models of Altman (1968) and Ohlson (1980) for publicly listed firms in the European Union. Whereas many studies only focus on predictive accuracy, the study of Machielsen (2015) also measures the information content of the models. Information content measures whether one model score contains more information about bankruptcy than another variable (or set of variables). A weakness of the study of Machielsen (2015) might be that 3 out of 25 countries are overrepresented in the samples, which could potentially lead to sampling bias. However, the robustness checks he conducted conclude that the effect of the sampling bias was marginal. A strength of the study is that he includes macroeconomic variables to absorb the change in macroeconomic environment to ensure that the model remains accurate and informative under changing macroeconomic circumstances.

Despite that several other students already conducted their master thesis on bankruptcy prediction, this master thesis still contributes to the existing literature because it focuses on three accounting-based bankruptcy prediction models for Dutch and Belgian public and large private firms, which has not been done before. This thesis is structured as follows. Chapter two provides a literature review of corporate bankruptcy, the bankruptcy procedure and the key bankruptcy prediction models. This chapter also features a review of the key empirical findings of prior research. Chapter three presents the conceptual framework in which the hypotheses are developed. Chapter four presents the research methodology. The empirical results of the hypotheses are presented in chapter five. Finally, the conclusion and discussion follows in chapter six.

2 Literature review

This chapter discusses the theoretical framework of this master thesis. The first section addresses corporate bankruptcy; the definition of financial distress and bankruptcy, the causes of bankruptcy, and the bankruptcy procedure in the Netherlands and Belgium will be discussed. In the second section, the focus will be on bankruptcy prediction, and in this section an overview of bankruptcy prediction models will be provided. The third section will be devoted to the key accounting-based bankruptcy prediction models of Altman (1968, 1983), Ohlson (1980), and Zmijewski (1984). The fourth section will review the two key market-based bankruptcy prediction models of Shumway (2001) and Hillegeist et al. (2004). This is followed by a comparison of the accounting-based and market-based bankruptcy prediction models in section five. Section six features the assessment of the bankruptcy prediction models. Finally, a summary table containing the most important contributions and results of key articles in the literature of bankruptcy prediction will be provided.

2.1 Corporate bankruptcy

2.1.1 Financial distress and bankruptcy

In corporate failure studies, the terms financial distress and bankruptcy are often used as synonyms, while they do not have the same definition (Karels & Prakash, 1987; Wruck, 1990; Balcaen & Ooghe, 2006). Financial distress is a broad concept that includes several situations in which firms face some form of financial difficulty (Doumpos & Zopounidis, 1999). There are many definitions of financial distress (Altman, 2013). According to Li and Li (1999), a firm is financially distressed when the firm's cash flows are insufficient to cover current obligations to creditors and/or the expected present value of the firm is below the outstanding debt level. Bankruptcy is a legal procedure where companies have already taken a legal action (Fejér-Király, 2015), bankruptcy is therefore described as the legal definition of financial distress (Doumpos & Zopounidis, 1999; Kahya & Theodossiou, 1999). Financially distressed firms still have the chance of being reorganized and to continue their activities (Fejér-Király, 2015). Financial distress precedes bankruptcy and persists until the firm or creditor decides to file a legal action (Karels & Prakash, 1987; Platt & Platt, 2002). Financially distressed firms are more likely to declare bankruptcy than firms that do not experience financial distress. However, a financially distressed firm does not inevitably file for bankruptcy (Grice Jr. & Dugan, 2003; Tinoco & Wilson, 2013).

A bankruptcy filing implies that the debtor cannot pay all of their debts to the creditors and the legal procedure of bankruptcy is aimed at relieving the debtor from all or some of their debts (Jackson, 1982; White, 1989). To keep the market economy healthy, it is necessary that firms that are no longer competitive disappear from the market so that their resources can be redistributed in favour of healthy firms. This results in a growing competition in the market economy and allows only the best firms to survive on the market (Garškiene & Garškaite, 2004; Ooghe & Waeyaert, 2004). The bankruptcy procedure must ensure that the liquidation of such firms proceeds in an orderly manner (Ooghe & Waeyaert, 2004). This theory suggests that only economically inefficient firms whose resources could be better used by healthier firms should file for bankruptcy. However, in practice firms can also file for bankruptcy voluntarily, meaning that firms in bankruptcy might not always be economically inefficient (White, 1989). Managers choose to voluntarily liquidate when financial conditions make it value-increasing for shareholders and managers (Fleming & Moon, 1995). For shareholders, the expected value of a voluntarily exit always exceeds the expected value of a court driven exit (Balcaen, Manigart, Buyze, & Ooghe, 2012).

2.1.2 Causes of bankruptcy

Generally, bankruptcy is not the result of a sudden event, but is caused by multiple factors (Ooghe & Waeyaert, 2004; Lukason & Hoffman, 2014; Kisman & Krisandi, 2019). Bankruptcy is the result of multiple failures of the company to run its business operations in the long term in order to achieve its economic goals (Kisman & Krisandi, 2019). Before a company files for bankruptcy, it experiences a failure process which varies in length in which the company gradually evolves towards the final stage of the decline process, bankruptcy (Ooghe & Waeyaert, 2004; Lukason & Hoffman, 2014). Ooghe and Waeyaert (2004) developed a conceptual failure model that explains the different causes of failure. The model distinguishes external factors and internal factors. External factors include the (1) general environment and (2) immediate environment. Internal factors include (1) management, (2) corporate policy and (3) company's characteristics (Ooghe & Waeyaert, 2004). Table 1 provides an overview of the causes of bankruptcy.

Table 1 Causes of bankruptcy

External factors	
General environment	Economics, technology, foreign countries, politics, social factors
Immediate environment	Customers, suppliers, competitors, banks and credit institutions, stockholders, government
Internal factors	
Management	Motivation, qualities, skills, personal characteristics
Corporate policy	Strategy and investments, commercial, operational, personnel, finance and administration, corporate governance
Company's characteristics	Maturity, size, industry, flexibility

Source: Ooghe and Waeyaert (2004)

Management has little or no control over external factors (Mellahi & Wilkinson, 2004; Ooghe & Waeyaert, 2004; Lukason & Hoffman, 2014). However, management should take these uncontrollable external factors into account in their strategy (Ooghe & Waeyaert, 2004). Inflation, tax systems, law, depression in foreign currencies, economic downturns, competition, changes in demographics, technology or regulations are external factors that can cause bankruptcy (Lukason & Hoffman, 2014; Kisman & Krisandi, 2019), and these factors require a response from management (Lukason & Hoffman, 2014). Internal causes of failure are within management's control (Mellahi & Wilkinson, 2004; Ooghe & Waeyaert, 2004; Lukason & Hoffman, 2014). Internal factors are the management's decisions/actions and can be operational (short term) or strategic (long term) (Lukason & Hoffman, 2014). Lack of knowledge and experience from the management in managing assets and liabilities effectively (Kisman & Krisandi, 2019), poor management skills, insufficient marketing, and lack of ability to compete with other similar business (Wu, 2010) are internal factors that increases the probability of bankruptcy. There are also uncontrollable internal factors such as illness or death of key personnel, or a fire (Lukason & Hoffman, 2014). In extreme cases, external and internal factors can have a direct effect on bankruptcy. For instance, because of a major environmental disaster, economic crisis, or management mistake (Mellahi & Wilkinson, 2004). It appears that internal factors are the main causes of bankruptcy (Ooghe & Waeyaert, 2004), in particular managerial errors and weaknesses in operational management (Hall, 1992; Ooghe & De Prijcker, 2008).

2.1.3 Bankruptcy procedure in the Netherlands

Financial distress of a firm can lead to reorganization under court supervision (Li & Li, 1999), private reorganization (Gilson, John, & Lang, 1990), a formal exit procedure, or a private exit (Li & Li, 1999; Balcaen et al., 2012). A formal exit procedure includes bankruptcy, and a private exit includes voluntary liquidation and merger and acquisition (Balcaen et al., 2012). Liquidation occurs when a firms sells all assets, pays off creditors, and distributes the residual funds to shareholders (Ghosh, Owers, & Rogers, 1991). Due to the high transaction costs, bankruptcies are the least preferred exit option (Balcaen et al., 2012). The Dutch Bankruptcy Code provides two in-court procedures for financially distressed firms in the Netherlands: suspension of payment or filing for bankruptcy, and one outside-court procedure: informal reorganization (Boot & Ligterink, 2000; Couwenberg & de Jong, 2008; Couwenberg & Lubben, 2011); Hummelen, 2015).

Firms in financial distress can request a suspension of payment only if the firm has prospects to recover in a short time (Couwenberg & de Jong, 2008). The purpose of suspension of payment is to provide the management of the firm the opportunity to prevent bankruptcy. This request can only be done by the debtor. If the court does not provide suspension of payment, firms often end up filing for bankruptcy. During the suspension of payment procedure, the management of the firm retains control (Boot & Ligterink, 2000). The suspension of payment procedure applies only to ordinary creditors, and does not apply to secured creditors and creditors holding preferred claims (Boot & Ligterink, 2000; Couwenberg & de Jong, 2008). The firm offers the ordinary creditors an agreement, and when the creditors accept the agreement, the procedure of suspension of payment ends. If the firm fails during the suspension of payment, it is not possible to request another suspension of payment in the bankruptcy procedure (Couwenberg & de Jong, 2008). Many firms use the suspension of payment procedure to enter bankruptcy, because company directors can start a suspension of payment procedure but cannot file for bankruptcy. Only shareholders of the firm can directly file for bankruptcy, but it takes too much time to organize a shareholder meeting (Couwenberg & Lubben, 2011).

The other option for firms in financial distress is filing for bankruptcy. The Dutch bankruptcy law system is a liquidation-based system, with a rudimentary reorganization provision, in which the rules facilitate, or even force, the trustee to sell the firm's assets in bankruptcy (Couwenberg, 2001; Couwenberg & Lubben, 2011). The bankruptcy starts with the filing of a petition with the court (Hummelen, 2015). Both the firm, through its shareholders, and the creditors of the firm, once a payment is missed, may file for bankruptcy (Boot & Ligterink, 2000; Couwenberg & de Jong, 2008). Like a Chapter 7 procedure in the U.S., the purpose of bankruptcy is to cash out all the assets of the firm and to distribute the proceeds among the creditors, where the interests of the creditors are paramount (Boot & Ligterink, 2000; Hummelen, 2015). The assets of the firm can be sold as piecemeal or going concern, by means of a private sale or a public auction (Couwenberg & de Jong, 2008). At the beginning of the bankruptcy process, the court appoints an independent trustee which takes over the control of the management of the firm. The trustee has the option to continue the operations of the firm as a going concern, if this results in a higher return than liquidation. Since 1992, as well as with the suspension of payment procedure, firms in financial distress are protected from its creditors by an automatic stay of assets provision in a cool down period of at most two months (Boot & Ligterink, 2000; Couwenberg & de Jong, 2008).

Unlike Chapter 11 in the U.S., the Dutch Bankruptcy Code has no separate reorganization procedure for which a debtor can file. However, firms in financial distress can enter an informal reorganization procedure in order to renegotiate with the creditors (Boot & Ligterink, 2000; Couwenberg, 2001; Hummelen, 2015). Only the debtor may propose such a reorganization plan (Hummelen, 2015). The solution can be asset restructuring, liabilities restructuring, or a combination of both (Boot & Ligterink, 2000). If the renegotiations fail, firms will in most cases file for bankruptcy (Couwenberg, 2001). Since the negotiations occur outside the bankruptcy proceedings, it is necessary that all creditors agree with the intended reorganization. These negotiations become more complex when more creditors are involved, therefore informal reorganization only succeeds if there is a dominant creditor. In the Netherlands, most of the time banks are the dominant creditor (Boot & Ligterink, 2000).

2.1.4 Bankruptcy procedure in Belgium

The Belgian Bankruptcy Code provides three restructuring and liquidation proceedings: bankruptcy, formal reorganization, and voluntary liquidation. The bankruptcy procedure is aimed at liquidation of the firm, as a going concern or through selling the assets piece by piece, in order to pay the debts of the firm. Under the Belgian Bankruptcy Code, a firm should file for bankruptcy if the firm has generally stopped paying its debts, and if the firm has lost the confidence of its creditors. Both the board of directors of the firm and the creditors of the firm may file for bankruptcy. If the bankruptcy is declared by the court, a curator is appointed who takes over all responsibilities from the board of directors. The curator assumes control over the assets, accounts, archives and information of the firm. The task of the curator is to sell the assets of the firm and pay the creditors of the firm, according to their priority rights. The court also appoints a judge-commissioner to supervise the curator. Generally, at the end of the bankruptcy procedure the firm will no longer exist and the shareholders lose their stake in the firm. However, if the proceeds of selling the firm as a going concern are higher than the proceeds of selling the assets piece by piece, the court may authorize that the firm temporarily continues its activities under the supervision of the curator (Baker & McKenzie, 2016).

Instead of an informal reorganization procedure, the Belgian Bankruptcy Code provides a formal reorganization procedure. Belgium, just as many other European countries, reformed their bankruptcy legislations to stimulate reorganization and firm survival. The liquidation focused bankruptcy system has transformed into a legislation encompassing both a formal reorganization and liquidation procedure similar to the U.S.. The formal reorganization procedure is almost similar with the legal reorganization rules of the U.S. Chapter 11. A firm that files for formal reorganization receives creditor protection for up to six months, and during this period a reorganization plan is composed which has to be approved by the majority of creditors and the bankruptcy court. Upon approval of the reorganization plan, the firm stays under protection of the court for up to three years. During this period, the management of the firm is assisted and supervised by a court appointed administrator (Dewaelheyns & Van Hulle, 2008). The board of directors, the public prosecutor and any other third party with a legitimate interest can file for formal reorganization (Baker & McKenzie, 2016).

In addition to the formal reorganization and liquidation procedure, the Belgian Bankruptcy Code also allows firms to apply for voluntary liquidation. The board of directors of the firm appoints a liquidator, which has to be confirmed by the court. During the voluntary liquidation procedure, the liquidator must sell the assets and pay the creditors of the firm. The shareholders of the firm receive the residual proceeds. After completing the liquidation procedure, the liquidator must prepare a plan for the distribution of the assets to the different creditors and submit this plan to the court for approval. After the plan is approved by the court, the liquidation can be closed and the firm does not longer exist as a legal entity (Baker & McKenzie, 2016).

In Europe, most of the bankruptcies are initiated by the creditor and thus involuntary. Creditors may not be aware of the real financial situation, because the debtor wants to continue operating the firm as long as possible and therefore hides the real financial situation. In that case, filing for bankruptcy by creditors may come too late and the value of the firm’s assets has already largely disappeared. Timely starting either liquidation or reorganization procedures is important. The bankruptcy procedure would be optimal when the maximum value of the firm is realized at the lowest costs (Brouwer, 2006).

2.2 Bankruptcy prediction

2.2.1 Bankruptcy or financial distress prediction?

Grice Jr. and Dugan (2003) state that it is not clear whether the corporate failure prediction models are specifically useful to predict the event of bankruptcy or to predict financial distress. Many studies use bankruptcy as the definition of failure, other studies define failure as financial distress, and some studies do not clarify the definition of failure used for the research at all. This makes it difficult to compare the different prediction models (Bellovary, Giacomino, & Akers, 2007). According to Gilbert, Menon and Schwartz (1990), the financial dimensions that separate bankrupt from healthy firms are different than the financial dimensions that separate bankrupt from financially distressed firms. Therefore, bankruptcy prediction models are not able to distinguish financially distressed firms filing for bankruptcy from financially distressed firms avoiding bankruptcy. Most corporate failure studies describe prediction models of bankruptcy, and limited studies attempt to develop prediction models of financial distress. This can be explained by the lack of a consistent definition of financial distress and the difficulty to objectively define the onset of financial distress, in contrast to the definition of bankruptcy and the definitive bankruptcy date (Platt & Platt, 2002; Balcaen & Ooghe, 2006).

The models of Altman (1968), Ohlson (1980) and Zmijewski (1984) are developed to predict the event of bankruptcy. The bankrupt group in the sample of Altman (1968) included *''manufacturers that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act''* (p. 593). The bankrupt group in the sample of Ohlson (1980) included failed firms that *''must have filed for bankruptcy in the sense of Chapter X, Chapter XI, or some other notification indicating bankruptcy proceedings''* (p. 114). Zmijewski (1984) included financially distressed firms in his sample on the basis of the following definition: *''financial distress is defined as the act of filing a petition for bankruptcy''* (p. 63). This definition of financial distress implies that the Zmijewski (1984) model predicts bankruptcy instead of financial distress. As in the study of Zmijewski (1984), several studies that intent to predict financial distress, based on the title of the study, instead predict bankruptcy, based on their definition of financial distress (Platt & Platt, 2002). Since the models of Altman (1968), Ohlson (1980) and Zmijewski (1984) predict the event of bankruptcy, this master thesis will also use the legal definition of bankruptcy for the firms that are included in the samples.

2.2.2 An overview of bankruptcy prediction models

In the 1930's the first literature appeared about the use of a firm's financial ratios to predict bankruptcy. The bankruptcy prediction models differ in the amount of ratios and which ratios are used, and the method used to develop the model. Till the mid-1960's, the bankruptcy prediction models were based on univariate ratio analysis. The most widely recognized univariate study is that of Beaver (1966) (Bellovary et al., 2007). Beaver (1966) examined the usefulness of accounting data, by comparing financial ratios one-by-one. Beaver (1966) noticed the possibility to use multivariate ratio analysis that would predict bankruptcy better than the single ratios, and suggested future research to use several different ratios over time. Altman (1968) elaborated this suggestion and developed the first bankruptcy prediction model based on multivariate ratio analysis in 1968 (Bellovary et al., 2007; Fejér-Király, 2015). The number and complexity of bankruptcy prediction models have increased enormously since Altman's (1968) model, due to the growing availability of data and the development of improved econometrical techniques (Bellovary et al., 2007; Lee & Choi, 2013). The dependent variable in bankruptcy prediction models is generally a dichotomous variable, where a company is either bankrupt or non-bankrupt. The independent variables are often financial ratios, including measures of profitability, liquidity, and leverage. Some studies include market-driven variables as independent variables, such as the volatility of stock returns and past excess returns (Wu et al., 2010).

On the basis of the type of technique applied, the bankruptcy prediction models can be categorized into two groups: statistical and intelligent models (Adnan Aziz & Dar, 2006; Kumar & Ravi, 2007; Demyanyk & Hasan, 2010). Statistical models can again be divided into accounting-based prediction models, using accounting data, and market-based prediction models, using market data (Singh & Mishra, 2016). Statistical models can be based on both univariate and multivariate analysis. In the early stages of bankruptcy prediction, multiple discriminant analysis (MDA) was a frequently used statistical method, and in the later stages, due to advancement and technology, other statistical methods such as logit analysis and probit analysis became more popular (Bellovary et al., 2007; Siddiqui, 2012). Intelligent models depend heavily on computer technology and are mainly multivariate (Adnan Aziz & Dar, 2006). Intelligent models have similarities with functions of the human brain (Demyanyk & Hasan, 2010). Examples of intelligent models are fuzzy models, neural networks, decision trees, rough sets, case-based reasoning, support vector machines, data envelopment analysis, and soft computing (Kumar & Ravi, 2007). The most widely used intelligent model is neural networks (Demyanyk & Hasan, 2010). Neural networks models mimic the biological neural networks of the human nervous system (Demyanyk & Hasan, 2010; Kumar & Ravi, 2007). Statistical models have some constraining assumptions, such as linearity, normality, and independence among variables. The effectiveness and validity of statistical models is limited when these assumptions are violated (Zhang, Hu, Patuwo, Indro, 1999; Shin, Lee, & Kim, 2005; Lee & Choi, 2013). In contrast, intelligent models are less vulnerable to these assumptions, and are therefore more useful as most financial data do not meet the assumptions of statistical models (Shin et al., 2005; Demyanyk & Hasan, 2010). Statistical and intelligent bankruptcy prediction models both have limitations. Both prediction models focus on the symptoms instead of the underlying causes of bankruptcy. Moreover, economic theoretical foundation why companies are expected to go bankrupt and other companies not is missing (Morris, 1997; Adnan Aziz & Dar, 2006). Because intelligent models use techniques that lie beyond the field of Business Administration, this master thesis will focus only on statistical models.

According to Wu et al. (2010), the key statistical bankruptcy prediction models are the MDA model of Altman (1968), the logit model of Ohlson (1980), the probit model of Zmijewski (1984), the hazard model of Shumway (2001), and the Black-Scholes-Merton option pricing model of Hillegeist et al. (2004). The models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are based on accounting data, and the models of Shumway (2001), and Hillegeist et al. (2004) are based on both accounting and market data. These bankruptcy prediction models will be explained in the next two sections.

2.3 Accounting-based bankruptcy prediction models

2.3.1 Altman (1968)

Altman (1968) had doubts about the outcomes of the traditional univariate ratio analysis regarding bankruptcy prediction, and extended the traditional univariate ratio analysis by combining several financial ratios into the first multivariate bankruptcy prediction model. Altman (1968) conducted a study to find out which financial ratios are most important in predicting bankruptcy, what weight should be attached to those selected ratios, and how the weight should objectively be established. Altman (1968) used MDA as statistical technique to construct the prediction model which is now known as the Altman Z-score. *''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). The advantage of MDA relative to traditional univariate ratio analysis is that MDA can consider an entire set of variables, as well as the interaction of these variables. A univariate analysis can only consider the measurements used for group assignments one at a time (Altman, 1968). The dependent variable in MDA is qualitative, and the independent variables are quantitative. The first step in MDA is to determine group classifications, with a minimum of two groups. In the study of Altman (1968) two groups are classified: bankrupt firms and non-bankrupt firms. The result of MDA is a linear combination of independent variables, which provides the best distinction between the group of bankrupt firms and non-bankrupt firms (Altman, 1968). The function is of the form:

$$Z = v_1x_1 + v_2x_2 + \cdots + v_nx_n \qquad \textit{(Equation 1)}$$

Where: v = Discriminant coefficients

x = Independent variables

In the original study of Altman (1968), the initial sample consisted of 66 manufacturing firms with 33 firms which filed for bankruptcy between 1946 and 1965 in group 1, and 33 firms which still existed in 1966 in group 2. Data for the initial sample are derived from financial statements one reporting period prior to bankruptcy. From the 22 potentially helpful financial ratios, classified into liquidity, profitability, leverage, solvency, and activity ratios, only the best predictive five financial ratios where included in the final model. The final discriminant function is as follows:

$$Z = 0.012x_1 + 0.014x_2 + 0.033x_3 + 0.006x_4 + 0.999x_5 \qquad \textit{(Equation 2)}$$

Where: x_1 = Working capital/Total assets

x_2 = Retained earnings/Total assets

x_3 = Earnings before interest and taxes/Total assets

x_4 = Market value equity/Book value of total debt

x_5 = Sales/Total assets

In MDA, the financial characteristics of a firm are combined into one single multivariate discriminant score. In the study of Altman (1968), this is called the Z-score. The discriminant score has a value between $-\infty$ and $+\infty$, and this score indicates the financial health of the firm. Based on the discriminant score and a certain cut-off point, firms are classified into the bankrupt or non-bankrupt group. Firms are assigned to the group they most closely resemble. Firms are classified into the bankrupt group if its Z-score is less than the cut-off point, and firms are classified into the non-bankrupt group if its Z-score exceeds or equals the cut-off point (Balcaen & Ooghe, 2006).

The use of MDA is based on several assumptions: (1) dependent variable must be dichotomous, (2) independent variables are multivariate normally distributed, (3) equal variance-covariance matrices across the bankrupt and non-bankrupt group, (4) prior probability of failure and the misclassification costs are specified, and (5) data must be absent of multicollinearity (Balcaen & Ooghe, 2006). According to Collins and Green (1982), two assumptions of the MDA model are mostly violated in bankruptcy prediction, the assumption about normal distribution of independent variables and the assumption about equal variance-covariance matrices. The first assumption is mostly violated because financial ratios generally are non-normal distributed. The second assumptions is mostly violated because the variability of the financial ratios of future bankrupt firms is generally different than the variability of non-bankrupt healthy firms.

The model of Altman (1968) is extremely accurate in predicting 95% of the total sample correctly one fiscal year prior to bankruptcy. The model predicted 94% of the bankrupt firms and 97% of the non-bankrupt firms correctly one fiscal year prior to bankruptcy. Firms having a Z-score >2.99 are predicted not to go bankrupt, while firms having a Z-score <1.81 are predicted to go bankrupt. Z-scores between 1.81 and 2.99 are defined as the ‘‘gray area’’ or ‘‘zone of ignorance’’. The Altman Z-score is also able to predict bankruptcy two years prior to the event, but with a decline in accuracy rate to 72%.

2.3.2 Altman (1983)

The original model of Altman (1968) is only applicable to publicly traded companies. Altman (1983) therefore developed a revised Z-score model that can be applied to firms in the private sector. In this revised model, the book value of equity is substituted for the market value of equity in variable X_4. The original model is completely re-estimated, and all coefficients have changed in the revised Z-score model. The revised Z-score model with a new X_4 variable is as follows:

$$Z' = 0.717x_1 + 0.847x_2 + 3.107x_3 + 0.420x_4 + 0.998x_5 \quad \textit{(Equation 3)}$$

Where: x_4 = Book value equity/Book value of total debt

The revised Z-score model of Altman (1983) predicted 90.9% of bankrupt firms and 97% of non-bankrupt firms correctly, one year prior to bankruptcy. Firms having a Z'-score >2.99 are predicted not to go bankrupt, while firms having a Z'-score <1.23 are predicted to go bankrupt. Z'-scores between 1.23 and 2.99 are defined as the ''gray area'' or ''zone of ignorance''.

2.3.3 Ohlson (1980)

Another accounting-based bankruptcy prediction model is the logit model of Ohlson (1980), known as the O-score. Ohlson (1980) used logit analysis instead of the MDA methodology Altman (1968) used, to avoid problems associated with MDA. According to Ohlson (1980), the following problems occur when using MDA:

- There are certain statistical requirements that must be fulfilled when using MDA, which limits the scope of the investigation.
- The output of the MDA model is an ordinal ranking score which has little intuitive interpretation.
- Bankrupt and non-bankrupt firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. It is by no means obvious what is really gained or lost by different matching procedures, including no matching at all.

Like in the MDA, the dependent variable in logit regression is qualitative, and the independent variables are quantitative. The logit regression combines several variables into a multivariate probability score for each firm, P, which indicates the probability of bankruptcy:

$$P = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\,\beta_n x_n)}} = \frac{1}{1+e^{-(D_i)}} \quad \textit{(Equation 4)}$$

Where: β = Coefficients, and β_0 = intercept

x = Independent variables

D_i = The logit for firm i

The logit score P has a value between 0 and 1 and is increasing in D_i. If D_i approaches negative infinity, P will be 0 and if D_1 approaches positive infinity, P will be 1. In logit regression, the probability of bankruptcy, P, follows the logistic distribution. Based on the logit score and a certain cut-off point, firms are assigned to the bankrupt or the non-bankrupt group. Like in the MDA model, firms will be assigned to the group they most closely resemble. Firms are classified into the bankrupt group if its logit score exceeds the cut-off point, and is classified into the non-bankrupt group if its score is lower than or equals the cut-ff point (Balcaen & Ooghe, 2006). Logit regression does not require the restrictive assumptions of MDA. Logit regression is based on three assumptions: (1) the dependent variable must be dichotomous, (2) the cost of type I and type II error rates should be considered in the selection of the optimal cut-off point probability, and (3) the data must be absent of multicollinearity since logit regression is extremely sensitive to multicollinearity (Balcaen & Ooghe, 2006).

In the study of Ohlson (1980), the sample consisted of 105 bankrupt firms and 2,058 non-bankrupt firms in the period from 1970 to 1976. The sample excludes small or privately held firms, because the firms in the sample had to be traded on some stock exchange or over-the-counter-market. The firms also must be classified as an industrial. Ohlson (1980) obtained three years of data prior to the date of bankruptcy and developed three logit models. Model 1 predicts bankruptcy within one year, model 2 within two years given that the company did not fail within the subsequent year, and model 3 within one or two years. Ohlson (1980) identified four factors that were statistically significant in affecting the probability of bankruptcy. These factors are:

1. The size of the company
2. Financial structure as reflected by a measure of leverage
3. Performance measure or combination of performance measures
4. Some measures of current liquidity.

The final logit model of Ohlson (1980) that predicts bankruptcy within one year consist of nine financial ratios and is as follows:

$$O = -1.32 - 0.407x_1 + 6.03x_2 - 1.43x_3 + 0.0757x_4 - 2.37x_5 - 1.83x_6 + 0.285x_7 - 1.72x_8 - 0.521x_9$$

(Equation 5)

Where: x_1 = log (Total assets/GNP price-level index)

x_2 = Total liabilities/Total assets

x_3 = Working capital/Total assets

x_4 = Current liabilities/Current assets

x_5 = 1 if total liabilities > total assets, 0 otherwise

x_6 = Net income/Total assets

x_7 = Funds provided by operations/Total liabilities

x_8 = 1 if net income was negative for the last two years, 0 otherwise

x_9 = $(NI_t – NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period

The outcome of the prediction model lies between 0 and 1. The optimal cut-off point which minimizes the sum of errors is 0.038, meaning that firms with a probability smaller than 0.038 are predicted not to go bankrupt and firms with a probability higher than 0.038 are predicted to go bankrupt. Using this cut-off point, 82.6% of the non-bankrupt firms and 87.6% of the bankrupt firms were correctly classified. The overall accuracy rate of the estimation-sample was 96% and for the hold-out sample 85% (Ohlson, 1980).

2.3.4 Zmijewski (1984)

Zmijewski (1984) used probit regression to develop a bankruptcy prediction model. Zmijewski (1984) examined two estimation biases, choice-based sample bias and sample selection bias, that are the result of data collection limitations in bankruptcy prediction studies. The first problem, related to choice-based sample bias, is the low frequency rate of firms filing for bankruptcy in the population, which will lead to oversampling bankrupt firms. The second problem, related to sample selection bias, is the unavailability of data for bankrupt firms, and sample selection bias arises when only observation with complete data are used to estimate the model and incomplete data observations occur nonrandomly.

Like in the MDA and the logit regression, the dependent variable in probit regression is qualitative, and the independent variables are quantitative. Probit regression is similar to logit regression, the main difference between these models is that probit regression models assume a cumulative normal distribution instead of logistic function (Balcaen & Ooghe, 2006). As in the logit model, the probability of bankruptcy, P, is bounded between 0 and 1.

$$P = \emptyset(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n) \qquad \textit{(Equation 6)}$$

Where: β = Coefficients

x = Independent variables

The sample in the study of Zmijewski (1984) consisted of all firms listed on the American and New York Stock Exchange during the period 1972 through 1978 which have industry codes of less than 6000. This restriction excludes firms in the financial, service and public administration sector. According to Zmijewski (1984), a firm is bankrupt if it filed a bankruptcy petition during this period and non-bankrupt if it did not. Zmijewski (1984) randomly partitioned the total sample into an estimation sample and a prediction sample. The estimation sample contained 40 bankrupt and 800 non-bankrupt firms, and the prediction sample contained 41 bankrupt and 800 non-bankrupt firms. The probit model of Zmijewski (1984) consist of three financial ratios and is as follows:

$$Z_m = -4.336 - 4.513x_1 + 5.679x_2 - 0.004x_3 \qquad \textit{(Equation 7)}$$

Where: x_1 = Net income/Total assets

x_2 = Total debt/Total assets

x_3 = Current assets/Current liabilities

Like the logit model of Ohlson (1980), the outcome of this probit model lies between 0 and 1. The cut-off point is 0.5, meaning that firms with a probability higher than or equal to 0.5 are classified as bankrupt, and firms with a probability smaller than 0.5 are classified as non-bankrupt. The accuracy rate of the model of Zmijewski (1984) for the estimation-sample was 99%, the accuracy rate for the hold-out sample was not reported.

2.4 Market-based bankruptcy prediction models

2.4.1 Shumway (2001)

Shumway (2001) argues that accounting-based bankruptcy prediction models produce bankruptcy probabilities that are biased and inconsistent, because these models ignore the fact that characteristics of firms change through time. In order to be more accurate than the accounting-based prediction, Shumway (2001) developed a simple hazard model that explicitly accounts for time, including both accounting ratios and market-driven variables. The dependent variable is the time spent by a firm in the healthy group. When firms are no longer part of the healthy group for some reason other than bankruptcy, for instance a merger, these firms are no longer observed. In the accounting-based prediction models, these firms stay in the healthy group. The hazard model can be seen as a binary logit model that includes each firm year as a separate observation (Shumway, 2001), and is similar to the logit model of Ohlson (1980). However, the main difference between the hazard model of Shumway (2001) and the logit model of Ohlson (1980) is that the hazard model of Shumway (2001) uses all firm-years for each firm. In contrast to the model of Ohlson (1980), which only uses one firm-year (single set of variables observed at a single point in time) for each observation (Wu et al., 2010).

The final sample contained 300 bankruptcies between 1962 and 1992. Shumway (2001) combines three market-driven variables with two financial ratios. The market-driven variables include market size, past stock returns, and idiosyncratic standard deviation of stock returns. The financial ratios are the ratio of net income to total assets, and the ratio of total liabilities to total assets.

2.4.2 Hillegeist, Keating, Cram, and Lundstedt (2004)

The Black-Scholes-Merton Probability of Bankruptcy (BSM-Prob) model of Hillegeist et al. (2004) is another market-based bankruptcy prediction model, and is based on the Black-Scholes-Merton option-pricing model from Black and Scholes (1973), and Merton (1974). Hillegeist et al. (2004) argue that the stock market provides information regarding bankruptcy prediction in addition to the financial statements. The variables that are used in the model to predict bankruptcy are the market value of equity, the standard deviation of equity returns, and total liabilities. In the model, equity can be seen as a call option on the value of the firm’s assets. If the value of the firm’s assets is lower than the value of the firm’s debt at maturity, the call option will not be exercised and the firm will be bankrupt and turned over to its debtholders. Option-pricing models provide guidance about the theoretical determinants of bankruptcy risk and the structure of the model ensures that bankruptcy-related information can be extracted from market prices. The final sample included 78.100 firm-year observations and 756 initial bankruptcies between 1980 and 2000. The probability of bankruptcy is the probability that the market value of assets, V_A, is less than the face value of the liabilities, X, at time T, and this probability is formulated as follows (Hillegeist et al., 2004):

$$BSM - Prob = N(-\frac{ln\frac{V_A}{X}+(\mu-\delta-(\frac{\sigma^2 A}{2}))(T)}{\sigma_A\sqrt{T}}) \qquad \textit{(Equation 8)}$$

Where: N = Cumulative density function of a standard normal distribution

V_A = Market value of assets

X = Face value of liabilities

μ = Expected return on assets

δ = Dividend rate

σ_A = Asset volatility

T = Time to maturity of debt (taken as 1)

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

Some authors question the validity of accounting-based bankruptcy prediction models (e.g., Hillegeist et al., 2004; Beaver, McNichols, & Rhie, 2005; Agarwal & Taffler, 2008, among others). As mentioned in the previous section, accounting-based bankruptcy prediction models use a firm's financial statement to calculate the financial ratios that are used to estimate a firm's probability of bankruptcy. Hillegeist et al. (2004) argue that financial statements are limited in predicting the probability of bankruptcy since financial statements are formulated under the going-concern principle, which assumes that the firm will not go bankrupt. Additionally, financial statements report the past performance of a firm and may therefore not be informative about predicting a firm's bankruptcy in the future. Due to the conservatism principle and historical cost accounting, the book value of an asset in the financial statement may differ from the market value of that asset (Hillegeist et al., 2004; Agarwal & Taffler, 2008). Agarwal and Taffler (2008) state that financial statements are subject to manipulation by management and that accounting-based bankruptcy prediction models might be too sample specific, because the financial ratios and their weightings used in those models are derived from sample analysis. Another critic about accounting-based bankruptcy prediction models is that these models do not provide measures of asset volatility, while, *ceteris paribus*, the probability of bankruptcy increases with volatility (Hillegeist et al., 2004; Beaver et al., 2005). Lastly, accounting-based prediction models lack theoretical grounding (Agarwal & Taffler, 2008). All these aspects limit the performance of accounting-based bankruptcy prediction models. However, market-based prediction models also have limitations. The BSM-Prob model of Hillegeist et al. (2004) has some simplifying assumptions that are violated in practice and impacts the performance of the model, leading to errors and biases in the bankruptcy prediction results. For instance, the model assumes that all of the firm's liabilities mature in one year, which substantially underestimates the actual duration of the liabilities and can lead to higher BSM-Prob estimates. Another assumption of the BSM-Prob model is that the asset returns are normally distributed (Hillegeist et al., 2004). Additionally, the stock market does not fully reflect all publicly available information in financial statements (Sloan, 1996). Finally, it is difficult to extract the bankruptcy prediction related information from market prices (Hillegeist et al., 2004).

The literature has not provided a conclusive answer to which models, accounting- or market-based, predict bankruptcy more accurate. Shumway (2001) states that hazard models, using both accounting and market data, predict bankruptcy more accurate than accounting-based prediction models because of three reasons. First, hazard prediction models control for each firm's period at risk automatically, in contrast to accounting-based prediction models that do not adjust for period at risk. Second, hazard models include independent variables that change with time. Third, hazard models profit by using much more data, resulting in more efficient bankruptcy prediction. According to Tinoco and Wilson (2013), market variables act as complement in accounting-based prediction models, because it adds information that is not contained in financial statements (Tinoco & Wilson, 2013). Agarwal and Taffler (2008) argue that, whereas accounting-based prediction models lack theoretical grounding, market-based prediction models do include theoretical grounds for bankruptcy prediction. Another profit of market-based prediction models is that market variables are not influenced by accounting policies, in contrast to the financial variables used in accounting-based prediction models. Moreover, market prices reflect future expected cashflows, hence should be more suitable to predict bankruptcy. Finally, the output of market-based prediction models is not time or sample dependent (Agarwal & Taffler, 2008). However, Agarwal and Taffler (2008) also argue that accounting-based prediction models have significant economic benefit over the market-based prediction models, because of the following reasons. Corporate failure is generally not a sudden event, instead it lasts several years and is therefore recorded in the firm's financial statements. These financial statements are used to calculate the variables in accounting-based prediction models. A financial measure that combines different accounting information simultaneously is minimally affected by window dressing, due to the double entry system of accounting. Finally, the accounting information that loan covenants are based on is more likely to be represented in accounting-based prediction models.

Several studies compared the performance of accounting-based bankruptcy prediction models with the performance of market-based bankruptcy prediction models. *''Whether a market-based probability of bankruptcy measure derived from an option-pricing model or an accounting-based probability of bankruptcy measure performs better is ultimately an empirical question''* (Hillegeist et al., 2004, p. 7). Hillegeist et al. (2004) compared the accuracy of the accounting-based models of Altman (1968) and Ohlson (1980) with the accuracy of their BSM-Prob model, and conclude that their market-based model outperforms the accounting-based models. Chava and Jarrow (2004) compare the hazard model of Shumway (2001) to the models of Altman (1968) and Zmijewski (1984), and conclude that the hazard model of Shumway (2001) predicts bankruptcy more accurate than the accounting-based models of Altman (1968) and Zmijewski (1984). Similarly, other authors state that hazard models, using both market and accounting data, outperform bankruptcy prediction models that are based on accounting data only (Wu et al., 2010; Bauer & Agarwal, 2014). Wu et al. (2010) conclude that a comprehensive model that includes accounting data, market data, and firm-characteristics provide the most accurate bankruptcy prediction. In contrast, Reisz and Perlich (2004) find that the accounting-based prediction model of Altman (1968) outperforms market-based prediction models over a 1 year period, although market-based prediction models perform better over longer forecast horizons. Consistent with the findings of Campbell, Hilscher, and Szilagyi (2008), that market-based variables become more important relative to accounting-based variables when increasing the forecast horizon. Agarwal and Taffler (2008) and Trujillo-Ponce, Samaniego-Medina, and Cardone-Riportella (2014) conclude that the predictive accuracy of accounting-based and market-based prediction models shows little difference.

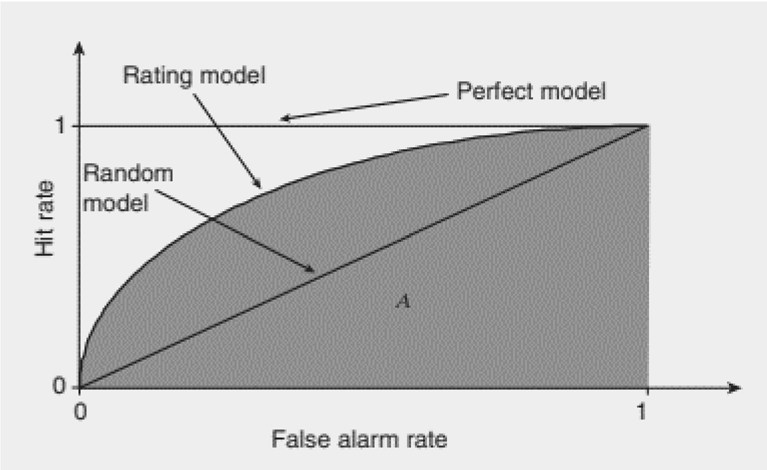
Due to the limited data availability of market data for private firms, this master thesis will focus only on the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984).

2.6 Assessing bankruptcy prediction models

Bankruptcy prediction models are mostly assessed on the basis of type I and type II error rates (Balcaen & Ooghe, 2006). A type I error means misclassifying a bankrupt firm as a non-bankrupt firm, and a type II error means misclassifying a non-bankrupt firm as bankrupt (Berg, 2007; Agarwal & Taffler, 2008). This measure requires the specification of a certain cut-off point (Balcaen & Ooghe, 2006). However, the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) use different cut-off points that distinguish the two groups (bankrupt and non-bankrupt firms), which makes it difficult to generalize. Balcaen and Ooghe (2006) suggested to use the receiver operating characteristic (ROC) curve, because this measure does not require the specification of a certain cut-off point. The ROC curve is a widely used method to compare the accuracy of different prediction models (e.g., Chava & Jarrow, 2004; Agarwal & Taffler, 2008; Giacosa, Halili, Mazzoleni, Teodori, & Veneziani, 2016, among others).

Figure 1 (Engelmann, Hayden, & Tasche, 2003, p. 83), is an example of a ROC curve plotted in a graph. The horizontal X-axis, false alarm rate, is the probability of misclassifying a non-bankrupt firm as bankrupt (Type II error). The vertical Y-axis, hit rate, is the probability of correctly classifying a bankrupt firm as bankrupt (1 – Type I error). The performance of a model is better the steeper the ROC curve is at the left, and the closer the ROC curve's position is to the point (0,1), presented as the perfect model in figure 1. The line of the rating model in figure 1 shows the ROC curve of the model being evaluated. The diagonal line shows the ROC curve of a random model that randomly classifies bankrupt and non-bankrupt firms.

Figure 1 Receiver operating characteristic curve



Note: Reprinted from ''Testing rating accuracy'', by Engelmann, B., Hayden, E., & Tasche, D., 2003, *Risk*, *16*(1), p. 83.

The area under the ROC curve (AUC) represents the effectiveness of the different models, the larger the AUC, the better the model can predict bankrupt and non-bankrupt firms (Engelmann et al., 2003; Giacosa et al., 2016). The AUC has a value between 0 and 1. A value of 0.5 indicates a random model without discriminative power, a value of 1.0 shows a perfect model (Engelmann et al., 2003; Chava & Jarrow, 2004; Singh & Mishra, 2016). The accuracy ratio (AR) is a scaled version of the AUC-statistic, and can be calculated as (Engelmann et al., 2003):

$$AR = 2 * (AUC - 0.50) \quad \textit{(Equation 9)}$$

The following test statistic will be used to compare the AUC-statistics for two different models, provided by Agarwal and Taffler (2007):

$$z = \frac{A_1 - A_2}{\sqrt{(SE(A_1))^2 + (SE(A_2))^2}} \quad \textit{(Equation 10)}$$

Where: A_1 = area under the ROC curve model 1
A_2 = area under the ROC curve model 2
$SE(A_1)$ = standard error model 1
$SE(A_2)$ = standard error model 2

The standard errors of the AUC-statistics will be computed using the following formula (Hanley & McNeil, 1982):

$$SE(A) = \sqrt{\frac{A(1-A) + (n_B - 1)(Q1 - A^2) + (n_{NB} - 1)(Q2 - A^2)}{n_B n_{NB}}} \quad \textit{(Equation 11)}$$

Where: A = area under the ROC curve
n_B = number of bankrupt firms in the sample

n_{NB} = number of non-bankrupt firms in the sample

$Q1 = A/(2 – A)$

$Q2 = 2A^2/(1 + A)$

The ROC curve does not distinguish between a type I error and a type II error (Agarwal & Taffler, 2008). However, the costs of a type I error and a type II error are different, type I errors are more costly than type II errors (Bellovary et al., 2007). A type I error can result in losing a whole loan amount, while the cost of a type II error is only the opportunity cost of not lending to that firm (Agarwal & Taffler, 2008). In order to be able to use the ROC curve for comparing the models, this master thesis does not have a preference for a type I or a type II error.

2.7 Review empirical findings prior research

Table 2 presents a short summary of the key articles in the literature of bankruptcy prediction, including the contributions and the results of the articles. The articles are sorted by publication date.

Table 2 Overview of key research papers in bankruptcy prediction

Authors	**Model**	**Contributions**	**Results**
Altman (1968)	Altman	Extended the traditional univariate ratio analysis, and introduced MDA for predicting bankruptcy.	Extremely accurate in predicting 95% of total sample correctly one year prior to bankruptcy.
Altman (1983)	Altman	Introduced the revised Z-score model for predicting bankruptcy that can be applied to firms in the private sector.	Predicted 90.9% of bankrupt firms and 97% of non-bankrupt firms correctly.
Ohlson (1980)	Ohlson	Used logit analysis for predicting bankruptcy to avoid problems associated with MDA.	Overall accuracy rate of the estimation sample was 96% and of the hold-out sample 85%.
Zmijewski (1984)	Zmijewski	Used probit regression for predicting bankruptcy and examined two estimation biases: choice-based sample bias and sample selection bias.	Accuracy rate of the estimation-sample was 99%.
Begley, Ming, & Watts (1996)	Altman Ohlson	Applying Altman's (1968) and Ohlson's (1980) original models to data from the 1980s and re-estimating both models using data from the 1980s.	The models of Altman (1968) and Ohlson (1980) do not perform as well in more recent periods, even when the coefficients are re-estimated. Ohlson's original model (1980) displays the strongest overall performance.

Moyer (1977)	Altman	Testing the predictive power of Altman's model (1968) when applied to a dataset from firms during the 1965 – 1975 time period. Re-estimating the coefficients of Altman's model (1968) based upon the new sample.	The original model of Altman (1968) is not generally suitable when applied to a sample of larger firms outside the original sample period. Those who wish to use the Altman model (1968) are advised to examine carefully its suitability to the particular data set being examined.
Mensah (1984)		Detailing why different macroeconomic environments can be expected to have an impact on the stationarity of bankruptcy prediction models.	The accuracy and structure of predictive models differ across different economic environments. The accuracy may improve if the models are re-estimated over different time periods.
Grice & Ingram (2001)	Altman	Testing the usefulness of Altman's original model (1968) for predicting bankruptcy in recent periods. Testing the usefulness for predicting bankruptcy of non-manufacturing firms.	Altman's original model (1968) is not as useful for predicting bankruptcy in recent periods as it was for the periods in which it was developed and tested by Altman (1968). Altman's original model (1968) is not as useful for predicting bankruptcy of non-manufacturing firms as it is for predicting bankruptcy of manufacturing firms.
Grice & Dugan (2001)	Ohlson Zmijewski	Evaluating the generalizability of the Ohlson (1980) and Zmijewski (1984) models using time periods, industries, and financial conditions other than those used to originally develop the models.	Both models are sensitive to time periods. The accuracy of the models declined when applied to time periods different from those used to develop the models. Researchers should use the bankruptcy prediction models cautiously.
Grice Jr. and Dugan (2003)	Ohlson Zmijewski	Evaluating the sensitivity of the Ohlson (1980) and Zmijewski (1984) models using time periods, industries, and financial conditions other than those used to originally develop the models.	The relation between the financial ratios and financial distress changes over time, and the relative importance of the financial ratios is not constant. Researchers who use the Ohlson (1980) and Zmijewski (1984) models using recent data should re-estimate the models' coefficients to improve the predictive accuracy of the models.
Shumway (2001)	Altman Ohlson Zmijewski	Developed a hazard model for predicting bankruptcy, including both accounting ratios and market-driven variables.	Some of the financial ratios used by Altman (1968), Ohlson (1980), and Zmijewski (1984) are not statistically significant, while several market-driven variables are strongly related to bankruptcy probability.

Chava & Jarrow (2004)	Altman Zmijewski	Compare the forecasting performance of the hazard model of Shumway (2001) with the forecasting performance of the models of Altman (1968) and Zmijewski (1984). Demonstrate the importance of including industry effects. Include monthly instead of yearly observations and extend the model to apply to financial firms.	Accounting-variables add little predictive power when market variables are already included in the bankruptcy model. Bankruptcy prediction is improved using monthly observation intervals and using industry groupings.
Hillegeist, Keating, Cram, Lundstedt (2004)	Altman Ohlson	Developed a market-based bankruptcy prediction model, based on the Black-Scholes-Merton option-pricing model.	The market-based bankruptcy prediction model provides more explanatory power than the models of Altman (1968) and Ohlson (1980).
Agarwal & Taffler (2008)	Altman	Compares the performance of two market-based prediction models with the Z-score model of Altman (1968).	There is little difference between the predictive accuracy of the market-based models and the accounting-based model.
Wu, Gaunt, & Gray (2010)	Altman Ohlson Zmijewski	Examine the empirical performance of a number of bankruptcy prediction models.	The model of Altman (1968) performs poorly relative to other models in the literature. The models of Ohlson (1980) and Zmijewski (1984) perform adequately during the 1970s but their performance has declined over more recent periods.
Singh & Mishra (2016)	Altman Ohlson Zmijewski	Developing a bankruptcy prediction model for Indian manufacturing companies and re-estimating the Altman (1968), Olson (1980), and Zmijewski (1984) models. Comparing the original and re-estimated models to explore the sensitivity of these models towards the change in time periods and financial conditions.	The overall predictive accuracy of all three models improves when the coefficients are re-estimated.
Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2017)	Altman	Assess the classification performance of the Z-score model (Altman, 1968) and the revised Z-score model (Altman, 1983), with the goal of examining the usefulness of Altman's model for all parties.	The original Z-score model (Altman, 1968) and the revised Z-score model (Altman, 1983) work consistently well internationally and are easy to implement and interpret. These models can be used by all interested parties, especially internationally active banks or other financial institutions.

In summary, the key articles state that the accounting-based bankruptcy prediction models of Altman (1968, 1983), Ohlson (1980), and Zmijewski (1984) do not perform satisfactory when applied to a different sample (e.g. more recent sample, different economic environment) than the original sample. Mensah (1984), Grice Jr. and Dugan (2003), and Singh and Mishra (2016) suggest to re-estimate the coefficients of the models to improve the prediction accuracy. This suggestion will be followed in this master thesis; the coefficients will be re-estimated using the more recent data of Dutch and Belgian public and large private firms. The articles also state that in general market-based bankruptcy prediction models perform better than the accounting-based models. However, section 2.5 already explained that due to the limited data availability of market data for private firms, this master thesis only examines the accounting-based models. Finally, the articles also test whether one of the models outperforms the others regarding their prediction power. However, the articles do not provide a conclusive answer about this. The hypotheses, described in chapter 3, will be based on the contributions and the results of these key research papers.

3 Conceptual Framework

In this chapter, several hypotheses will be provided in order to test the predictive accuracy of the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) when applied to Dutch and Belgian public and large private firms.

3.1 Hypothesis 1: Model performance

This master thesis features the accounting-based bankruptcy prediction models of Altman (1983)[1], Ohlson (1980) and Zmijewski (1984). All three bankruptcy prediction models are constructed using different statistical techniques and different samples, and include different (amount of) financial ratios. Altman's model (1983) includes five financial ratios as independent variables, Ohlson's model (1980) nine, and Zmijewski's model (1984) three. The original studies show that the accuracy rate of the three models are all high. Considering that the relative importance of the financial ratios used in the bankruptcy prediction models change over time and when applied to a different environment (Mensah, 1984; Platt & Platt, 1990; Grice Jr & Dugan, 2003), it is interesting to test how these models perform for Dutch and Belgian public and large private firms at present time. The question that arises is whether one of these models outperforms the others regarding their prediction power when applied to Dutch and Belgian public and large private firms.

The five financial ratios of Altman (1968, 1983) can be classified into liquidity, profitability, leverage, solvency, and activity. Altman (1968) did not select these ratios on a theoretical basis, but on the basis of their popularity in the literature and his belief about their potential relevancy to bankruptcy (Grice & Ingram, 2001). The nine financial ratios of Ohlson (1980) can be classified into size, leverage, liquidity and profitability. Ohlson (1980) selected these ratios because they appeared to be the ones most frequently mentioned in the literature. The three financial ratios of Zmijewski (1984) can be classified into profitability, leverage and liquidity. Zmijewski (1984) also did not select these ratios on a theoretical basis, but on the basis of their performance in prior studies (Grice Jr. & Dugan, 2003). The model of Ohlson (1980) includes the most financial ratios, but the model of Altman (1983) includes more different classifications. The model of Zmijewski (1984) includes the least number of financial ratios and different classifications. The study of Yap, Yong, and Poon (2010) examined the extent to which financial ratios predict bankruptcy of Malaysian firms. Their results suggest that the financial ratio categories liquidity and profitability are most significant in predicting the event of bankruptcy. The results of the study of Liang, Lu, Tsai, and Shih (2016), based on a sample of Taiwan firms, suggest that the financial ratios that measure solvency and profitability are the most important ratios in bankruptcy

[1] Side note: The revised Z-score model of Altman (1983) is based on the original Z-score model of Altman (1968) and includes the same variables as the original model of Altman (1968), only the market value of equity is replaced by the book value of equity. The revised model (1983) is therefore almost equal to the original model of Altman (1968), and because the original model (1968) is more reviewed in the existing literature, this comparison of the predictive power for the first hypothesis includes reviews of the original model of Altman (1968).

prediction. The study of Cultrera and Brédart (2016) developed a bankruptcy prediction model for Belgian firms and concludes that financial ratios reflecting the profitability and liquidity are the best predictors of bankruptcy for Belgian firms. According to Son, Hyun, Phan, and Hwang (2019) the ratio classifications liquidity and solvency appear to be the most important ratios for predicting bankruptcy. Concluding, according to the literature the financial ratio categories profitability, liquidity and solvency are the best for predicting bankruptcy. The models of Altman (1983) and Zmijewski (1984) include these categories, the model of Ohlson (1980) lacks the category solvency. Koh and Killough (1990) suggest that it is not necessary to include a large number of financial ratios in a model to predict bankruptcy. All that it needs is a set of dominant ratios derived from a larger set of related ratios. Using a smaller set of financial ratios, duplication of information resulting from highly correlated financial ratios or the problem of multicollinearity will be avoided. Therefore, on the basis of the financial ratios included in the models, it is expected that Zmijewski's (1984) model outperforms the models of Altman (1983) and Ohlson (1980). However, Shumway (2001) states that Zmijewski's model (1984) is essentially a one-variable model, because only one of three variables is significantly related to bankruptcy and two variables are strongly correlated.

Existing literature extensively analysed the predictive power of the three bankruptcy prediction models. For example, the study of Ashraf, Félix, and Serrasqueiro (2019) compared the predictive accuracy of the three models for firms in Pakistan which are at an early stage and advanced stage of financial distress. They concluded that Zmijewski's model (1984) has the highest overall prediction accuracy, Altman's model (1968) predicts bankruptcy most accurate for both types of firms (at an early stage and advanced stage of financial distress), and the model of Ohlson (1980) performed poorly relative to Altman's (1968) and Zmijewski's (1984) model. The study of Begley et al. (1996) re-estimated the models of Altman (1968) and Ohlson (1980) and compared the performance of Ohlson's original model to the re-estimated model and to that of Altman's original and re-estimated models. They conclude that Ohlson's original model displays the strongest overall performance. According to Wu et al. (2010), the model of Altman (1968) performs poorly relative to other models, among which the models of Ohlson (1980) and Zmijewski (1984). The models of Ohlson and Zmijewski perform adequately during the 1970's, but their performance had deteriorated over more recent periods. Agarwal and Taffler (2008) argue that neither of the accounting-based prediction models are a sufficient statistic for predicting bankruptcy. Finally, Grice and Ingram (2001) and Grice Jr. and Dugan (2003) conclude that the results of all three models to predict bankruptcy should be interpreted cautiously. In the study of Grice Jr. and Dugan (2003), the models of Ohlson (1980) and Zmijewski (1984) were not sensitive to industry classifications. In contrast, in the study of Grice and Ingram (2001) Altman's model (1968) was sensitive to industry classifications, meaning that the overall accuracy of the model was significantly higher for manufacturing firms than for the entire sample that included non-manufacturing firms. All three models were not sensitive to types of financial distress (Grice & Ingram, 2001; Grice Jr. & Dugan, 2003). It can be concluded that, on the basis of the predictive power of the models, none of

the models outperforms the other, according to the existing literature. Therefore, the first hypothesis is that there is no difference in the predictive power between the three models.
H1: There is no difference in the predictive power between the models of Altman (1983), Ohlson (1980), and Zmijewski (1984).

3.2 Hypothesis 2: Econometric method performance

Whereas the first hypothesis tests the difference between the three models, this hypothesis tests the difference between the econometric method used to develop the models. The prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) are developed using different econometric methods. Altman (1983) used MDA, Ohlson (1980) used logit regression and Zmijewski (1984) used probit regression. The question is whether one of these econometric methods outperforms the others regarding their prediction power. Probit regression is similar to logistic regression, only the calculation of probability differs (Dimitras et al., 1996). According to Balcaen and Ooghe (2006), logit regression is a much more popular econometric method in bankruptcy prediction studies than probit regression. MDA is based on certain assumptions which are mentioned in section 2.3.1. However, these assumptions are often violated in empirical financial ratio analysis (Charitou, Neophytou, & Charalambous, 2004; Altman et al., 2017). Logit and probit regression overcome the restricting statistical assumptions inherent in MDA, including the assumptions that the independent variables (the financial ratios) must be multivariate normally distributed and that the bankrupt and non-bankrupt group have equal variance-covariance matrices (Ohlson, 1980; Begley et al., 1996; Altman et al., 2017). In addition to the less strict assumptions, logit and probit regression have the following advantages over MDA models: (1) logit and probit regression permit an evaluation of the significance of the individual independent variables in the model (Mensah, 1984), and (2) the output of the MDA model is an ordinal ranking score which has little intuitive interpretation and the output of the logit and probit models are a probability score, which makes the results more accurate (Ohlson, 1980). The second hypothesis is that the econometric methods logit and probit regression are more accurate than the econometric method MDA, regarding bankruptcy prediction.
H2: All else equal, a bankruptcy prediction model using logit or probit regression is more accurate than a bankruptcy prediction model using multiple discriminant analysis.

3.3 Hypothesis 3: Non-stationarity of the coefficients of the models

The models of Altman (1983), Ohlson (1980) and Zmijewski (1984) estimate the possibility of bankruptcy by using a group of financial ratios. A condition to accurate predict bankruptcy is stationarity of the independent variables (Wood & Piesse, 1987; Platt & Platt, 1990). This means that the relationship between the independent variables and the dependent variable must be similar in the forecast and estimation periods (Platt & Platt, 1990). However, the relative importance of the financial ratios used in the bankruptcy prediction models changes over time (Platt & Platt, 1990; Grice Jr & Dugan, 2003).

Several studies (e.g., Begley et al., 1996; Hillegeist et al., 2004; Singh & Mishra, 2016, among others) conclude that after re-estimating the coefficients of the accounting-based bankruptcy prediction models, the coefficients of the models changed from the original values. This finding indicates that the accounting variables are not stable over time, and that utilizing the bankruptcy prediction models using recent data results in lower predictive ability than utilizing the models using the original data. The study of Begley et al. (1996) shows that the models of Altman (1968) and Ohlson (1980) do not predict bankruptcy as well in more recent periods. It appears that the prediction power of bankruptcy prediction models declines when applied to a different environment than the original environment of the model, which implies that the accuracy of a bankruptcy prediction model is affected by factors relating to the environment (Mensah, 1984; Karas & Režňáková, 2014). Platt and Platt (1990) indicate that a different environment may change the relationships between the dependent variable (bankruptcy) and independent variables (financial ratios), the average range of the independent variables, and the relationships among the independent variables. These differences are a result of phases of the business cycle, changes in competition, changes in corporate strategy, and technological changes. For example, Begley et al. (1996) argue that during the 1980s the acceptable amount of corporate debt increased and the bankruptcy law changed, which affected the variables in the bankruptcy prediction models. The former change affects the predictive ability of the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) because these models include leverage variables. Therefore, the same amount of debt indicates a different probability of bankruptcy during the 1980s compared to the probability during the period before the 1980s. Due to a change in the bankruptcy law, firms could also file for bankruptcy because of strategic reasons. This strategic use of bankruptcy might be uncorrelated with the variables in the bankruptcy prediction models, resulting in classification errors. Mensah (1984) states that the financial condition of firms might be affected by external economic environments, and that these environments change over time. Due to these external economic environmental changes, non-stationarity in the independent variables is suspected. Mensah (1984) identifies three external macroeconomic factors that can change over time: (1) inflation, (2) interest rates and credit availability, and (3) business cycle (recession/expansion phases). Changes in the inflation rate leads to higher production costs, but these costs cannot always be passed on to selling prices. However, if these costs do get passed on, a fall in demand is the result. Higher interest rates and credit unavailability can cause firms to fail due to the higher borrowing costs in excess of profit margins. Firms that file for bankruptcy in the recession phase of the business cycle, are firms which cannot succeed if the sales declines continuously. The effects that can cause failure are inadequate capitalization, insufficient cash flows, the lack of dependable relationships with creditors, and higher than normal levels of receivables and inventories. In contrast to an expansionary environment, where failure can occur if interest rate and inflation dominate. The third hypothesis is divided in two parts. Hypothesis 3a states that due to the non-stationarity of the financial ratios, the accounting-based bankruptcy prediction models will not retain their accuracy over time.

H3a: The accounting-based bankruptcy prediction models will not retain their accuracy over time.

Mensah (1984), Grice Jr and Dugan (2003), and Singh and Mishra (2016), suggest that the original prediction model's coefficients should be re-estimated, when using a sample of firms from time periods, industries, and financial conditions other than those used to develop the models, in order to get higher predictive accuracy. In their study, the prediction power of the re-estimated models was higher than the prediction power of the original models, when applied to their recent sample. Therefore, hypothesis 3b holds that re-estimating the coefficients of the accounting-based prediction models improves the predictive accuracy.

H3b: Re-estimating the coefficients of the accounting-based bankruptcy prediction models improves the predictive accuracy.

3.4 Hypothesis 4: Optimal time horizon

As described earlier, bankruptcy is mostly the result of multiple causes, but can also be the result of a single cause (external shock or management mistake). A single factor that causes bankruptcy is probably not indicated by the financial information in the firm's annual statements prior to bankruptcy. Multiple factors that causes bankruptcy are more easily identified in the firm's financial reports prior to the event of bankruptcy, because the causes tend to accumulate over a longer period and the firm's decline starts earlier (Lukason & Hoffman, 2014). The optimal time horizon for predicting bankruptcy is usually one year, and the accuracy decreases when the time horizon of the prediction exceeds one year (Jardin, 2017). Confirming, the study of Lukason & Hoffman (2014) concludes that there is no indication of failure in the annual report two years before the actual onset of bankruptcy. According to Philosophov, Batten, and Philosophov (2005), accounting-based bankruptcy prediction models can discriminate bankruptcy in the firm two or three years prior to the event because of the monotonic deterioration of the firm's financial characteristics as it approaches bankruptcy. However, the models are generally unable to do so optimally and do not calculate bankruptcy probabilities two or three years prior to bankruptcy. Therefore, the fourth hypothesis is that for accounting-based bankruptcy prediction models the optimal time horizon for predicting bankruptcy is one fiscal year prior to bankruptcy, and that the predictive power decreases when the time horizon exceeds one fiscal year.

H4: For the accounting-based bankruptcy prediction models, the optimal time horizon for predicting bankruptcy is one fiscal year prior to bankruptcy.

4 Research methodology

In this chapter, the research methodology of this master thesis will be discussed. First, the focus will be on the research design to test the hypotheses. The second section will present the variables that are used in this master thesis. The third section, the sample selection, will describe which data and sample source will be used in this master thesis and includes the criteria for inclusion of a firm in the samples. Finally, a section will be devoted to testing of the model assumptions.

4.1 Hypothesis testing

4.1.1 Hypothesis 1: Model performance

Hypothesis 1 tests whether there is a statistical significant difference in the prediction power between the models of Altman (1983), Ohlson (1980), and Zmijewski (1984). The statistical analysis begins with re-estimating the coefficients of the models using the methodology originally employed to derive the model. This is also done in the studies of Grice Jr and Dugan (2003), Singh and Mishra (2016) and Altman et al. (2017). The methodologies used by the original studies of Altman (1983), Ohlson (1980), and Zmijewski (1984) are: MDA, logit regression, and probit regression, respectively. In order to avoid possible non-stationarity of the independent variables, the coefficients should be re-estimated as closely as possible to the prediction period in the hope that no fundamental changes occur in the economic environment (Mensah, 1984). Therefore, the coefficients of the models will be estimated with observations from 2012 – 2015 and tested on a hold-out sample with observations from 2016 – 2019. The predictive accuracy of the re-estimated models is assessed by the AUC-statistic of the hold-out sample (see section 2.6). The difference in the prediction power between the re-estimated models is assessed by testing the statistical significance of the difference between the AUC-statistics for the three models. This comparison will be done using the test statistic provided by Agarwal and Taffler (2007), formulated as equation 9 in section 2.6.

4.1.2 Hypothesis 2: Econometric method performance

Hypothesis 2 holds that a bankruptcy prediction model based on logit regression or probit regression is more accurate than a bankruptcy prediction model based on MDA. To test this hypothesis, all three econometric methods will be applied to all three prediction models. The models of Altman (1983), Ohlson (1980), and Zmijewski (1984) will be re-estimated using MDA, logit regression, and probit regression to assess the effect of the econometric estimation method. By using three different sets of financial ratios, the possibility that a particular set of financial ratios causes a model performing better than another can be excluded. Again, to avoid possible non-stationarity of the independent variables, the estimation period should be as close as possible to the prediction period. Therefore, the model coefficients will be estimated with observations from 2012 – 2015 and tested on a hold-out sample with observations from 2016 – 2019. The predictive accuracy of the re-estimated models is assessed by the AUC-statistic of the hold-out sample. For the models of Altman (1983), Ohlson (1980) and Zmijewski (1984), the AUC-statistics of the re-estimated models using logit and probit regression will be compared to the AUC-statistics of the re-estimated models using MDA. The test statistic of Agarwal and Taffler (2007) will be used to test if the differences between the AUC-statistics are statistically significant.

4.1.3 Hypothesis 3: Non-stationarity of the coefficients of the models

Hypothesis 3a assumes that the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) will not retain their accuracy over time. Hypothesis 3b assumes that re-estimating the coefficients of these models improves the predictive accuracy. According to Grice Jr. and Dugan (2003) the accuracy rate of the hold-out sample is upwardly biased if (1) the time periods of the estimation and the hold-out sample are not substantially different, (2) the hold-out sample consists of firms from the same restricted set of industries as those in the estimation sample, and (3) the hold-out samples are small. The first bias will be addressed by using an estimation sample from a substantially different period than the hold-out sample. The second bias will be addressed by using a wide variety of industries in both estimation and hold-out samples. The third bias will be addressed by using a hold-out sample that is not smaller than the estimation sample. Unlike hypothesis 1 and 2, the coefficients of the models will be estimated with observations from 2007 – 2010 and tested on a hold-out sample with observations from 2016 – 2019. These time periods are chosen because of the different economic environments. Several important events occurred during the period 2007 – 2010, such as the financial crisis in 2007 and the European debt crisis in 2010 and the regulatory response to the financial crisis, Basel III. Basel III imposes stricter capital requirements for banks, by increasing more liquid assets and longer-term sources of funding (Agnese, Rizzo, & Vento, 2018). For all observations in the estimation sample, from 2007 – 2010, bankruptcy probabilities will be computed according to each model. The bankruptcy probabilities are also calculated for all observations in the hold-out sample, from 2016-2019. The predictive accuracy for each model of both the estimation sample and the hold-out sample is assessed by the AUC-statistic. For hypothesis 3a, the AUC-statistic of each model in the hold-out sample will be compared to the AUC-statistic of the models in the estimation sample, using the test statistic of Agarwal and Taffler (2007). For hypothesis 3b, the AUC-statistics of the hold-out sample will be compared to the AUC-statistics of the hold-out sample of hypothesis 1. The AUC-statistics of the hold-out sample of hypothesis 1 are estimated with observations from 2012 – 2015 instead of observations from 2007 – 2010, which makes it possible to test if the predictive accuracy increases when the coefficients are re-estimated more closely to the hold-out sample.

4.1.4 Hypothesis 4: Optimal time horizon

Hypothesis 4 states that the optimal time horizon for predicting bankruptcy is one fiscal year prior to bankruptcy for the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984), and that the predictive power decreases when the time horizon exceeds one fiscal year. Again, to avoid possible non-stationarity of the independent variables, the estimation period should be as close as possible to the prediction period. Therefore, the coefficients of the models will be estimated with observations from 2012 – 2015 and tested on a hold-out sample with observations form 2016 – 2019. The firms in these samples will be analysed one (t-1) and two (t-2) fiscal years prior to the event of bankruptcy or non-bankruptcy, meaning that for each firm in the sample per year data is gathered from one and two fiscal years before the event. The predictive accuracy of the models will be estimated for predicting bankruptcy one fiscal year and two fiscal years before the event. The AUC-statistics of all three models from predicting bankruptcy one fiscal year before the event will be compared to the AUC-statistics from predicting bankruptcy two fiscal years before the event, using the test statistic of Agarwal and Taffler (2007).

4.2 Variables

4.2.1 Dependent variables

The dependent variable in all models is a dichotomous variable, a firm is either bankrupt or non-bankrupt. For MDA, firms are classified into the bankrupt group if the score is less than the cut-off point, and firms are classified into the non-bankrupt group if the score exceeds or equals the cut-off point. For logit and probit regression, firms are classified into the bankrupt group if the probability score is higher than or equal to 0.5, and firms are classified into the non-bankrupt group if the probability score is smaller than 0.5.

4.2.2 Independent variables

The independent variables are the different financial ratios used by the three prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984). The independent variable *market value of equity / book value of total debt* of the original Z-score model of Altman (1968) cannot be applied to private firms, because there are no market values available for private firms. The revised Z-score model of Altman (1983) replaced this independent variable by *book value of equity / book value of total debt*. The other variables of the revised Z-score model of Altman (1983) are the same variables as in the original Z-score model of Altman (1968). The independent variables are summarized in appendix A. For all hypotheses, the independent variables of all three model will be used.

4.3 Sample selection

The financial ratios used in the prediction models (see appendix A) have to be calculated on the basis of the financial statements of the Dutch and Belgian public and large private firms. Data will be obtained from ORBIS, a database of the University of Twente. ORBIS provides data about the financial ratios of the companies and provides information about whether a company is bankrupt or not. This master thesis includes two different estimation samples, used to estimate the coefficients of the models, and one hold-out sample, used to validate the models. The samples include Dutch and Belgian public and large private firms for which all relevant variables are available to calculate the financial ratios of the three models (see appendix A), during the investigation periods. For hypothesis 1, 2, and 4 the estimation sample includes firms that went bankrupt from 2012 to 2015. This sample is augmented by parallel observations of non-bankrupt firms in the same period. For hypothesis 3, the estimation sample includes firms that went bankrupt from 2007 to 2010, and is also augmented by parallel observations of non-bankrupt firms in the same period. The hold-out sample, for all four hypotheses, includes firms that went bankrupt from 2016 to 2019, and is augmented by parallel observations of non-bankrupt firms in the same period. This is summarized in table 3. The non-bankrupt firms will be augmented in the samples by approximately factor 10. The total number of non-bankrupt firms in the samples will be determined based on the total number of bankrupt firms in the sample, meaning that the ratio might differ per year. Altman (1983) used equal group sizes for bankrupt and non-bankrupt firms and these firms where matched based on industry and size. However, the actual frequency rate of non-bankrupt firms is much higher than the actual frequency rate of bankrupt firms, which will lead to oversampling bankrupt firms. Oversampling bankrupt firms leads to a misstatement of type I and type II errors, where the type I error is understated and the type II error is overstated. To avoid this choice-based sample bias, as examined by Zmijewski (1984), the samples must be proportionately representative of the actual bankruptcy rate (Grice & Ingram, 2001; Balcaen & Ooghe, 2006). However, the actual percentage declared bankruptcies are relatively low[2], and due to the limited data availability this would lead to samples with only a few bankrupt firms. Therefore, due to the limited data availability, the ratio of bankrupt firms to non-bankrupt firms in the samples of this master thesis is approximately 1:10. Following Altman (1983), the non-bankrupt firms will be matched with the bankrupt firms on the basis of industry.

Table 3 Investigation period estimation and hold-out samples

Hypotheses	**Estimation sample**	**Hold-out sample**
Hypothesis 1 *Model performance*	2012 – 2015	2016 – 2019
Hypothesis 2 *Method performance*	2012 – 2015	2016 – 2019
Hypothesis 3 *Non-stationarity*	2007 – 2010	2016 – 2019
Hypothesis 4 *Time horizon*	2012 – 2015	2016 – 2019

To identify bankrupt and non-bankrupt firms, the status of the firms can be selected in ORBIS, whereas the status *Bankruptcy* represents bankrupt firms and the status *Active* represents non-bankrupt firms. The samples includes private and public firms from all industries, except the financial and insurance industry. Firms from these industries are excluded because they have a different structure of

[2] For instance, the actual bankruptcy rate in the Netherlands was 0.78% in 2018. Centraal Bureau voor de Statistiek: http://statline.cbs.nl

capital than firms in other industries. Therefore, firms with a NACE Rev. 2 classification of *Financial and Insurance activities* are excluded from the samples. Small firms are also excluded from the samples, because financial reports of small firms do not provide sufficient information about the likelihood of bankruptcy (Balcaen & Ooghe, 2006; Gupta, Gregoriou, & Healy, 2015). ORBIS divides companies on the criteria size into four categories: *Small*, *Medium*, *Large*, and *Very large*. Only the categories *Large* and *Very Large* are included in the samples. Meaning that companies are included in the samples when they have an operating revenue >= €10 million, total assets >= €20 million, and number of employees >= 150. Table 4 provides an overview of the criteria of the samples that will be used in this master thesis.

Table 4 Criteria of the samples

Criteria	**Value**
Status (bankrupt firms)	Bankruptcy
Status (non-bankrupt firms)	Active
Country	The Netherlands + Belgium
Legal form	Private limited company + public limited company
Size	Large + very large
Investigation period	See table 3
NACE Rev. 2	All except *financial and insurance activities*

The firms in the samples will be analysed one and two fiscal years prior to the event of bankruptcy or non-bankruptcy. Therefore, for each private firm in the samples per year, the accounting data is gathered from financial statements one and two fiscal years before the event. Only Dutch and Belgian private and public firms for which all relevant financial information is available during the investigation periods will be included in the samples. After the elimination of missing values and matching the non-bankrupt firms to bankrupt firms with a ratio of 1:10 based on industry, the final estimation sample for hypothesis 1, 2, and 4 (period 2012 – 2015) contains 113 bankrupt and 1130 non-bankrupt firms. The final estimation sample for hypothesis 3 (period 2007 – 2010) contains 43 bankrupt and 412 non-bankrupt firms. The hold-out sample for all hypotheses (period 2016 – 2019) contains 71 bankrupt and 710 non-bankrupt firms. Table 5 shows the sample composition, where panel A shows the characteristics of the 2007 – 2010 estimation sample, panel B of the 2012 – 2015 estimation sample and panel C of the 2016 – 2019 hold-out sample. Appendix B provides a list of all the bankrupt firms in the samples.

Table 5 Sample composition

Industry name	NACE Rev. 2 section	Bankrupt firms	Non-bankrupt firms	Total
Panel A: estimation sample 2007 – 2010				
Administrative and support service activities	N	2	13	15
Construction	F	2	20	22
Information and communication	J	3	27	30
Manufacturing	C	11	121	132
Professional, scientific and technical activities	M	5	42	47
Transportation and storage	H	4	32	36
Water supply	E	1	7	8
Wholesale and retail trade	G	14	150	165
Total:		**42**	**412**	**454**
Panel B: estimation sample 2012 – 2015				
Accommodation and food service activities	I	1	10	11
Administrative and support service activities	N	7	70	77
Agriculture, forestry and fishing	A	1	10	11
Arts, entertainment and recreation	R	2	20	22
Construction	F	16	160	176
Human health and social work activities	Q	2	20	22
Information and communication	J	1	10	11
Manufacturing	C	35	350	385
Professional, scientific and technical activities	M	6	60	66
Transportation and storage	H	6	60	66
Water supply	E	1	10	11
Wholesale and retail trade	G	35	350	385
Total:		**113**	**1130**	**1243**
Panel C: hold-out sample 2016 – 2019				
Administrative and support service activities	N	3	30	33
Construction	F	13	130	143
Information and communication	J	3	30	33
Manufacturing	C	11	110	121
Professional, scientific and technical activities	M	6	60	66
Real estate activities	L	2	20	22
Transportation and storage	H	2	20	22
Water supply	E	1	10	11
Wholesale and retail trade	G	30	300	330
Total:		**71**	**710**	**781**

4.4 Testing model assumptions

4.4.1 Multivariate normality

Multivariate normality is an assumption for the MDA method. According to Looney (1995), many practitioners are reluctant to test this assumption. However, testing the multivariate normality assumption can be done using tests of the univariate normality assumption. Each variable separately will be tested for univariate normality. One of the most commonly used test for univariate normality is the Shapiro-Wilks test (Looney, 1995). This test calculates the level of significance for the differences from a normal distribution (Hair, Black, Babin, & Anderson, 2010). If the variables are not univariate normally distributed, multivariate normality can also be rejected because all univariate marginal distributions of a multivariate distribution are themselves univariate normal (Looney, 1995). The null hypothesis of the Shapiro-Wilks test is that the data are normally distributed. If the null hypothesis is rejected ($p<0.05$), there is evidence that the data are not normally distributed, indicating that the assumption of multivariate normality is violated. Appendix C.I presents the results of testing this assumption.

4.4.2 Equality of variance-covariance

Equality of variance-covariance is also an assumption only for the MDA method. This assumption that the dependent variable exhibits equal levels of variance and covariance across the range of independent variables can be tested using the Box's M statistic (Hair et al., 2010). The null hypothesis of the Box' M test assumes that the covariance matrices are equal. If the Box's M statistic is statistically significant ($p<0.05$), it means that the null hypotheses can be rejected and that the assumption of equal variance and covariance is violated. Appendix C.II presents the results of testing this assumption.

4.4.3 Multicollinearity

Absence of multicollinearity is an assumption for MDA, logit regression and probit regression. The financial ratios as input for the MDA, logit regression and probit regression must be absent of multicollinearity. If the data are present of multicollinearity, the independent variables are highly correlated. The data will be checked for the presence of multicollinearity via the VIF-statistic. Large VIF-statistics indicate multicollinearity, if any of the VIF-statistics exceeds 10, it can be stated that the data are not absent of multicollinearity (Paul, 2006). Appendix C.III presents the results of testing this assumption.

5 Empirical results

This chapter will provide the empirical results of this master thesis. First, the descriptive statistics for every variable used in the different samples will be presented. Second, for each hypothesis separately, the results of the tests will be reported.

5.1 Descriptive statistics

Table 6 presents the descriptive statistics of the data that are used to test the hypotheses. Panel A shows the descriptive statistics of the estimation sample used in hypothesis 3, panel B the estimation sample used in hypotheses 1 and 2, panel C the estimation sample used in hypothesis 4, panel D the hold-out sample used in hypothesis 1, 2, and 3, and panel E the hold-out sample used in hypothesis 4. Following Altman et al. (2017), the independent variables are winsorized to prevent the influence of outliers. In the study of Altman et al. (2017), the independent variables are winsorized at 1 and 99 per cent. However, Nyitrai and Virág (2019) conducted a study about different approaches for identifying and handling outliers in bankruptcy prediction models and how these approaches affect the predictive power of the models. They concluded that in the case of discriminant analysis and logistic regression, winsorization is more effective when it is applied at higher cut values of the distribution, at the third or fifth percentiles instead of the first. Therefore, in this master thesis all independent variables are winsorized at 5 and 95 per cent to minimize outliers.

A t-test is conducted in order to determine whether there is a statistical significant difference between the two group means. The null hypothesis of the t-test assumes equality of means between the bankrupt and non-bankrupt group. Rejecting the null hypothesis ($p<0.05$) indicates that the means of the two groups are significantly different. Additionally, an independent samples t-test is conducted to test if the two groups have equal medians. The null hypothesis of the independent samples t-test assumes that the medians for the bankrupt group and the non-bankrupt group are equal. Rejecting the null hypothesis ($p<0.05$) indicates that the medians of the two groups are significantly different. The p-values as a result of the t-test and median-test are presented in table 6. Panel A, B, and C show similar results, in these three samples the means and medians of all financial ratios are significantly different between the bankrupt and non-bankrupt group. The results of the sample presented in panel D show that only the financial ratio SALES/TA (x_5) of the model of Altman (1983) has equal means and medians between the bankrupt and non-bankrupt group. In the sample of panel E, again the mean and median of Altman's (1983) financial ratio SALES/TA (x_5) and the mean of Ohlson's (1980) financial ratio OENEG (x_5) show no significant difference between the bankrupt and non-bankrupt group. The means and medians of all other financial ratios are significantly different between the two groups.

A comparison of the bankrupt and non-bankrupt means indicates that for the Altman (1983) variables WC/TA (x_1), RE/TA (x_2), EBIT/TA (x_3), and BVEQ/BVTD (x_4) the bankrupt means are lower than the non-bankrupt means. For the SALES/TA (x_5) variable, the bankrupt means are higher than the non-bankrupt means. The data looks comparable to the data used by Grice and Ingram (2001), the mean differences for x_1, x_2, x_3 and x_5 show the same direction. For x_4, Grice and Ingram (2001) did not have a significant mean difference. For the Ohlson (1980) variables SIZE (x_1), WC/TA (x_3), NI/TA (x_6), FU/TL (x_7), and CHNI (x_9), the bankrupt means are lower than the non-bankrupt means. For the variables TL/TA (x_2), CL/CA (x_4), OENEG (x_5), and INTWO (x_8), the bankrupt means are higher than the non-bankrupt means. The data used for the Ohlson (1980) variables is comparable to the data used by Grice Jr. and Dugan (2003), the mean differences for all variables show the same direction. For the Zmijewski (1984) variables NI/TA (x_1) and CA/CL (x_3) the bankrupt means are lower than the non-bankrupt means. For the variable TD/TA (x_2) the bankrupt means are higher than the non-bankrupt means. The mean differences in this data are also comparable to the mean differences in the data used by Grice Jr. and Dugan (2003) for all three variables. The general finding of the descriptive statistics is that the financial ratios are significantly different between the bankrupt and the non-bankrupt group.

Table 6 Descriptive statistics

Panel A: Estimation sample 2007 – 2010 one fiscal year before bankruptcy																		
Altman	**WC/TA**		**RE/TA**		**EBIT/TA**		**BVEQ/BVTD**		**SALES/TA**									
	B[a]	**NB[b]**	**B**	**NB**	**B**	**NB**	**B**	**NB**	**B**	**NB**								
N	42	412	42	412	42	412	42	412	42	412								
Mean	-0.100	0.219	-0.167	0.289	-0.114	0.082	0.059	1.024	2.686	1.924								
Median	-0.019	0.205	0.002	0.288	-0.020	0.056	0.065	0.579	2.246	1.678								
SD	0.294	0.243	0.411	0.255	0.212	0.117	0.294	1.229	1.877	1.273								
Min	-0.934	-0.256	-1.405	-0.221	-0.704	-0.108	-0.496	-0.037	0.117	0.169								
Max	0.311	0.640	0.288	0.745	0.070	0.355	0.801	4.801	6.915	5.102								
p (mean)	0.000***		0.000***		0.000***		0.000***		0.014**									
p (median)	0.000***		0.000***		0.000***		0.000***		0.034**									
Ohlson	**SIZE**		**TL/TA**		**WC/TA**		**CL/CA**		**OENEG**		**NI/TA**		**FU/TL**		**INTWO**		**CHNI**	
N	42	412	42	412	42	412	42	412	42	412	42	412	42	412	42	412	42	412
Mean	1.984	2.459	1.028	0.622	-0.100	0.219	1.193	0.742	0.333	0.061	-0.159	0.060	-0.089	0.176	0.381	0.114	-0.409	0.067
Median	1.969	2.438	0.939	0.633	-0.019	0.205	1.039	0.698	0	0	-0.047	0.041	-0.021	0.094	0	0	-0.722	0.045
SD	0.407	0.555	0.337	0.243	0.294	0.243	0.483	0.372	0.477	0.239	0.260	0.101	0.165	0.258	0.492	0.318	0.661	0.633
Min	1.314	1.556	0.559	0.172	-0.934	-0.256	0.584	0.216	0	0	-0.824	-0.131	-0.538	-0.161	0	0	-1	-1
Max	3.038	3.650	1.984	1.039	0.311	0.640	2.392	1.695	1	1	0.088	0.290	0.089	0.855	1	1	1	1
p (mean)	0.000***		0.000***		0.000***		0.000***		0.001***		0.000***		0.000***		0.001***		0.000***	
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.002***	
Zmijewski	**NI/TA**		**TD/TA**		**CA/CL**													
N	42	412	42	412	42	412												
Mean	-0.159	0.060	1.028	0.622	0.953	1.766												
Median	-0.047	0.041	0.939	0.633	0.963	1.433												
SD	0.260	0.101	0.337	0.243	0.321	1.024												
Min	-0.824	-0.131	0.559	0.172	0.418	0.590												
Max	0.088	0.290	1.984	1.039	1.718	4.630												
p (mean)	0.000***		0.000***		0.000***													
p (median)	0.000***		0.000***		0.000***													

Panel B: Estimation sample 2012 – 2015 one fiscal year before bankruptcy																		
Altman	**WC/TA**		**RE/TA**		**EBIT/TA**		**BVEQ/BVTD**		**SALES/TA**									
	B[a]	**NB[b]**	**B**	**NB**	**B**	**NB**	**B**	**NB**	**B**	**NB**								
N	113	1130	113	1130	113	1130	113	1130	113	1130								
Mean	-0.127	0.230	-0.189	0.291	-0.116	0.071	0.122	1.189	2.840	1.881								
Median	-0.047	0.231	-0.030	0.280	-0.045	0.051	0.118	0.568	2.117	1.646								
SD	0.365	0.260	0.512	0.266	0.200	0.093	0.386	1.561	2.033	1.445								
Min	-1.034	-0.285	-1.638	-0.237	-0.682	-0.079	-0.529	0.005	0.525	0.053								
Max	0.370	0.706	0.497	0.781	0.137	0.297	1.094	6.172	8.533	5.630								
p (mean)	0.000***		0.000***		0.000***		0.000***		0.000***									
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***									
Ohlson	**SIZE**		**TL/TA**		**WC/TA**		**CL/CA**		**OENEG**		**NI/TA**		**FU/TL**		**INTWO**		**CHNI**	
N	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130
Mean	1.967	2.462	1.011	0.608	-0.127	0.230	1.327	0.756	0.336	0.047	-0.145	0.056	-0.090	0.164	0.496	0.106	-0.225	0.029
Median	1.916	2.383	0.894	0.638	-0.047	0.231	1.057	0.668	0	0	-0.061	0.040	-0.055	0.084	0	0	-0.155	0.020
SD	0.420	0.609	0.396	0.249	0.365	0.260	0.795	0.463	0.475	0.212	0.213	0.083	0.180	0.240	0.502	0.308	0.646	0.542
Min	1.134	1.502	0.479	0.139	-1.034	-0.285	0.466	0.160	0	0	-0.733	-0.094	-0.482	-0.138	0	0	-1	-1
Max	2.757	3.761	2.122	0.995	0.370	0.706	3.764	2.102	1	1	0.128	0.257	0.300	0.830	1	1	1	1
p (mean)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***	
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.003***	
Zmijewski	**NI/TA**		**TD/TA**		**CA/CL**													
N	113	1130	113	1130	113	1130												
Mean	-0.145	0.056	1.011	0.608	0.977	1.941												
Median	-0.061	0.040	0.894	0.638	0.946	1.497												
SD	0.213	0.083	0.396	0.249	0.461	1.406												
Min	-0.733	-0.094	0.479	0.139	0.266	0.476												
Max	0.128	0.257	2.122	0.995	2.150	6.256												
p (mean)	0.000***		0.000***		0.000***													
p (median)	0.000***		0.000***		0.000***													

Panel C: Estimation sample 2012 – 2015 two fiscal years before bankruptcy																		
Altman	**WC/TA**		**RE/TA**		**EBIT/TA**		**BVEQ/BVTD**		**SALES/TA**									
	B[a]	**NB[b]**	**B**	**NB**	**B**	**NB**	**B**	**NB**	**B**	**NB**								
N	113	1130	113	1130	113	1130	113	1130	113	1130								
Mean	-0.013	0.224	-0.037	0.284	-0.037	0.074	0.209	1.111	2.465	1.886								
Median	0.026	0.224	0.036	0.272	0.002	0.053	0.128	0.567	2.040	1.598								
SD	0.228	0.263	0.356	0.265	0.117	0.097	0.386	1.381	1.693	1.457								
Min	-0.508	-0.316	-1.031	-0.238	-0.356	-0.083	-0.407	-0.016	0.409	0.052								
Max	0.401	0.711	0.482	0.767	0.111	0.323	1.288	5.335	7.636	5.702								
p (mean)	0.000***		0.000***		0.000***		0.000***		0.000***									
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***									
Ohlson	**SIZE**		**TL/TA**		**WC/TA**		**CL/CA**		**OENEG**		**NI/TA**		**FU/TL**		**INTWO**		**CHNI**	
N	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130	113	1130
Mean	2.033	2.440	0.903	0.616	-0.013	0.224	1.091	0.763	0.230	0.053	-0.066	0.053	-0.038	0.164	0.354	0.118	-0.255	-0.001
Median	1.958	2.372	0.886	0.638	0.026	0.224	0.967	0.680	0	0	-0.017	0.037	0.002	0.088	0	0	-0.285	0.011
SD	0.430	0.610	0.269	0.250	0.228	0.263	0.413	0.464	0.423	0.224	0.125	0.087	0.143	0.244	0.480	0.322	0.616	0.544
Min	1.154	1.445	0.437	0.158	-0.508	-0.316	0.531	0.159	0	0	-0.405	-0.107	-0.424	-0.169	0	0	-1	-1
Max	2.881	3.718	1.688	1.016	0.401	0.711	2.244	2.108	1	1	0.088	0.273	0.169	0.833	1	1	1	1
p (mean)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***	
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***	
Zmijewski	**NI/TA**		**TD/TA**		**CA/CL**													
N	113	1130	113	1130	113	1130												
Mean	-0.066	0.053	0.903	0.616	1.037	1.920												
Median	-0.017	0.037	0.886	0.638	1.035	1.470												
SD	0.125	0.087	0.269	0.250	0.356	1.404												
Min	-0.405	-0.107	0.437	0.158	0.446	0.474												
Max	0.088	0.273	1.688	1.016	1.885	6.297												
p (mean)	0.000***		0.000***		0.000***													
p (median)	0.000***		0.000***		0.000***													

Panel D: Estimation sample 2016 – 2019 one fiscal year before bankruptcy																		
Altman	**WC/TA**		**RE/TA**		**EBIT/TA**		**BVEQ/BVTD**		**SALES/TA**									
	B[a]	**NB**[b]	**B**	**NB**	**B**	**NB**	**B**	**NB**	**B**	**NB**								
N	71	710	71	710	71	710	71	710	71	710								
Mean	-0.101	0.209	-0.258	0.297	-0.158	0.067	0.286	0.966	2.045	2.040								
Median	-0.043	0.190	0.004	0.257	-0.043	0.057	0.090	0.529	1.770	1.764								
SD	0.484	0.247	0.839	0.235	0.311	0.076	0.819	1.140	1.395	1.480								
Min	-1.551	-0.234	-3.529	-0.080	-1.195	-0.075	-0.617	0.017	0.213	0.112								
Max	0.692	0.873	0.685	0.771	0.145	0.244	3.005	4.313	5.800	5.682								
p (mean)	0.000***		0.000***		0.000***		0.000***		0.975									
p (median)	0.000***		0.000***		0.000***		0.000***		0.902									
Ohlson	**SIZE**		**TL/TA**		**WC/TA**		**CL/CA**		**OENEG**		**NI/TA**		**FU/TL**		**INTWO**		**CHNI**	
N	71	710	71	710	71	710	71	710	71	710	71	710	71	710	71	710	71	710
Mean	2.067	2.650	1.015	0.628	-0.101	0.209	1.361	0.778	0.282	0.034	-0.219	0.049	-0.118	0.148	0.437	0.076	-0.243	0.017
Median	2.021	2.513	0.917	0.654	-0.043	0.190	1.045	0.720	0	0	-0.083	0.041	-0.043	0.091	0	0	-0.293	0.042
SD	0.379	0.675	0.534	0.231	0.484	0.246	1.072	0.407	0.453	0.181	0.361	0.072	0.242	0.188	0.499	0.265	0.669	0.527
Min	1.403	1.693	0.250	0.188	-1.551	-0.234	0.232	0.188	0	0	-1.300	-0.097	-0.781	-0.098	0	0	-1	-1
Max	2.891	4.144	2.736	0.983	0.692	0.689	4.935	1.882	1	1	0.091	0.228	0.286	0.659	1	1	1	1
p (mean)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.002***	
p (median)	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.000***		0.081*	
Zmijewski	**NI/TA**		**TD/TA**		**CA/CL**													
N	71	710	71	710	71	710												
Mean	-0.219	0.049	1.015	0.628	1.156	1.751												
Median	-0.083	0.041	0.917	0.654	0.957	1.388												
SD	0.361	0.072	0.534	0.231	0.912	1.156												
Min	-1.300	-0.097	0.250	0.188	0.204	0.532												
Max	0.091	0.228	2.736	0.983	4.383	5.306												
p (mean)	0.000***		0.000***		0.000***													
p (median)	0.000***		0.000***		0.000***													

Panel E: Estimation sample 2016 – 2019 two fiscal years before bankruptcy																		
Altman	**WC/TA**		**RE/TA**		**EBIT/TA**		**BVEQ/BVTD**		**SALES/TA**									
	B[a]	**NB[b]**	**B**	**NB**	**B**	**NB**	**B**	**NB**	**B**	**NB**								
N	71	710	71	710	71	710	71	710	71	710								
Mean	0.073	0.208	0.042	0.293	-0.034	0.067	0.498	0.960	1.854	2.045								
Median	0.066	0.184	0.047	0.270	0.000	0.057	0.216	0.510	1.641	1.736								
SD	0.271	0.248	0.341	0.230	0.123	0.070	0.952	1.151	1.163	1.462								
Min	-0.515	-0.255	-0.988	-0.055	-0.388	-0.055	-0.312	0.023	0.134	0.155								
Max	0.653	0.691	0.703	0.756	0.123	0.224	3.919	4.424	4.870	5.562								
p (mean)	0.000***		0.000***		0.000***		0.000***		0.200									
p (median)	0.006***		0.000***		0.000***		0.000***		0.804									
Ohlson	**SIZE**		**TL/TA**		**WC/TA**		**CL/CA**		**OENEG**		**NI/TA**		**FU/TL**		**INTWO**		**CHNI**	
N	71	710	71	710	71	710	71	710	71	710	71	710	71	710	71	710	71	710
Mean	2.136	2.640	0.802	0.630	0.073	0.208	0.994	0.767	0.085	0.030	-0.046	0.050	-0.031	0.142	0.408	0.082	-0.138	0.037
Median	2.116	2.518	0.822	0.662	0.066	0.184	0.903	0.719	0	0	-0.002	0.039	-0.005	0.090	0	0	-0.172	0.038
SD	0.358	0.692	0.259	0.230	0.271	0.248	0.492	0.377	0.280	0.170	0.107	0.064	0.153	0.169	0.495	0.274	0.618	0.496
Min	1.466	1.672	0.204	0.184	-0.515	-0.255	0.213	0.206	0	0	-0.366	-0.075	-0.403	-0.086	0	0	-1	-1
Max	2.939	4.178	1.456	0.977	0.653	0.691	2.358	1.732	1	1	0.071	0.199	0.287	0.593	1	1	1	1
p (mean)	0.000***		0.000***		0.000***		0.000***		0.109		0.000***		0.000***		0.000***		0.024**	
p (median)	0.000***		0.000***		0.006***		0.000***		0.029**		0.000***		0.000***		0.000***		0.001***	
Zmijewski	**NI/TA**		**TD/TA**		**CA/CL**													
N	71	710	71	710	71	710												
Mean	-0.046	0.050	0.802	0.630	1.338	1.725												
Median	-0.002	0.039	0.822	0.662	1.108	1.391												
SD	0.107	0.064	0.259	0.230	0.965	1.070												
Min	-0.366	-0.075	0.204	0.184	0.432	0.577												
Max	0.071	0.199	1.456	0.977	4.699	4.846												
p (mean)	0.000***		0.000***		0.002***													
p (median)	0.000***		0.000***		0.000***													

Variable definitions are as follows: WC/TA = working capital/total assets, RE/TA = retained earnings/total assets, EBIT/TA = earnings before interest and taxes/total assets, BVEQ/BVTD = book value equity/book value of total debt, SALES/TA = sales/total assets, SIZE = log(total assets/GNP price-level index), TL/TA = total liabilities/total assets, WC/TA = working capital/total assets, CL/CA = current liabilities/current assets, OENEG = 1 if total liabilities > total assets, 0 otherwise, NI/TA = net income/total assets, FU/TL = funds provided by operations/total liabilities, INTWO = 1 if net income was negative for the last two years, 0 otherwise, CHNI = change in net income for the last to previous year, NI/TA = net income/total assets, TD/TA = total debt/total assets, CA/CL = current assets/current liabilities [a] B= bankrupt firms [b] NB = non-bankrupt firms ***<1% **<5% *<10%

5.2 Difference between Dutch and Belgian firms

The Netherlands and Belgium have different bankruptcy procedures, which are discussed in section 2.1.3 and 2.1.4. Therefore, before testing the hypotheses, it is tested if the prediction accuracy differs between these two countries. For this test, the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) are developed using the estimation sample with firm observations from 2012 – 2015 and tested on the hold-out sample with firm observations from 2016 – 2019. Each model is developed when applied only on Dutch firms and when applied only on Belgian firms, and data from one fiscal year before the event of bankruptcy is used. The test statistic (z) of Agarwal and Taffler (2007) is used to compare the AUC-statistics of the two countries. The results are shown in table 7, where panel A shows the results of Dutch firms, panel B the results of Belgian firms, and panel C the test statistics. The table reports both the in sample and out-of-sample results, however, only the out-of-sample results will be further analysed since the in sample results only measure classification accuracy, not predictive accuracy.

The model of Altman (1983) has an out-of-sample AUC-score of 0.564 (AR = 12.80%) when applied to Dutch firms only, and 0.658 (AR = 31.60%) when applied to Belgian firms only. Ohlson's model (1980) has an out-of-sample AUC-score of 0.667 (AR = 33.40%) when applied to Dutch firms only, and 0.737 (47.40%) when applied to Belgian firms only. Zmijewski's model (1984) has an out-of-sample AUC-score of 0.667 (AR = 33.40%) when applied to Dutch firms only, and 0.714 (AR = 42.80%) when applied to Belgian firms only. All three test statistics, as reported in panel C of table 7, are not statistical significant. This indicates that the prediction accuracy does not differ between the Netherlands and Belgium.

Table 7 Comparing predictive accuracy Dutch and Belgian firms

	AUC-statistic		Accuracy ratio	
	In sample	Out-of-sample	In sample	Out-of-sample
Panel A: Dutch firms				
N	605	350	605	350
I. Altman (1983)	0.639**	0.564	27.80%	12.80%
MDA	(0.066)	(0.078)		
II. Ohlson (1980)	0.690***	0.667**	38.00%	33.40%
Logit regression	(0.065)	(0.078)		
III. Zmijewski (1984)	0.619*	0.667**	23.80%	33.40%
Probit regression	(0.066)	(0.078)		
Panel B: Belgian firms				
N	638	431	638	431
IV. Altman (1983)	0.687***	0.658***	37.40%	31.60%
MDA	(0.032)	(0.042)		
V. Ohlson (1980)	0.735***	0.737***	47.00%	47.40%
Logit regression	(0.031)	(0.040)		
VI. Zmijewski (1984)	0.722***	0.714***	44.40%	42.80%
Probit regression	(0.032)	(0.041)		
Panel C: Test statistic				
z (IV – I)	0.654	1.061		
z (V – II)	0.625	0.799		
z (VI – III)	1.404	0.533		

The AUC-statistic measures predictive accuracy and has a value between 0 and 1. A value of 0.5 indicates a random model and a value of 1.0 shows a perfect model. Standard errors in parentheses. The accuracy ratio (AR) is a scaled version of the AUC-statistic. The test statistic z is used to compare the AUC-statistics.
***<1%
**<5%
*<10%

5.3 Hypothesis tests

5.3.1 Hypothesis 1: Model performance

Hypothesis 1 holds that there is no difference in the predictive power between the models of Altman (1983), Ohlson (1980) and Zmijewski (1984). An overview of the coefficients of the models used in this hypothesis can be found in appendix E.I. Table 8 shows the out-of-sample classification matrix for each bankruptcy prediction model. The overall accuracy rate of the Altman model is 93.47%, and the model classified 32.39% of the bankrupt firms and 99.58% of the non-bankrupt firms correctly. Ohlson's model has an overall accuracy rate of 95.01%, and classified 47.89% of the bankrupt firms and 99.72% of the non-bankrupt firms correctly. The model of Zmijewski has an overall accuracy of 94.37%, and 38.03% of the bankrupt firms and 100.00% of the non-bankrupt firms where correctly classified. For all models the frequency type I errors, misclassifying a bankrupt firm as a non-bankrupt firm, is relatively high compared to the frequency type II errors, misclassifying a non-bankrupt firm as a bankrupt firm. Due to the low frequency type II errors and the higher amount of non-bankrupt firms than bankrupt firms in the sample, all models have a high overall predictive accuracy. Oude Avenhuis (2013) and Grice Jr. and Dugan (2003) also found in their studies that the classification accuracy of the bankrupt group is lower than the classification accuracy of the non-bankrupt group.

Table 8 Classification matrix hypothesis 1

		Predicted			
	Observed	**Bankrupt**	**Active**	**Total**	**Good predictions**
Altman (1983)	Bankrupt	23 (32.39%)	48 (67.61%)	71	23
MDA	Active	3 (0.42%)	707 (99.58%)	710	707
	Overall			781	730 (93.47%)
Ohlson (1980)	Bankrupt	34 (47.89%)	37 (52.11%)	71	34
Logit regression	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	742 (95.01%)
Zmijewski (1984)	Bankrupt	27 (38.03%)	44 (61.97%)	71	27
Probit regression	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	737 (94.37%)

To determine whether there is a significant difference in the predictive power between the three models, the AUC-statistics of the models will be compared using the test statistic (z) of Agarwal and Taffler (2007). Standard errors are calculated using the formula of Hanley and McNeil (1982). Table 9 reports the AUC-statistics and accuracy ratios of the models in panel A, and panel B shows the test-statistics. The table reports both the in sample and out-of-sample results, however, only the out-of-sample results will be further analysed since the in sample results only measure classification accuracy, not predictive accuracy. The model of Altman (1983) has an out-of-sample AUC-score of 0.660 which refers to an accuracy ratio of 32.00%. The out-of-sample AUC-score of Ohlson's model (1980) is 0.738, and its accuracy ratio 47.60%. Zmijewski's model (1984) has an out-of-sample AUC-score of 0.690 and accuracy ratio of 38.00%. It is clear that not one of the models outperforms the other models, since all three test statistics, as reported in panel B of table 9, are not statistical significant. This indicates that there is no statistical significant difference between the three prediction models. Therefore, hypothesis 1 is not rejected.

Table 9 Comparing predictive accuracy hypothesis 1

Panel A: AUC-statistic and accuracy ratio				
	AUC-statistic		**Accuracy ratio**	
	In sample	Out-of-sample	In sample	Out-of-sample
N	1243	781	1243	781
I. Altman (1983)	0.683***	0.660***	36.60%	32.00%
MDA	(0.029)	(0.037)		
II. Ohlson (1980)	0.714***	0.738***	42.80%	47.60%
Logit regression	(0.028)	(0.035)		
III. Zmijewski (1984)	0.704***	0.690***	40.80%	38.00%
Probit regression	(0.028)	(0.036)		
Panel B: Test statistic				
z (II – I)	0.769	1.531		
z (III – I)	0.521	0.581		
z (III – II)	-0.253	-0.956		

The AUC-statistic measures predictive accuracy and has a value between 0 and 1. A value of 0.5 indicates a random model and a value of 1.0 shows a perfect model. Standard errors in parentheses. The accuracy ratio (AR) is a scaled version of the AUC-statistic. The test statistic z is used to compare the AUC-statistics.
***<1%
**<5%
*<10%

5.3.2 Hypothesis 2: Econometric method performance

Hypothesis 2 holds that a bankruptcy prediction model using logit regression or probit regression is more accurate than a bankruptcy prediction model using MDA. An overview of the coefficients of the models used in this hypothesis can be found in appendix E.I. Table 10 shows the out-of-sample classification matrix of each particular prediction model, where panel A represents the models with the variables of Altman (1983), panel B the models with the variables of Ohlson (1980), and panel C the models with the variables of Zmijewski (1984). For each set of variables, the models are estimated by MDA, logit regression and probit regression. The original econometric method for the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) are MDA, logit regression, and probit regression, respectively. The out-of-sample classification results of the prediction models estimated with their original econometric method are already reported in table 8 from hypothesis 1, but for clarity also reported in table 10. The models estimated by MDA classified 32.39% (Altman's variables), 39.44% (Ohlson's variables), and 36.62% (Zmijewski's variables) of the bankrupt firms correctly. The models estimated by logit regression classified 38.03% (Altman's variables), 47.89% (Ohlson's variables), and

39.44% (Zmijewski's variables) of the bankrupt firms correctly. The models estimated by probit regression classified 33.80% (Altman's variables), 43.66% (Ohlson's variables), and 38.03% (Zmijewski's variables) of the bankrupt firms correctly. For each set of variables, all three econometric methods classified a high percentage of non-bankrupt firms correctly. For all models the frequency type I errors, misclassifying a bankrupt firm as a non-bankrupt firm, is again relatively high compared to the frequency type II errors, misclassifying a non-bankrupt firm as a bankrupt firm.

Table 10 Classification matrix hypothesis 2

		Panel A: Altman (1983) variables			
		Predicted			
	Observed	**Bankrupt**	**Active**	**Total**	**Good predictions**
MDA	Bankrupt	23 (32.39%)	48 (67.61%)	71	23
	Active	3 (0.42%)	707 (99.58%)	710	707
	Overall			781	730 (93.47%)
Logit regression	Bankrupt	27 (38.03%)	44 (61.97%)	71	27
	Active	6 (0.85%)	704 (99.15%)	710	704
	Overall			781	731 (93.60%)
Probit regression	Bankrupt	24 (33.80%)	47 (66.20%)	71	24
	Active	3 (0.42%)	707 (99.58%)	710	707
	Overall			781	731 (93.60%)
		Panel B: Ohlson (1980) variables			
MDA	Bankrupt	28 (39.44%)	43 (60.56%)	71	28
	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	736 (94.24%)
Logit regression	Bankrupt	34 (47.89%)	37 (52.11%)	71	34
	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	742 (95.01%)
Probit regression	Bankrupt	31 (43.66%)	40 (56.34%)	71	31
	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	739 (94.62%)
		Panel C: Zmijewski (1984) variables			
MDA	Bankrupt	26 (36.62%)	45 (63.38%)	71	26
	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	736 (94.24%)
Logit regression	Bankrupt	28 (39.44%)	43 (60.56%)	71	28
	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	738 (94.49%)
Probit regression	Bankrupt	27 (38.03%)	44 (61.97%)	71	27
	Active	0	710 (100.00%)	710	710
	Overall			781	737 (94.37%)

Table 11 shows the AUC-statistics and accuracy ratios for each bankruptcy prediction model, where panel A shows the results of the models with the Altman (1983) variables, panel B with the

Ohlson (1980) variables, panel C with the Zmijewski (1984) variables. Each model is estimated by MDA, logit regression and probit regression. The AUC-statistics and accuracy ratios of the prediction models estimated with their original econometric method are already reported in table 9 from hypothesis 1, but for clarity also reported in table 11. Again, for the same reason as in hypothesis 1, only the out-of-sample results will be analysed. The Agarwal and Taffler (2007) test statistic (z) is used to compare the AUC-statistics. The out-of-sample AUC-score of the model with the Altman (1983) variables is 0.660 (AR = 32.00%) when estimated by MDA, 0.686 (AR = 37.20%) when estimated by logit regression, and 0.667 (AR = 33.40%) when estimated by probit regression. The test statistics are not statistically significant, indicating that estimating prediction models with logit regression or probit regression instead of MDA does not significantly improve the AUC-score with the Altman (1983) variables. The models with the Ohlson (1980) variables show similar results. The out-of-sample AUC-score of this model is 0.696 (AR = 39.20%) when estimated by MDA, 0.738 (AR = 47.60%) when estimated by logit regression, and 0.717 (AR = 43.40%) when estimated by probit regression. The test statistics are not statistically significant, the AUC-scores are not significantly improved by using logit regression or probit regression instead of MDA for the Ohlson (1980) variables. The models with the Zmijewski (1984) variables also show similar results. This model has an out-of-sample AUC-score of 0.683 (AR = 36.60%) when estimated by MDA, 0.697 (AR = 39.40%) when estimated by logit regression, and 0.690 (AR = 38.00%) when estimated by probit regression. Again, all the test statistics are not significant. The AUC-score for the Zmijewski (1984) variables is not significantly improved when estimating the models by logit regression or probit regression instead of MDA. Concluding, prediction models estimated by logit regression or probit regression are not significantly more accurate than the bankruptcy prediction models estimated by MDA. Therefore, hypothesis 2 is rejected.

Table 11 Comparing predictive accuracy hypothesis 2

	AUC-statistic		Accuracy ratio	
Panel A: Altman (1983) variables				
	In sample	Out-of-sample	In sample	Out-of-sample
N	1243	781	1243	781
I. MDA	0.683***	0.660***	36.60%	32.00%
	(0.029)	(0.037)		
II. Logit regression	0.709***	0.686***	41.80%	37.20%
	(0.028)	(0.036)		
III. Probit regression	0.701***	0.667***	40.20%	33.40%
	(0.028)	(0.036)		
z (II – I)	0.645	0.504		
z (III – I)	0.447	0.136		
z (II – III)	0.202	0.373		
Panel B: Ohlson (1980) variables				
N	1243	781	1243	781
I. MDA	0.699***	0.696***	39.80%	39.20%
	(0.028)	(0.036)		
II. Logit regression	0.714***	0.738***	42.80%	47.60%
	(0.028)	(0.035)		
III. Probit regression	0.709***	0.717***	41.80%	43.40%
	(0.028)	(0.035)		
z (II – I)	0.379	0.836		
z (III – I)	0.253	0.418		
z (II – III)	0.126	0.424		
Panel C: Zmijewski (1984) variables				
N	1243	781	1243	781
I. MDA	0.695***	0.683***	39.00%	36.60%
	(0.029)	(0.036)		
II. Logit regression	0.708***	0.697***	41.60%	39.40%
	(0.028)	(0.036)		
III. Probit regression	0.704***	0.690***	40.80%	38.00%
	(0.028)	(0.036)		
z (II – I)	0.322	0.275		
z (III – I)	0.223	0.137		
z (II – III)	0.101	0.137		

The AUC-statistic measures predictive accuracy and has a value between 0 and 1. A value of 0.5 indicates a random model and a value of 1.0 shows a perfect model. Standard errors in parentheses. The accuracy ratio (AR) is a scaled version of the AUC-statistic. The test statistic z is used to compare the AUC-statistics.
***<1%
**<5%
*<10%

5.3.3 Hypothesis 3: Non-stationarity of the coefficients of the models

Hypothesis 3a holds that the accounting-based bankruptcy prediction models will not retain their accuracy over time. Hypothesis 3b holds that re-estimating the coefficients of these models will improve the predictive accuracy. An overview of the coefficients of the models used in this hypothesis can be found in appendix E.II. Table 12 shows the classification matrix of the models, where panel A shows the in-sample results of the estimation sample 2007 – 2010, panel B the out-of-sample results of the estimation sample 2007 – 2010 (tested on the hold-out sample 2016 – 2019), and panel C the out-of-sample results of the estimation sample 2012 – 2015 from hypothesis 1 (tested on the hold-out sample 2016 – 2019).

To test hypothesis 3a, the out-of-sample results in panel A will be compared to the in sample results of panel B. If the prediction models do not retain their accuracy over time, the results in panel B should be lower than the results in panel A. The model of Altman (1983) classified 28.57% of the bankrupt firms correctly with the estimation sample and 29.58% with the hold-out sample. Ohlson's model (1980) classified 42.86% of the bankrupt firms correctly with the estimation sample and 43.66% with the hold-out sample. Zmijewski's model (1984) classified 28.57% of the bankrupt firms correctly with the estimation sample and 36.62% with the hold-out sample.

To test hypothesis 3b, the out-of-sample results in panel B will be compared to the out-of-sample results in panel C. If re-estimating the coefficients of the models does improve the predictive accuracy, the results in panel C should be higher than the results in panel B. For Altman's model (1983) the classification percentage of bankrupt firms is 29.58% when estimated with observations from 2007 – 2010, and 32.39% when the coefficients are re-estimated with observations from 2012 – 2015. For Ohlson's model (1980) the classification percentage of bankrupt firms is 43.66% for the 2007 – 2010 observations and 47.89% for the 2012 – 2015 observations. The model of Zmijewski (1984) classified 36.62% of the bankrupt firms correctly with the estimation sample 2007 – 2010 and 38.03% with the estimation sample 2012 – 2015.

All models are able to classify (most of) the non-bankrupt firms correctly. Again, for all models the frequency type I errors, misclassifying a bankrupt firm as a non-bankrupt firm, is relatively high compared to the type II errors, misclassifying a non-bankrupt firm as a bankrupt firm.

Table 12 Classification matrix hypothesis 3

Panel A: In sample (estimation sample 2007 – 2010)					
		Predicted			
	Observed	**Bankrupt**	**Active**	**Total**	**Good predictions**
Altman (1983)	Bankrupt	12 (28.57%)	30 (71.43%)	42	12
MDA	Active	4 (0.97%)	408 (99.03%)	412	408
	Overall			454	420 (92.51%)
Ohlson (1980)	Bankrupt	18 (42.86%)	24 (57.14%)	42	18
Logit regression	Active	5 (1.21%)	407 (98.77%)	412	407
	Overall			454	425 (93.61%)
Zmijewski (1984)	Bankrupt	12 (28.57%)	30 (71.43%)	42	12
Probit regression	Active	0 (0.00%)	412 (100.00%)	412	412
	Overall			454	424 (93.39%)
Panel B: Out-of-sample (estimation sample 2007 – 2010 tested on hold-out sample 2016 – 2019)					
Altman (1983)	Bankrupt	21 (29.58%)	50 (70.42%)	71	21
MDA	Active	4 (0.56%)	706 (99.44%)	710	706
	Overall			781	727 (93.09%)
Ohlson (1980)	Bankrupt	31 (43.66%)	40 (56.34%)	71	31
Logit regression	Active	4 (0.56%)	706 (99.44%)	710	706
	Overall			781	737 (94.37%)
Zmijewski (1984)	Bankrupt	26 (36.62%)	45 (63.38%)	71	26
Probit regression	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	736 (94.24%)
Panel C: Out-of-sample H1 (estimation sample 2012 – 2015 tested on hold-out sample 2016 – 2019)					
Altman (1983)	Bankrupt	23 (32.39%)	48 (67.61%)	71	23
MDA	Active	3 (0.42%)	707 (99.58%)	710	707
	Overall			781	730 (93.47%)
Ohlson (1980)	Bankrupt	34 (47.89%)	37 (52.11%)	71	34
Logit regression	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	742 (95.01%)
Zmijewski (1984)	Bankrupt	27 (38.03%)	44 (61.97%)	71	27
Probit regression	Active	0	710 (100.00%)	710	710
	Overall			781	737 (94.37%)

Table 13 shows the AUC-statistics and accuracy ratios to test hypothesis 3a and 3b. The test statistic (z) of Agarwal and Taffler (2007) is used to test whether the difference between the AUC-statistics is statistically significant. For hypothesis 3a, the AUC-scores of the columns I and II will be compared. For Altman's model (1983) the in sample AUC-score is 0.638 (AR = 27.60%), and the out-of-sample AUC-score is 0.645 (AR = 29.00%). The model of Ohlson (1980) has an in sample AUC-score of 0.708 (AR = 41.60%), and an out-of-sample AUC-score of 0.715 (AR = 43.00%). Zmijewski's model (1984) has an in sample AUC-score of 0.643 (AR = 28.60%), and an out-of-sample AUC-score of 0.683 (AR = 36.60%). For this hypothesis, the first test statistic z (II – I) compares the AUC-statistics. For all three models, this test statistic is not statistically significant. This indicates that the bankruptcy prediction models do retain their accuracy over time. Therefore, hypothesis 3a is rejected.

For hypothesis 3b, the AUC-scores of the columns III and II will be compared. Altman's model (1983) has an out-of-sample AUC-score of 0.645 (AR = 29.00%) for the estimation sample 2007 – 2010, and an out-of-sample AUC-score of 0.660 (AR = 32.00%) for the estimation sample 2012 – 2015. For the model of Ohlson (1980), the out-of-sample AUC-score for the estimation sample 2007 – 2010 is 0.715 (AR = 43.00%), and the out-of-sample AUC-score for the estimation sample 2012 – 2015 is 0.738 (AR = 47.60%). The model of Zmijewski (1984) has an out-of-sample AUC-score of 0.683 (AR = 36.60%) for the estimation sample 2007 – 2010, and an out-of-sample AUC-score of 0.690 (AR = 38.00%) for the estimation sample 2012 – 2015. For this hypothesis, the second test statistic z (III – II) is used. For all three models, this test statistic is not statistically significant, indicating that re-estimating the coefficients of the models does not improve the predictive accuracy. Therefore, hypothesis 3b is also rejected.

Table 13 Comparing predictive accuracy hypothesis 3

Panel A: AUC-statistics and accuracy ratios						
	AUC-statistic			**Accuracy ratio**		
	I. In sample	II. Out-of-sample	III. Out-of-sample H1	In sample	Out-of-sample	Out-of-sample H1
N	454	781	781	454	781	781
Altman (1983)	0.638***	0.645***	0.660**	27.60%	29.00%	32.00%
MDA	(0.048)	(0.037)	(0.037)			
Ohlson (1980)	0.708***	0.715***	0.738***	41.60%	43.00%	47.60%
Logit regression	(0.046)	(0.036)	(0.035)			
Zmijewski (1984)	0.643***	0.683***	0.690***	28.60%	36.60%	38.00%
Probit regression	(0.048)	(0.036)	(0.036)			

Panel B: Test statistic			
	Altman (1983)	**Ohlson (1980)**	**Zmijewski (1984)**
z (II – I)	0.116	0.120	0.667
z (III – II)	0.287	0.458	0.137

The AUC-statistic measures predictive accuracy and has a value between 0 and 1. A value of 0.5 indicates a random model and a value of 1.0 shows a perfect model. Standard errors in parentheses. The accuracy ratio (AR) is a scaled version of the AUC-statistic. The test statistic z is used to compare the AUC-statistics.
***<1%
**<5%
*<10%

5.3.4 Hypothesis 4: Optimal time horizon

Hypothesis 4 holds that the optimal time horizon for predicting bankruptcy is one fiscal year prior to bankruptcy. An overview of the coefficients of the models used in this hypothesis can be found in appendix E.III. Table 14 shows the out-of-sample classification matrix of the prediction models, where panel A shows the results of the prediction one fiscal year before bankruptcy, and panel B the results of the prediction two fiscal years before bankruptcy. The results in panel A are the same results as reported in table 8 of hypothesis 1. Altman's model (1983) classified 32.39% of the bankrupt firms correctly with a time horizon of one year, and 12.68% with a time horizon of two years. The model of Ohlson (1980) classified 47.89% bankrupt firms correctly with a time horizon of one year, and 19.72% bankrupt firm with a time horizon of two years. Zmijewski's model (1984) classified 38.03% bankrupt firms correctly with a time horizon of one year, and 11.27% with a time horizon of two years. Models with a time horizon of two fiscal years before bankruptcy, just as the models with a time horizon of one fiscal year before bankruptcy, classified almost every non-bankrupt firm correctly. Like in the other hypotheses, for all models the frequency type I errors, misclassifying a bankrupt firm as a non-bankrupt firm, is relatively high compared to the frequency type II errors, misclassifying a non-bankrupt firm as a bankrupt firm.

Table 14 Classification matrix hypothesis 4

		Panel A: One fiscal year before bankruptcy			
		Predicted			
	Observed	**Bankrupt**	**Active**	**Total**	**Good predictions**
Altman (1983)	Bankrupt	23 (32.39%)	48 (67.61%)	71	23
MDA	Active	3 (0.42%)	707 (99.58%)	710	707
	Overall			781	730 (93.47%)
Ohlson (1980)	Bankrupt	34 (47.89%)	37 (52.11%)	71	34
Logit regression	Active	2 (0.28%)	708 (99.72%)	710	708
	Overall			781	742 (95.01%)
Zmijewski (1984)	Bankrupt	27 (38.03%)	44 (61.97%)	71	27
Probit regression	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	737 (94.37%)
		Panel B: Two fiscal years before bankruptcy			
Altman (1983)	Bankrupt	9 (12.68%)	62 (87.32%)	71	9
MDA	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	719 (92.06%)
Ohlson (1980)	Bankrupt	14 (19.72%)	57 (80.28%)	71	14
Logit regression	Active	1 (0.14%)	709 (99.86%)	710	709
	Overall			781	723 (92.57%
Zmijewski (1984)	Bankrupt	8 (11.27%)	63 (88.73%)	71	8
Probit regression	Active	0 (0.00%)	710 (100.00%)	710	710
	Overall			781	718 (91.93%)

Table 15 shows the AUC-statistics and accuracy ratios to test hypothesis 4, where panel A reports the results of the models with data from one year before bankruptcy, panel B the results of the models with data from two years before bankruptcy, and panel C the test statistic (z) of Agarwal and Taffler (2007). Panel A shows the same results as in table 9 panel A from hypothesis 1. Again, for the same reason as in hypothesis 1 and 2, only the out-of-sample results will be analysed. To determine if the predictive power of the models with a time horizon of one fiscal year before bankruptcy is significantly higher than the predictive power of the models with a time horizon of two fiscal years before bankruptcy, the test statistic (z) is used. Increasing the time horizon from one fiscal year to two fiscal years before bankruptcy deteriorates the AUC-score with the Altman (1983) variables from 0.660 (AR = 32.00%) to 0.563 (AR = 12.60%), with the Ohlson (1980) variables from 0.738 (AR = 47.60%) to 0.598 (AR = 19.60%), and with the Zmijewski (1984) variables from 0.690 (AR = 38.00%) to 0.556 (11.20%). For all bankruptcy prediction models, the test statistic is statistically significant. This indicates that the predictive models with a time horizon of two fiscal years before bankruptcy perform worse than the predictive models with a time horizon of one fiscal year before bankruptcy. Therefore, hypothesis 4, that the optimal time horizon for predicting bankruptcy is one fiscal year prior to bankruptcy, is not rejected.

Table 15 Comparing predictive accuracy hypothesis 4

Panel A: One fiscal year before bankruptcy				
	AUC-statistic		**Accuracy ratio**	
	In sample	Out-of-sample	In sample	Out-of-sample
N	1243	781	1243	781
I. Altman (1983)	0.683***	0.660***	36.60%	32.00%
MDA	(0.029)	(0.037)		
II. Ohlson (1980)	0.714***	0.738***	42.80%	47.60%
Logit regression	(0.028)	(0.035)		
III. Zmijewski (1984)	0.704***	0.690***	40.80%	38.00%
Probit regression	(0.028)	(0.036)		
Panel B: Two fiscal years before bankruptcy				
N	1243	781	1243	781
IV. Altman (1983)	0.604***	0.563*	20.80%	12.60%
MDA	(0.029)	(0.037)		
V. Ohlson (1980)	0.642***	0.598***	28.40%	19.60%
Logit regression	(0.029)	(0.037)		
VI. Zmijewski (1984)	0.615***	0.556	23.00%	11.20%
Probit regression	(0.029)	(0.037)		
Panel C: Test statistic				
z (IV – I)	-1.926**	-1.854**		
z (V – II)	-1.786**	-2.749***		
z (VI – III)	-2.208**	-2.596***		

The AUC-statistic measures predictive accuracy and has a value between 0 and 1. A value of 0.5 indicates a random model and a value of 1.0 shows a perfect model. Standard errors in parentheses. The accuracy ratio (AR) is a scaled version of the AUC-statistic. The test statistic z is used to compare the AUC-statistics.
***<1%
**<5%
*<10%

6 Conclusion and discussion

This chapter includes the conclusion and discussion of this study. First, a summary of the results will be reported. Second, the limitations of this study will be discussed. Finally, suggestions for future research will be provided.

6.1 Summary of results

This study examined the prediction power of the accounting-based bankruptcy prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) for Dutch and Belgian public and large private firms. These bankruptcy prediction models include different financial ratios as independent variables and are developed using different econometric methods (MDA, logit regression, and probit regression). This study addressed the following research question:

How accurate are the accounting-based bankruptcy prediction models for Dutch and Belgian public and large private firms?

Four hypotheses were tested in order to assess the predictive accuracy of these bankruptcy prediction models. The first hypothesis states that there is no difference in the predictive power between the models of Altman (1983), Ohlson (1980) and Zmijewski (1984). Several researchers conducted a similar study on the performance of these accounting-based bankruptcy prediction models, but reported different results about which model outperformed the other models (e.g. Begley et al., 1996; Grice & Ingram, 2001; Grice Jr. & Dugan, 2003; Wu et al., 2010; Ashraf et al., 2019). The results of this study show that there indeed is no difference in predictive power between the models for Dutch and Belgian public and large private firms. The accuracy ratio, which is the scaled version of the AUC-statistic, for the models of Altman (1983), Ohlson (1980), and Zmijewski (1984), are respectively 32.00%, 47.60%, and 38.00%. The difference in predictive power is not statistically significant and therefore hypothesis 1 is not rejected.

With the second hypothesis, this study tries to examine whether a bankruptcy prediction model using logit regression or probit regression is more accurate than a bankruptcy prediction model using MDA. Theory does imply that logit and probit regression are better econometric methods for predicting bankruptcy, due to the restricting statistical assumptions inherent in MDA which are mostly violated in bankruptcy prediction. However, Altman (2017) conducted a similar test with only logit regression, and concluded that re-estimation of the coefficients using logit regression only marginally improved the predictive accuracy. This master thesis shows similar results. First, in line with the conclusion of Collins and Green (1982), two assumptions of the MDA model are violated, the assumption about multivariate normality and the assumption about equality of variance-covariance. Violation of these assumptions limits the effectiveness and validity of MDA (Zhang et al., 1999; Shin et al., 2005; Lee & Choi, 2013).

The sets of variables of the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) are used to estimate bankruptcy prediction models using MDA, logit regression, and probit regression. The results show that logit regression and probit regression do not outperform MDA. Hypothesis 2 is rejected and therefore there is no reason to recommend future practitioners of bankruptcy prediction models to use logit regression or probit regression instead of MDA for estimating the prediction model.

Hypothesis 3a states that the prediction models of Altman (1983), Ohlson (1980), and Zmijewski (1984) will not retain their accuracy over time. Several researchers found that the accuracy of a bankruptcy prediction model is affected by factors relating to the environment and that a different environment may change the relationships between variables (e.g. Mensah, 1984; Platt & Platt, 1990; Grice Jr & Dugan, 2003; Karas & Režňáková, 2014). To test hypothesis 3a, coefficients of the models are re-estimated with observations from 2007 – 2010 and evaluated with observations from 2016 – 2019. These time periods are chosen because of the different economic environments. Several important events occurred during the period 2007 – 2010, such as the financial crisis in 2007 and the European debt crisis in 2010 and the regulatory response to the financial crisis, Basel III (stricter capital requirements for banks). However, the results show that the bankruptcy prediction models do retain their accuracy over time because the differences in accuracy ratios were not statistically significant. The accuracy ratio of Altman's model (1983) is 27.60% in the 2007 – 2010 period and 29.00% in the 2016 – 2019 period. Ohlson's model (1980) has an accuracy ratio of 41.60% in the first period and 43.00% in the latter period. The accuracy ratio of Zmijewski's model (1984) is 28.60% in the first period and 36.60% in the latter period. Therefore, hypothesis 3a is rejected.

Hypothesis 3b states that re-estimating the coefficients of the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) will improve the predictive accuracy. Several researchers suggest that the coefficients of the models should be re-estimated when for instance using a sample of firms from time periods other than those used to develop the models (Mensah, 1984; Grice Jr and Dugan, 2003; Singh and Mishra, 2016). However, the results of this study show that re-estimating the coefficients of the models with observations from a more recent period does not improve the predictive accuracy. The accuracy ratio of Altman's model (1983) is 29.00% when estimated with observations of 2007 – 2010, and 32.00% when estimated with the more recent observations of 2012 – 2015 (both tested on the hold-out sample of 2016 – 2019). Ohlson's model (1980) has an accuracy ratio of 43.00% for the time period 2007 – 2010, and 47.60% for the more recent time period 2012 – 2015. The model of Zmijewski (1984) has an accuracy ratio of 36.60% for the first time period, and 38.00% for the latter (more recent) time period. Because these differences in accuracy ratios are not statistically significant, hypothesis 3b is rejected.

The fourth hypothesis provides a test whether the optimal time horizon for predicting bankruptcy with the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) is one fiscal year prior to bankruptcy. Other researchers, such as Philosophov et al. (2005) and Jardin (2017) concluded that the predictive accuracy decreases when the time horizon exceeds one year. Lukason & Hoffman

(2014) state that there is no indication of failure in the financial statements two years before the actual onset of bankruptcy. This study shows similar results, because the accuracy ratio of all three models decreased when the time horizon increased from one year to two years. The accuracy ratio of Altman's model (1983) decreased from 32.00% to 12.60%, of Ohlson's model (1980) from 47.60% to 19.60%, and of Zmijewski's model (1984) from 38.00% to 11.20%. These differences are statistically significant, therefore hypothesis 4 is not rejected.

Finally answering the main research question of this master thesis of how accurate the accounting-based bankruptcy prediction models are for Dutch and Belgian public and large private firms. Estimated with the econometric methods originally employed to derive the models and with a time horizon of predicting bankruptcy one fiscal year prior to bankruptcy, the overall accuracy of the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) are 93.47%, 95.01%, and 94.37%, respectively. However, the models predicted respectively 32.39%, 47.89%, and 38.03% of the bankrupt firms correctly, and 99.58%, 99.72%, and 100.00% of the non-bankrupt firms correctly. This means that all three models have a relatively high frequency type I errors, compared to the frequency type II errors. The overall accuracy is high because for every bankrupt firm, 10 non-bankrupt firms are included in the samples and thus 90.91% of the total samples consists of non-bankrupt firms. The low prediction accuracy of bankrupt firms indicate that neither of the accounting-based bankruptcy prediction models is a sufficient model for predicting bankruptcy for Dutch and Belgian public and large private firms (Agarwal and Taffler, 2008 reach the same conclusion with their data). In line with Grice and Ingram (2001), and Grice Jr. and Dugan (2003), it is recommended that those who want to employ one of these models for predicting bankruptcy should do so cautiously.

6.2 Limitations

This master thesis is subject to several limitations. The major limitation of this study is the limited data availability. First, to avoid choice-based sample bias, the samples must be proportionately representative of the actual bankruptcy rate (Grice & Ingram, 2001; Balcaen & Ooghe, 2006). However, due to the limited data availability, this would lead to samples with only a few bankrupt firms. Therefore the ratio of bankrupt firms to non-bankrupt firms is set to 1:10, instead of the actual bankruptcy rate, meaning that the bankrupt firms are oversampled. Second, the estimation sample with observations from 2007 to 2010 consisted of a limited set of firms for which all financial data was available. This resulted in a relatively low sample size of 42 bankrupt and 412 non-bankrupt firms compared to the sample size of the estimation sample with observations from 2012 to 2015 which consisted of 113 bankrupt and 1130 non-bankrupt firms. Third, due to the limited data availability of Dutch bankrupt firms, Belgian bankrupt firms were overrepresented in the samples which could potentially lead to sampling bias. The last limitation due to the limited data availability is the time period of the estimation sample used for testing hypothesis 3a and 3b. To test the hypotheses that the prediction models will not retain their accuracy over time, and that re-estimating the coefficients improves the predictive accuracy, the estimation sample was supposed to contain observations from 2004 to 2007. This time period would be optimal, because after this period, the financial crisis in 2007 and the European debt crisis in 2010 happened. Firms in this pre-crisis estimation sample should therefore have a different economic environment than firms in the after-crisis hold-out sample. However, due to the limited data availability it was not possible to include a pre-crisis sample with observations from 2004 to 2007, but eventually the sample consisted of observations during the crisis, from 2007 to 2010. Therefore, the difference in economic environment between the estimation and hold-out sample is likely less than the difference if there was enough data available to include observations from 2004 to 2007 in the estimation sample.

Another limitation of this master thesis is the definition used for bankrupt firms. In this study, the definition of bankrupt firms that are included in the samples is based on a legal definition of bankruptcy. However, firms can also file for bankruptcy for other reasons than financial distress. For example, lawsuits as a result of strategic management decisions could also result in a firm filing for bankruptcy (Grice & Dugan, 2001), and firms also file for bankruptcy voluntarily when financial conditions make it value-increasing for shareholders and managers (Fleming & Moon, 1995). Therefore, firms in bankruptcy might not always be economically inefficient (White, 1989). However, the variables of the models of Altman (1983), Ohlson (1980), and Zmijewski (1984) do not incorporate proxies for non-financial events that cause bankruptcy (Grice & Dugan, 2001). Using the legal definition of bankruptcy and not excluding bankrupt firms that have filed for bankruptcy due to a non-financial event could lead to biased results.

A limitation of this study is that it analysed only three accounting-based bankruptcy prediction models and focused only on predicting bankruptcy with data from financial statements. However, financial statement are limited in predicting the probability of bankruptcy, among other things because financial statements are formulated under the going-concern principle and because financial statements report the past performance of a firm and may therefore not be informative about predicting bankruptcy in the future (Hillegeist et al., 2004). Additionally, accounting-based prediction models lack theoretical grounding (Agarwal & Taffler, 2008). Future research suggestions that addresses this limitation will be given in the next section.

The predictive accuracy of the models was assessed using the AUC-statistic, but this statistic does not distinguish between a type I error and a type II error (Agarwal & Taffler, 2008). Therefore, using the AUC-statistic for comparing the predictive accuracy indicates that this study does not have a preference for a type I or a type II error. However, a type I error is more costly than a type II error, because the former can result in losing a whole loan amount while the latter results in only the opportunity cost of not lending to that firm (Agarwal & Taffler, 2008).

6.3 Future research

Future research on bankruptcy prediction in a Dutch and Belgian setting should also analyse market-based bankruptcy prediction models, like the models of Shumway (2001) and Hillegeist et al. (2004), in addition to the accounting-based bankruptcy prediction models in order to compare the performance of these two types of prediction models. Additionally, this master thesis only analysed the original variables of the models of Altman (1983), Ohlson (1980), and Zmijewski (1984). Future research should focus on modifications and extensions of these models to increase the predictive accuracy, such as introducing new variables: financial, non-financial, and macroeconomic variables.

The results of this study indicate that the optimal time horizon for predicting bankruptcy with the accounting-based prediction models is one fiscal year before bankruptcy and that the predictive accuracy decreases drastically when the time horizon increases. A suggestion for future research is therefore to focus on how to predict bankruptcy several years before the event instead of one year. Because if a potential bankruptcy can be predicted a few years in advance, actions like reorganization or merger of the firm can be undertaken (Dimitras et al, 1996; Pompe & Bilderbeek, 2005; Fejér-Király, 2015).

Due to the limited data availability this study focused on both public and private firms and on both Dutch and Belgian firms. Future research should focus on testing the usefulness of the prediction models with data from only private firms, since most studies focus on public firms. To ensure sufficient data availability, more European countries could be included. Additionally, future research should test its usefulness with data from only the Netherlands or only Belgium.

References

Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand? *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

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

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance*, *32*(8), 1541-1551.

Agnese, P., Rizzo, M., & Vento, G. A. (2018). SMEs finance and bankruptcies: the role of credit guarantee schemes in the UK. *Journal of Applied Finance and Banking*, *8*(3), 1-16.

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

Altman, E. I. (1983). Corporate financial distress: A complete guide to predicting, avoiding, and dealing with bankruptcy. Wiley Interscience, John Wiley and Sons.

Altman, E. I. (2013). Predicting financial distress of companies: revisiting the Z-score and ZETA® models. In *Handbook of Research Methods and Applications in Empirical Finance*. Edward Elgar Publishing.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting, 28*(2), 131-171.

Ashraf, S., GS Félix, E., & Serrasqueiro, Z. (2019). Do traditional financial distress prediction models predict the early warning signs of financial distress? *Journal of Risk and Financial Management*, *12*(2), 55.

Atiya, A. F. (2001). Bankruptcy prediction for credit risk using neural networks: A survey and new results. *IEEE Transactions on Neural Networks, 12*(4), 929-935.

Baker & McKenzie (2016). *Global restructuring & insolvency guide 2016*. Retrieved from http://restructuring.bakermckenzie.com/wp-content/uploads/sites/23/2016/12/Global-Restructuring-Insolvency-Guide-New-Logo-Belgium.pdf

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

Balcaen, S., Manigart, S., Buyze, J., & Ooghe, H. (2012). Firm exit after distress: differentiating between bankruptcy, voluntary liquidation and M&A. *Small Business Economics*, *39*(4), 949-975.

Bauer, J., & Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking & Finance*, *40*, 432-442.

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

Beaver, W. H., McNichols, M. F., & Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting studies*, *10*(1), 93-122.

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

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

Berg, D. (2007). Bankruptcy prediction by generalized additive models. *Applied Stochastic Models in Business and Industry*, *23*(2), 129-143.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637-654.

Boekhorst, P. (2018). *Bankruptcy prediction for Dutch private firms using the Altman Z-score model*. (Unpublished master's thesis). University of Twente, Enschede, Netherlands.

Boot, A. W. A., & Ligterink, J. E. (2000). Faillissementswetgeving in internationaal perspectief. *MAB*, *74*(11), 492-499.

Brouwer, M. (2006). Reorganization in US and European bankruptcy law. *European Journal of Law and Economics*, *22*(1), 5-20.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance*, *63*(6), 2899-2939.

Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: empirical evidence for the UK. *European Accounting Review*, *13*(3), 465-497.

Chava, S., & Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, *8*(4), 537-569.

Collins, R. A., & Green, R. D. (1982). Statistical methods for bankruptcy forecasting. *Journal of Economics and Business*, *34*(4), 349-354.

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

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

Couwenberg, O., & Lubben, S. J. (2011). The costs of chapter 11 on context: American and Dutch business bankruptcy. *American Bankruptcy Law Journal*, *85*(1), 63-89.

Cultrera, L., & Brédart, X. (2016). Bankruptcy prediction: the case of Belgian SMEs. *Review of Accounting and Finance*, *15*(1), 101-119.

Demyanyk, Y., & Hasan, I. (2010). Financial crises and bank failures: A review of prediction methods. *Omega*, *38*(5), 315-324.

Dewaelheyns, N., & Van Hulle, C. (2008). Legal reform and aggregate small and micro business bankruptcy rates: evidence from the 1997 Belgian bankruptcy code. *Small Business Economics*, *31*(4), 409.

Dimitras, A. I., Zanakis, S. H., Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research*, *90*(3), 487-513.

Doumpos, M., & Zopounidis, C. (1999). A multicriteria discrimination method for the prediction of financial distress: The case of Greece. *Multinational Finance Journal*, *3*(2), 71-101.

du Jardin, P. (2017). Dynamics of firm financial evolution and bankruptcy prediction. *Expert Systems with Applications*, *75*, 25-43.

Elferink, N. (2018). *Financial distress prediction in the Netherlands: an application of multiple discriminant analysis, logistic regression and neural network*. (Unpublished master's thesis). University of Twente, Enschede, Netherlands.

Engelmann, B., Hayden, E., & Tasche, D. (2003). Testing rating accuracy. *Risk*, *16*(1), 82-86.

Fejér-Király, G. (2015). Bankruptcy prediction: A survey on evolution, critiques, and solutions. *Acta Universitatis Sapientiae, Economics and Business*, *3*(1), 93-108.

Filipe, S. F., Grammatikos, T., & Michala, D. (2016). Forecasting distress in European SME portfolios. *Journal of Banking & Finance*, *64*, 112-135.

Fleming, M. J., & Moon, J. J. (1995). Preserving firm value through exit: the case of voluntary liquidations. *FRB of New York Staff Report*, *8*.

Garškiene, A., & Garškaite, K. (2004). Enterprise bankruptcy in Lithuania. *Journal of Business Economics and Management*, *5*(1), 51-58.

Ghosh, C., Owers, J. E., & Rogers, R. C. (1991). The financial characteristics associated with voluntary liquidations. *Journal of Business Finance & Accounting*, *18*(6), 773-789.

Giacosa, E., Halili, E., Mazzoleni, A., Teodori, C., & Veneziani, M. (2016). Re-estimation of company insolvency prediction models: Survey on Italian manufacturing companies. *Corporate Ownership and Control*, *14*(1), 159-174.

Gilbert, L. R., Menon, K., & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business Finance & Accounting*, *17*(1), 161-171.

Gilson, S. C., John, K., & Lang, L. H. (1990). Troubled debt restructurings: An empirical study of private reorganization of firms in default. *Journal of Financial Economics*, *27*(2), 315-353.

Grice Jr, J. S., & Dugan, M. T. (2003). Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. *Advances in Accounting*, *20*, 77-93.

Grice, J. S., & Dugan, M. T. (2001). The limitations of bankruptcy prediction models: some cautions for the researcher. *Review of Quantitative Finance and Accounting, 17*(2), 151-166.

Grice, J. S., & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research*, *54*(1), 53-6.

Gupta, J., Gregoriou, A., & Healy, J. (2015). Forecasting bankruptcy for SMEs using hazard function: To what extend does size matter? *Review of Quantitative Finance and Accounting*, *45*(4), 845-869.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (Vol. 7). Upper Saddle River, NJ: Pearson Prentice Hall.

Hall, G. (1992). Reasons for insolvency amongst small firms – a review and fresh evidence. *Small Business Economics*, *4*(3), 237-250.

Hanley, J. A., & McNeil, B. J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*, *143*(1), 29-36.

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

Hummelen, J. M. (2015). Shaping bankruptcy law: what form should it take? *Norton Journal of Bankruptcy Law and Practice*, *24*(1), 52-88.

Jackson, T. H. (1982). Bankruptcy, non-bankruptcy entitlements, and the creditors' bargain. *The Yale Law Journal*, *91*(5), 857-907.

Jones, S., & Wang, T. (2019). Predicting private company failure: A multi-class analysis. *Journal of International Financial Markets, Institutions and Money*, *61*, 161-188.

Kahya, E., & Theodossiou, P. (1999). Predicting corporate financial distress: A time-series CUSUM methodology. *Review of Quantitative Finance and Accounting*, *13*(4), 323-345.

Karamzadeh, M. S. (2013). Application and comparison of Altman and Ohlson models to predict bankruptcy of companies. *Research Journal of Applied Sciences, Engineering and Technology*, *5*(6), 2007-2011.

Karas, M., & Režňáková, M. (2014). To what degree is the accuracy of a bankruptcy prediction model affected by the environment? The case of the Baltic States and the Czech Republic. *Procedia-Social and Behavioral Sciences*, *156*, 564-568.

Karels, G. V., & Prakash, A. J. (1987). Multivariate normality and forecasting of business bankruptcy. *Journal of Business Finance & Accounting*, *14*(4), 573-593.

Kisman, Z., & Krisandi, D. (2019). How to predict financial distress in the wholesale sector: lesson from Indonesion Stock Exchange. *Journal of Economics and Business*, *2*(3), 569-585.

Koh, H. C., & Killough, L. N. (1990). The use of multiple discriminant analysis in the assessment of the going-concern status of an audit client. *Journal of Business Finance & Accounting*, *17*(2), 179-192.

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

Lang, L. H., & Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics*, *32*(1), 45-60.

Lee, S., & Choi, W. S. (2013). A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. *Expert Systems with Applications*, *40*(8), 2941-2946.

Li, D. D., & Li, S. (1999). An agency theory of the bankruptcy law. *International Review of Economics & Finance*, *8*(1), 1-24.

Liang, D., Lu, C. C., Tsai, C. F., & Shih, G. A. (2016). Financial ratios and corporate governance indicators in bankruptcy prediction: a comprehensive study. *European Journal of Operational Research*, *252*(2), 561-572.

Looney, S. W. (1995). How to use tests for univariate normality to assess multivariate normality. *The American Statistician*, *49*(1), 64-70.

Lukason, O., & Hoffman, R. C. (2014). Firm bankruptcy probability and causes: an integrated study. *International Journal of Business and Management*, *9*(11), 80-91.

Machielsen, B. (2015). *The accuracy and information content of two traditional statistical methods in forecasting bankruptcy: evidence from European countries*. (Unpublished master's thesis). University of Twente, Enschede, Netherlands.

Mellahi, K., & Wilkinson, A. (2004). Organizational failure: a critique of recent research and a proposed integrative framework. *International Journal of Management Reviews*, *5*(1), 21-41.

Mensah, Y. M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: A methodological study. *Journal of Accounting Research*, 380-395.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449-470.

Mihalovic, M. (2016). Performance comparison of multiple discriminant analysis and logit models in bankruptcy prediction. *Economics & Sociology*, *9*(4), 101-118.

Morris, R. (1997). *Early warning indicators of corporate failure: A critical review of previous research and further empirical evidence*. Brookfield, United States of America: Ashgate Publishing Ltd.

Moyer, R. C. (1977). Forecasting financial failure: a re-examination. *Financial Management (pre-1986), 6*(1), 11-17.

Nyitrai, T., & Virág, M. (2019). The effects of handling outliers on the performance of bankruptcy prediction models. *Socio-Economic Planning Sciences, 67*, 34-42.

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

Ooghe, H., & Waeyaert, N. (2004). Oorzaken van faling: literatuuroverzicht en conceptueel verklaringsmodel. *Economisch en Sociaal Tijdschrift*, *57*(4), 367-393.

Ooghe, H., & De Prijcker, S. (2008). Failure processes and causes of company bankruptcy: a typology. *Management Decision*, *46*(2), 223-242.

Paul, R. K. (2006). Multicollinearity: causes, effects and remedies. *IASRI*, *New Delhi*, 58-65.

Philosophov, L. V., Batten, J. A., & Philosophov, V. L. (2005). Assessing the time horizon of bankruptcy using financial ratios and the maturity schedule of long-term debt. *Proceedings of the European Finance Association 32nd Annual Meeting*, 1-39.

Platt, H. D., & Platt, M. B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance & Accounting*, *17*(1), 31-51.

Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of Economics and Finance*, *26*(2), 184-199.

Pompe, P. P., & Bilderbeek, J. (2005). Bankruptcy prediction: The influence of the year prior to failure selected for model building and the effects in a period of economic decline. *Intelligent Systems in Accounting, Finance & Management: International Journal, 13*(2), 95-112.

Reisz, A. S., & Perlich, C. (2007). A market-based framework for bankruptcy prediction. *Journal of Financial Stability, 3*(2), 85-131.

Shin, K. S., Lee, T. S., & Kim, H. J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications*, *28*(1), 127-135.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, *74*(1), 101-124.

Siddiqui, S. A. (2012). Business bankruptcy prediction models: A significant study of the Altman's Z-score model. *Available at SSRN 2128475*.

Singh, B. P., & Mishra, A. K. (2016). Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies. *Financial Innovation*, *2*(1), 6.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review*, 289-315.

Son, H., Hyun, C., Phan, D., & Hwang, H. J. (2019). Data analytic approach for bankruptcy prediction. *Expert Systems with Applications*, *138*, 112816.

Statbel. (2020, April 22). Maart 2020: 869 faillissementen. Retrieved from: https://statbel.fgov.be/nl/themas/ondernemingen/faillissementen#figures

Statistics Netherlands. (2019, June 12). *Fewer bankruptcies in May*. Retrieved from: https://www.cbs.nl/en-gb/news/2019/24/fewer-bankruptcies-in-may

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394-419.

Trujillo-Ponce, A., Samaniego-Medina, R., & Cardone-Riportella, C. (2014). Examining what best explains corporate credit risk: accounting-based versus market-based models. *Journal of Business and Economics and Management*, *15*(2), 253-276.

White, M. J. (1989). The corporate bankruptcy decision. *Journal of Economic Perspectives*, *3*(2), 129-151.

Wood, D., & Piesse, J. (1987). The information value of MDA based financial indicators. *Journal of Business Finance & Accounting*, *14*(1), 27-38.

Wruck, K. H. (1990). Financial distress, reorganization, and organization efficiency. *Journal of Financial Economics*, *27*(2), 419-444.

Wu, W. W. (2010). Beyond business failure prediction. *Expert systems with applications*, *37*(3), 2371-2376.

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

Yap, B. C. F., Yong, D. G. F., & Poon, W. C. (2010). How well do financial ratios and multiple discriminant analysis predict company failures in Malaysia. *International Research Journal of Finance and Economics*, *54*(13), 166-175.

Zhang, G., Hu, M. Y., Patuwo, B. E., & Indro, D. C. (1999). Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research*, *116*(1), 16-32.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research, 22*, 59-82.

Appendices

Appendix A: Financial ratios of the bankruptcy prediction models

Table 16 Financial ratios bankruptcy prediction models

Model	**Financial ratios**	**Variable**	**Ratio classification**
Altman (1983)	x_1 = Working capital/Total assets	WC/TA	Liquidity
	x_2 = Retained earnings/Total assets	RE/TA	Leverage
	x_3 = Earnings before interest and taxes/Total assets	EBIT/TA	Profitability
	x_4 = Book value equity/Book value of total debt	BVEQ/BVTD	Solvency
	x_5 = Sales/Total assets	SALES/TA	Activity
Ohlson (1980)	x_1 = log (Total assets/GNP price-level index)	SIZE	Size
	x_2 = Total liabilities/Total assets	TL/TA	Leverage
	x_3 = Working capital/Total assets	WC/TA	Liquidity
	x_4 = Current liabilities/Current assets	CL/CA	Liquidity
	x_5 = 1 if total liabilities > total assets, 0 otherwise	OENEG	Leverage
	x_6 = Net income/Total assets	NI/TA	Profitability
	x_7 = Funds provided by operations/Total liabilities	FU/TL	Liquidity
	x_8 = 1 if net income was negative for the last two years, 0 otherwise	INTWO	Liquidity
	$x_9 = (NI_t – NI_{t-1}) / (\lvert NI_t\rvert + \lvert NI_{t-1}\rvert)$, where NI_t is net income for the most recent period	CHNI	Profitability
Zmijewski (1984)	x_1 = Net income/Total assets	NI/TA	Profitability
	x_2 = Total debt/Total assets	TD/TA	Solvency/leverage
	x_3 = Current assets/Current liabilities	CA/CL	Liquidity

Appendix B: List of bankrupt firms in sample

Table 17 Bankrupt firms in samples

Company name	Type	Industry	Country	Year
1st Belgium Service	Private	Administrative and support service activities	Belgium	2012
A.T.M.	Public	Manufacturing	Belgium	2010
Abs Distribution	Public	Wholesale and retail trade	Belgium	2012
Adriana Benelux	Private	Wholesale and retail trade	Belgium	2008
Agro Technics	Public	Wholesale and retail trade	Belgium	2016
Aktiesport B.V.	Private	Wholesale and retail trade	Netherlands	2016
Alfacam	Public	Art, entertainment and recreation	Belgium	2013
Algemene Aannemingen Merckx	Public	Construction	Belgium	2008
Algemene Bouwonderneming Frans Willems	Public	Construction	Belgium	2019
Algrondbo	Private	Construction	Belgium	2013
Alpha Technologies	Public	Professional, scientific and technical activities	Belgium	2017
Aluminium Delfzijl B.V.	Private	Manufacturing	Netherlands	2013
Antwerp Ship Repair	Public	Manufacturing	Belgium	2013
Apollo Fruit B.V.	Private	Wholesale and retail trade	Netherlands	2012
Arend-Sosef B.V.	Private	Wholesale and retail trade	Netherlands	2014
Aristophil	Public	Art, entertainment and recreation	Belgium	2014
Arlex International	Public	Wholesale and retail trade	Belgium	2014
Asap Maintenance & Shipping	Private	Wholesale and retail trade	Belgium	2014
ATMR & E	Public	Manufacturing	Belgium	2015
Autos	Public	Wholesale and retail trade	Belgium	2010
Belgo Metal	Public	Manufacturing	Belgium	2015
Belucon	Public	Wholesale and retail trade	Belgium	2014
Bernard Langeraet	Private	Wholesale and retail trade	Belgium	2016
Best Medical Belgium S.A.	Public	Manufacturing	Belgium	2012
Bfan	Public	Manufacturing	Belgium	2013
Big Fish	Private	Wholesale and retail trade	Belgium	2019
Bmtech	Public	Manufacturing	Belgium	2012
Bois et Materiaux de Construction	Public	Wholesale and retail trade	Belgium	2015
Bonustijd	Private	Transportation and storage	Belgium	2013
Bosal Benelux	Public	Manufacturing	Belgium	2015
Bouwbedrijf Loix	Public	Construction	Belgium	2018
Bouwcentrale Modern	Public	Construction	Belgium	2016
Buro Immo	Private	Construction	Belgium	2014
Casterman Printing	Public	Manufacturing	Belgium	2016
Casters Algemene Ondernemingen	Public	Construction	Belgium	2018
Cegeac	Public	Wholesale and retail trade	Belgium	2014
Centratec	Public	Wholesale and retail trade	Belgium	2017
Charles Vogele (Netherlands) B.V.	Private	Wholesale and retail trade	Netherlands	2017
Chateau – Caravans	Public	Manufacturing	Belgium	2007

Cib Incentives	Public	Administrative and support service activities	Belgium	2007
Cipla Europe	Public	Wholesale and retail trade	Belgium	2018
Construction Tour et Finition	Private	Construction	Belgium	2015
Cool Cat Nederland B.V.	Private	Real estate activities	Netherlands	2019
Corsan	Public	Information and communication	Belgium	2016
De Boever's Brandstoffen	Public	Wholesale and retail trade	Belgium	2007
Dejaeghere-Spinning Mills	Public	Manufacturing	Belgium	2007
DH-Group	Public	Wholesale and retail trade	Belgium	2016
Domotech	Private	Construction	Belgium	2016
Domotherm	Public	Wholesale and retail trade	Belgium	2016
Dorleska Diamonds	Public	Wholesale and retail trade	Belgium	2007
Draka Polymer Films B.V.	Private	Manufacturing	Netherlands	2019
Duro Home	Public	Construction	Belgium	2013
Durobor	Public	Manufacturing	Belgium	2012
Durobor Group	Public	Manufacturing	Belgium	2017
Dwbel	Private	Manufacturing	Belgium	2015
Eagle Construct	Public	Manufacturing	Belgium	2015
ECS Technics	Public	Construction	Belgium	2012
EKB Container Logistic Group Belgium	Public	Transportation and storage	Belgium	2013
Electrawinds	Public	Professional, scientific and technical activities	Belgium	2019
Elgeka	Private	Construction	Belgium	2017
Erudict	Public	Information and communication	Belgium	2009
Etablissements Lequet et Herkenne	Public	Wholesale and retail trade	Belgium	2015
Euroferco	Public	Wholesale and retail trade	Belgium	2012
Euro-Med 2005	Private	Wholesale and retail trade	Belgium	2008
Europem	Public	Professional, scientific and technical activities	Belgium	2019
Eurotube Industries	Public	Manufacturing	Belgium	2015
Exelco Sourcing	Private	Wholesale and retail trade	Belgium	2018
Facility Services	Private	Administrative and support service activities	Belgium	2014
Ferryways	Public	Transportation and storage	Belgium	2008
Firestar Diamond	Private	Wholesale and retail trade	Belgium	2018
First Line Telecom	Public	Information and communication	Belgium	2009
Fishco	Private	Wholesale and retail trade	Belgium	2018
FL Sport B.V.	Private	Wholesale and retail trade	Netherlands	2016
Flash Travel	Public	Administrative and support service activities	Belgium	2012
Fleks Kinderopvangorganisatie B.V.	Private	Human health and social work activities	Netherlands	2013
Fontijne Grotnes B.V.	Private	Manufacturing	Netherlands	2016
Free Record Shop Belgium	Public	Wholesale and retail trade	Belgium	2013
G & G International	Public	Manufacturing	Belgium	2015
Gacssolutions	Public	Manufacturing	Belgium	2012
Garage Regniers	Public	Wholesale and retail trade	Belgium	2015
Garage Vanderkeilen	Private	Wholesale and retail trade	Belgium	2014

Garpet	Public	Professional, scientific and technical activities	Belgium	2016
Gateway	Public	Information and communication	Belgium	2016
GDB International	Public	Wholesale and retail trade	Belgium	2012
Gebroeders de Waele	Public	Construction	Belgium	2015
Geens	Public	Wholesale and retail trade	Belgium	2007
Geens Benelux	Public	Wholesale and retail trade	Belgium	2007
Gevalo	Public	Manufacturing	Belgium	2013
Gibson Innovations Netherlands B.V.	Private	Manufacturing	Netherlands	2018
Gilleman Textiles	Public	Wholesale and retail trade	Belgium	2016
Giraud Belgie	Public	Transportation and storage	Belgium	2010
Goemaere	Public	Wholesale and retail trade	Belgium	2015
Goes International Transport B.V.	Private	Transportation and storage	Netherlands	2014
Grandeco Wallfashion Group	Public	Manufacturing	Belgium	2013
Grondinvest	Public	Construction	Belgium	2017
Hacherelle	Public	Wholesale and retail trade	Belgium	2018
Harry Verbinnen	Private	Manufacturing	Belgium	2013
Helio Charleroi	Public	Manufacturing	Belgium	2019
Hoebeek	Public	Wholesale and retail trade	Belgium	2017
Ideal-Services	Private	Human health and social work activities	Belgium	2014
Idem Papers – Idempapers	Public	Manufacturing	Belgium	2017
Inalco	Public	Manufacturing	Belgium	2016
Innoconcepts N.V.	Public	Administrative and support service activities	Netherlands	2010
Internationaal Transport & Logistiek Europe	Public	Transportation and storage	Belgium	2012
International Russian Import and Lease	Public	Wholesale and retail trade	Belgium	2012
Jory	Public	Professional, scientific and technical activities	Belgium	2013
Jurriens West B.V.	Private	Construction	Netherlands	2016
K. Vijay	Private	Wholesale and retail trade	Belgium	2017
Karlie Flamingo	Public	Wholesale and retail trade	Belgium	2016
Kesar	Public	Wholesale and retail trade	Belgium	2012
Koster Metalen B.V.	Private	Construction	Netherlands	2015
Koxka Belgium	Public	Manufacturing	Belgium	2015
Kroonservice Logistics	Public	Transportation and storage	Belgium	2013
L.C.M.C.	Public	Manufacturing	Belgium	2014
LBG Bakeries	Public	Professional, scientific and technical activities	Belgium	2015
Liefmans Breweries	Public	Manufacturing	Belgium	2007
Link2biz International Verkort Link2Biz	Public	Transportation and storage	Belgium	2010
Lintor	Public	Manufacturing	Belgium	2013
Liza Dimon	Private	Wholesale and retail trade	Belgium	2013
Macintosh Retail Group N.V.	Public	Wholesale and retail trade	Netherlands	2015
Marconi Oranje B.V.	Private	Construction	Netherlands	2016

Mare Tours	Public	Administrative and support service activities	Belgium	2018
Marval Gems	Private	Wholesale and retail trade	Belgium	2010
McGregor Retail Belgium	Public	Wholesale and retail trade	Belgium	2017
Meister Coordination Center	Public	Manufacturing	Belgium	2014
Memory Corp	Public	Information and communication	Belgium	2007
Metaal Constructies Couwenberg en Schellens	Public	Manufacturing	Belgium	2019
Mexx Belgium	Public	Wholesale and retail trade	Belgium	2014
Mitra Energy & Infrastructure	Public	Manufacturing	Belgium	2010
Mitro	Public	Construction	Belgium	2018
Momitube	Public	Manufacturing	Belgium	2015
Montagny B.V.	Private	Real estate activities	Netherlands	2019
Mooy Logistics B.V.	Private	Transportation and storage	Netherlands	2018
Myliti	Public	Wholesale and retail trade	Belgium	2017
Nedfield N.V.	Public	Manufacturing	Netherlands	2009
Nelca	Public	Manufacturing	Belgium	2007
Neochim	Public	Manufacturing	Belgium	2012
Niche Trading	Public	Wholesale and retail trade	Belgium	2019
Nordvries	Private	Wholesale and retail trade	Belgium	2019
O.W. Bunker (Belgium)	Public	Wholesale and retail trade	Belgium	2014
O.W. Bunker (Netherlands) B.V.	Private	Wholesale and retail trade	Netherlands	2014
Oceanwide	Private	Wholesale and retail trade	Belgium	2018
Ondernemingen Arthur Moens – Entreprises Arthur Moens	Public	Construction	Belgium	2008
OXL	Public	Transportation and storage	Belgium	2015
Packing Creative Systems	Public	Manufacturing	Belgium	2012
Parallel Groep ETB Vos B.V.	Private	Construction	Netherlands	2015
Paulus Henri en Zonen	Public	Wholesale and retail trade	Belgium	2007
PDC B.V.	Private	Wholesale and retail trade	Netherlands	2016
Phanos Westwijk B.V.	Private	Construction	Netherlands	2012
Photo Hall Multimedia	Public	Wholesale and retail trade	Belgium	2012
Plastruco Technics	Public	Manufacturing	Belgium	2012
Poets & Strijkhuisje	Private	Administrative and support service activities	Belgium	2017
Polygone International S.A.	Public	Manufacturing	Belgium	2012
Potato Masters	Public	Wholesale and retail trade	Belgium	2014
Pouw Automotive B.V.	Private	Wholesale and retail trade	Netherlands	2014
Prime Champ Materials B.V.	Private	Wholesale and retail trade	Netherlands	2013
Prime Champ Packaging B.V.	Private	Administrative and support service activities	Netherlands	2013
Prime Champ Production B.V.	Private	Agriculture, forestry and fishing	Netherlands	2013
Prime Champ Sales B.V.	Private	Wholesale and retail trade	Netherlands	2013
Primo-Stadion	Public	Wholesale and retail trade	Belgium	2016

Print and Display	Public	Professional, scientific and technical activities	Belgium	2012
Prodac	Public	Wholesale and retail trade	Belgium	2012
Proficos	Public	Manufacturing	Belgium	2015
Provad	Public	Wholesale and retail trade	Belgium	2014
Quintens Bakeries Morlanwelz	Public	Manufacturing	Belgium	2015
R. en F. Folding Boxes	Public	Manufacturing	Belgium	2008
Raamfabriek Vlieghe	Public	Manufacturing	Belgium	2016
Raben Belgium	Private	Transportation and storage	Belgium	2007
Racking Storage	Public	Manufacturing	Belgium	2008
Reef Hout B.V.	Private	Manufacturing	Netherlands	2012
Refining & Trading Holland N.V.	Public	Water supply	Netherlands	2015
Reklameadviesbureau Indus	Public	Professional, scientific and technical activities	Belgium	2009
Retrain	Public	Administrative and support service activities	Belgium	2014
Royal Imtech N.V.	Public	Construction	Netherlands	2015
RSB Transmissions Belgium	Public	Manufacturing	Belgium	2014
Ruby Belgium	Public	Professional, scientific and technical activities	Belgium	2016
Safetic	Public	Administrative and support service activities	Belgium	2012
SC Retail	Public	Wholesale and retail trade	Belgium	2015
Service Innovation Group Belgium	Public	Professional, scientific and technical activities	Belgium	2014
Signature Vermeulen	Public	Construction	Belgium	2014
Sikan	Public	Wholesale and retail trade	Belgium	2009
Sinomet Recycling	Public	Water supply	Belgium	2009
Sisyphus	Public	Professional, scientific and technical activities	Belgium	2017
SL Services B.V.	Private	Wholesale and retail trade	Netherlands	2016
Slavenburg B.V.	Private	Construction	Netherlands	2013
SLC	Public	Wholesale and retail trade	Belgium	2019
Sleurs Energy	Public	Manufacturing	Belgium	2012
Sobelmar Shipping	Public	Transportation and storage	Belgium	2016
Societe Mediterraneenne de Participations	Public	Professional, scientific and technical activities	Belgium	2010
Solfruit International B.V.	Private	Wholesale and retail trade	Netherlands	2012
Sowaco	Public	Construction	Belgium	2012
Spidiam	Private	Wholesale and retail trade	Belgium	2010
Squatra	Private	Administrative and support service activities	Belgium	2014
Starman Bruxelles Hotel	Private	Accommodation and food service activities	Belgium	2014
Star-Oil	Private	Professional, scientific and technical activities	Belgium	2009
Steverlynck Group	Public	Manufacturing	Belgium	2007
Strongbow Hvac	Private	Construction	Belgium	2017
Sunswitch	Public	Construction	Belgium	2014

T. Palm – Elbo	Public	Construction	Belgium	2018
Taylormail Belgique	Public	Information and communication	Belgium	2018
TDS	Public	Manufacturing	Belgium	2015
Tec Servicegroup	Public	Professional, scientific and technical activities	Belgium	2012
Teidem B.V.	Private	Wholesale and retail trade	Netherlands	2016
Thieme Mediacenter Rotterdam B.V.	Private	Professional, scientific and technical activities	Netherlands	2010
Thieme Rotatie Zwolle B.V.	Private	Manufacturing	Netherlands	2010
Thomas Cook Belgium	Public	Administrative and support service activities	Belgium	2019
THR B.V.	Private	Wholesale and retail trade	Netherlands	2019
Tissage de Kalken	Public	Wholesale and retail trade	Belgium	2016
Topcom Europe	Public	Wholesale and retail trade	Belgium	2012
Trading, Maintenance et Services	Public	Professional, scientific and technical activities	Belgium	2010
Trinity Group B.V.	Private	Wholesale and retail trade	Netherlands	2015
Triple S	Public	Manufacturing	Belgium	2019
V & R Electrics Solar Company	Private	Construction	Belgium	2013
Valdunes Belux	Public	Manufacturing	Belgium	2014
Vanhaverbeke Automotive	Private	Wholesale and retail trade	Belgium	2010
Veehandel R. van Calster	Private	Wholesale and retail trade	Belgium	2010
Verlihold	Public	Professional, scientific and technical activities	Belgium	2013
Verona	Public	Construction	Belgium	2018
Video Square	Private	Wholesale and retail trade	Belgium	2009
Viva Services	Private	Wholesale and retail trade	Belgium	2015
Waste Oil Services	Public	Water supply	Belgium	2016
Wegenbouw Huijbregts	Private	Construction	Belgium	2013
Westcoast	Public	Wholesale and retail trade	Belgium	2013
Wetenschappelijke Boekhandel J. Story – Scientia	Public	Information and communication	Belgium	2014
Win System	Public	Manufacturing	Belgium	2014
Windeo Green Futur Benelux	Public	Manufacturing	Belgium	2014

Appendix C: Testing model assumptions

C.I Multivariate normality

Multivariate normality is an assumption for the MDA method. This assumption is tested using the Shapiro-Wilks test, where the null hypothesis is that the data are normally distributed. Table 18 shows the results of the Shapiro-Wilks test, where panel A presents the results for the Altman (1983) variables, panel B for the Ohlson (1980) variables, and panel C for the Zmijewski (1984) variables. For Altman's model (1983) the results are presented for all three estimation samples, and for Ohlson's model (1980) and Zmijewski's model (1984) only the results for the estimation sample 2012 – 2015 (t-1) are presented. All p-values are statistically significant at the 1% level, meaning that for all financial ratios for all three models in all samples the null hypothesis that the data are normally distributed can be rejected and that this assumption is violated.

Table 18 Shapiro-Wilks test

Panel A: Model of Altman (1983)				
Financial ratio	**Status**	**Shapiro-Wilk** 2007 – 2010 (t-1)	**Shapiro-Wilk** 2012 – 2015 (t-1)	**Shapiro-Wilk** 2012 – 2015 (t-2)
WC/TA	Bankrupt	0.893***	0.920***	0.966***
		(0.001)	(0.000)	(0.005)
	Non-bankrupt	0.974***	0.979***	0.979***
		(0.000)	(0.000)	(0.000)
RE/TA	Bankrupt	0.720***	0.869***	0.855***
		(0.000)	(0.000)	(0.000)
	Non-bankrupt	0.976***	0.977***	0.976***
		(0.000)	(0.000)	(0.000)
EBIT/TA	Bankrupt	0.758***	0.862***	0.876***
		(0.000)	(0.000)	(0.000)
	Non-bankrupt	0.935***	0.935***	0.926***
		(0.000)	(0.000)	(0.000)
BVEQ/BVTD	Bankrupt	0.948*	0.930***	0.853***
		(0.056)	(0.000)	(0.000)
	Non-bankrupt	0.740***	0.695***	0.732***
		(0.000)	(0.000)	(0.000)
SALES/TA	Bankrupt	0.927***	0.819***	0.841***
		(0.010)	(0.000)	(0.000)
	Non-bankrupt	0.922***	0.904***	0.903***
		(0.000)	(0.000)	(0.000)

Note: Statistical significance indicated in parentheses.
***<1%
**<5%
*<10%

Panel B: Model of Ohlson (1980)		
		Shapiro-Wilk
		2012 – 2015 (t-1)
SIZE	Bankrupt	0.976**
		(0.043)
	Non-bankrupt	0.960***
		(0.000)
TL/TA	Bankrupt	0.856***
		(0.000)
	Non-bankrupt	0.959***
		(0.000)
WC/TA	Bankrupt	0.920***
		(0.000)
	Non-bankrupt	0.979***
		(0.000)
CL/CA	Bankrupt	0.802***
		(0.000)
	Non-bankrupt	0.864***
		(0.000)
OENEG	Bankrupt	0.596***
		(0.000)
	Non-bankrupt	0.215***
		(0.000)
NI/TA	Bankrupt	0.864***
		(0.000)
	Non-bankrupt	0.946***
		(0.000)
FU/TL	Bankrupt	0.941***
		(0.000)
	Non-bankrupt	0.836***
		(0.000)
INTWO	Bankrupt	0.636***
		(0.000)
	Non-bankrupt	0.354***
		(0.000)
CHNI	Bankrupt	0.904***
		(0.000)
	Non-bankrupt	0.955***
		(0.000)

Note: Statistical significance indicated in parentheses.
***<1%
**<5%
*<10%

Panel C: Model of Zmijewski (1984)		
		Shapiro-Wilk
		2012 – 2015 (t-1)
NI/TA	Bankrupt	0.864***
		(0.000)
	Non-bankrupt	0.946***
		(0.000)
TD/TA	Bankrupt	0.856***
		(0.000)
	Non-bankrupt	0.959***
		(0.000)
CA/CL	Bankrupt	0.945***
		(0.000)
	Non-bankrupt	0.773***
		(0.000)

Note: Statistical significance indicated in parentheses.
***<1%
**<5%
*<10%

C.II Equality of variance-covariance

Equality of variance-covariance is an assumption for the MDA method. This assumption is tested using the Box's M test, where the null hypothesis assumes that the observed variance-covariance matrices for the dependent variables are equal across groups. Table 19 presents the results of the Box's M test for all three models. Again, as in the multivariate normality test, for Altman's model (1983) the results are presented for all three estimation samples, and for Ohlson's model (1980) and Zmijewski's model (1984) only the results for the estimation sample 2012 – 2015 (t-1) are presented. The p-values of the three models are all statistically significant at the 1% level, meaning that for all three models the null hypothesis of equal variance-covariance matrices can be rejected and that this assumption is violated.

Table 19 Box's M test

	Box's M 2007 – 2010 (t-1)	**Box's M** 2012 – 2015 (t-1)	**Box's M** 2012 – 2015 (t-2)
Altman (1983)	215.404***	725.521***	325.788***
(MDA)	(0.000)	(0.000)	(0.000)
Ohlson (1980)		1185.351***	
(MDA)		(0.000)	
Zmijewski (1984)		570.007***	
(MDA)		(0.000)	

Note: Statistical significance indicated in parentheses.
***<1%
**<5%
*<10%

C.III Multicollinearity

Absence of multicollinearity is an assumption for the MDA, logit and probit method. This assumption is tested with the VIF-statistic. VIF-statistics exceeding 10 indicates that the data are not absent of multicollinearity. Table 20 shows the VIF-statistics of all financial ratios in all three estimation samples, where panel A presents the model of Altman (1983), panel B the model of Ohlson (1980), and panel C the model of Zmijewski (1984). All VIF-statistics are below 10, indicating that the data are absent of multicollinearity and that this assumption is met.

Table 20 VIF-statistic

Panel A: Model of Altman (1983)			
Financial ratio	**VIF** 2007 – 2010 (t-1)	**VIF** 2012 – 2015 (t-1)	**VIF** 2012 – 2015 (t-2)
WC/TA	1.640	1.674	1.505
RE/TA	2.511	2.514	2.246
EBIT/TA	1.414	1.456	1.330
BVEQ/BVTD	1.897	1.686	1.901
SALES/TA	1.124	1.128	1.161
Panel B: Model of Ohlson (1980)			
SIZE	1.122	1.111	1.095
TL/TA	2.477	2.310	1.957
WC/TA	7.036	5.402	5.255
CL/CA	6.634	4.716	4.699
OENEG	1.669	1.593	1.543
NI/TA	3.431	2.865	3.581
FU/TL	2.518	2.307	2.983
INTWO	1.348	1.428	1.510
CHNI	1.205	1.193	1.194
Panel C: Model of Zmijewski (1984)			
NI/TA	1.460	1.292	1.223
TD/TA	2.183	1.834	1.726
CA/CL	1.623	1.512	1.484

Appendix D: Goodness of fit measures

For the three econometric methods used in this master thesis, MDA, logit regression, and probit regression, the goodness of fit will be reported in the following appendices below the estimated coefficients of the models. For MDA the Eigenvalue and Wilks' lambda statistics will be reported. The Eigenvalue represents the amount of variance accounted for by a factor, the higher the Eigenvalue the better the model can differentiate between groups. Wilks' lambda tests the overall significance between groups and measures how well the model separates cases into groups. A statistically significant Wilks' lambda statistic indicates that there is a relationship between the dependent groups and the independent variables (Hair et al., 2010).

For logit regression, the -2 Log likelihood (-2LL), Cox and Snell R^2, and Hosmer-Lemeshow statistics will be reported. The -2LL statistic shows how well the maximum likelihood estimation procedure fits. The minimum value for -2LL is 0, which corresponds to a perfect fit. A lower -2LL value indicates a better fit of the model. The Hosmer and Lemeshow test provides a comprehensive measure of predictive accuracy that is not based on the likelihood value, but rather on the actual prediction of the dependent variable. A smaller difference in the observed and predicted classification indicates better model fit. If the Hosmer and Lemeshow test statistic is statistically significant, it means that there is a significant difference between the expected values and the data and that the model is not well calibrated. Cox and Snell R^2 is based on the log likelihood for the model compared to the log likelihood for a baseline model. Higher values of the Cox and Snell R^2 statistic indicates greater model fit. This measure is limited in that it cannot reach the maximum value of 1 (Hair et al., 2010).

For probit regression, the Log likelihood statistic will be reported. The Log likelihood statistic measures the goodness of fit of the models estimated by probit regression. The value can lie between negative infinity and positive infinity, and the higher the value, the better is the model.

Appendix E: Coefficients of the models

E.I Estimation sample 2012 – 2015 (t-1)

Table 21 shows the coefficients of the models used in hypothesis 1, 2, 3, and 4, obtained from the estimation sample 2012 – 2015 with data from one fiscal year before bankruptcy. For these hypotheses, the models are estimated by their original econometric method.

Table 21 Coefficients of the models with sample 2012 – 2015 (t-1)

Altman		**Ohlson**		**Zmijewski**	
MDA		Logit regression		Probit regression	
Intercept	-0.283	Intercept	-2.180	Intercept	-2.279***
			(0.108)		(0.000)
WC/TA	0.917	SIZE	-1.329***	NI/TA	-7.043***
			(0.000)		(0.000)
RE/TA	1.197	TL/TA	3.163***	TD/TA	1.551***
			(0.000)		(0.000)
EBIT/TA	6.105	WC/TA	-3.103**	CA/CL	-0.197**
			(0.021)		(0.049)
BVEQ/BVTD	-0.069	CL/CA	-0.812		
			(0.164)		
SALES/TA	-0.229	OENEG	1.446***		
			(0.002)		
		NI/TA	-15.032***		
			(0.000)		
		FU/TL	-0.506		
			(0.791)		
		INTWO	0.031		
			(0.928)		
		CHNI	0.212		
			(0.365)		
N	1243	N	1243	N	1243
Eigenvalue	0.398	-2 Log likelihood	409.974	Log likelihood	-226.880
Wilks' lambda	0.715***	Cox and Snell R^2	0.244		
	(0.000)	Nagelkerke R^2	0.534		
		Hosmer-Lemeshow	13.484*		
			(0.096)		

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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Table 22 shows the coefficients of the models used in hypothesis 2, obtained from the estimation sample 2012 – 2015 with data from one fiscal year before bankruptcy. For this hypothesis, the models are estimated by MDA, logit regression and probit regression. Panel A reports the coefficients of Altman's model (1983), panel B the coefficients of Ohlson's model (1980), and panel C the coefficients of Zmijewski's model (1984).

Table 22 Coefficients of the models with sample 2012 – 2015 (t-1)

Panel A: Altman (1983) variables			
	MDA	**Logit regression**	**Probit regression**
Intercept	-0.283	-2.180***	-1.253***
		(0.000)	(0.000)
WC/TA	0.917	-1.755***	-0.936***
		(0.005)	(0.004)
RE/TA	1.197	-0.517	-0.342
		(0.460)	(0.339)
EBIT/TA	6.105	-13.570***	-6.833***
		(0.000)	(0.000)
BVEQ/BVTD	-0.069	-1.015**	-0.400**
		(0.029)	(0.049)
SALES/TA	-0.229	0.255**	0.142***
		(0.001)	(0.000)
N	1243	1243	1243
Eigenvalue	0.398		
Wilks' lambda	0.715***		
	(0.000)		
-2 Log likelihood		438.927	
Cox and Snell R^2		0.226	
Nagelkerke R^2		0.495	
Hosmer-Lemeshow		15.789**	
		(0.045)	
Log likelihood			-223.112

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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Panel B: Ohlson (1980) variables			
	MDA	**Logit regression**	**Probit**
Intercept	-0.932	-2.180	-0.104
		(0.108)	(0.867)
SIZE	0.493	-1.329***	-0.777***
		(0.000)	(0.000)
TL/TA	-1.062	3.163***	1.510***
		(0.000)	(0.001)
WC/TA	1.116	-3.103**	-1.730**
		(0.021)	(0.012)
CL/CA	0.207	-0.812	-0.465
		(0.164)	(0.129)
OENEG	-0.109	1.446***	-0.717***
		(0.002)	(0.006)
NI/TA	8.124	-15.032***	-8.431***
		(0.000)	(0.000)
FU/TL	-1.429	-0.506	0.344
		(0.791)	(0.698)
INTWO	-0.407	0.031	-0.018
		(0.928)	(0.924)
CHNI	-0.010	0.212	0.116
		(0.365)	(0.342)
N	1243	1243	1243
Eigenvalue	0.481		
Wilks' lambda	0.675***		
	(0.000)		
-2 Log likelihood		409.974	
Cox and Snell R^2		0.244	
Nagelkerke R^2		0.534	
Hosmer-Lemeshow		13.484*	
		(0.096)	
Log likelihood			-205.776

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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Panel C: Zmijewski (1984) variables			
	MDA	**Logit regression**	**Probit**
Intercept	0.940	-4.295***	-2.279***
		(0.000)	(0.000)
NI/TA	7.492	-13.917***	-7.043***
		(0.000)	(0.000)
TD/TA	-1.765	3.060***	1.551***
		(0.000)	(0.000)
CA/CL	-0.044	-0.402*	-0.197**
		(0.053)	(0.049)
N	1243	1243	1243
Eigenvalue	0.391		
Wilks' lambda	0.719***		
	(0.000)		
-2 Log likelihood		446.900	
Cox and Snell R^2		0.221	
Nagelkerke R^2		0.484	
Hosmer-Lemeshow		13.301	
		(0.102)	
Log likelihood			-226.880

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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E.II Estimation sample 2007 – 2010 (t-1)

Table 23 shows the coefficients of the models used in hypothesis 3, obtained from the estimation sample 2007 – 2010 with data from one fiscal year before bankruptcy. For this hypothesis, the models are estimated by their original econometric method.

Table 23 Coefficients of the models with sample 2007 – 2010 (t-1)

Altman		**Ohlson**		**Zmijewski**	
MDA		Logit regression		Probit regression	
Intercept	-0.267	Intercept	-7.184**	Intercept	-2.550***
			(0.014)		(0.000)
WC/TA	0.950	SIZE	-1.816***	NI/TA	-4.393***
			(0.000)		(0.001)
RE/TA	2.035	TL/TA	7.296***	TD/TA	2.087***
			(0.000)		(0.002)
EBIT/TA	4.148	WC/TA	0.209	CA/CL	-0.346
			(0.940)		(0.151)
BVEQ/BVTD	-0.153	CL/CA	0.606		
			(0.668)		
SALES/TA	-0.270	OENEG	2.410***		
			(0.002)		
		NI/TA	-5.089		
			(0.273)		
		FU/TL	-5.702*		
			(0.072)		
		INTWO	0.240		
			(0.666)		
		CHNI	-0.453		
			(0.200)		
N	454	N	454	N	454
Eigenvalue	0.374	-2 Log likelihood	149.374	Log likelihood	-88.496
Wilks' lambda	0.728***	Cox and Snell R^2	0.250		
	(0.000)	Nagelkerke R^2	0.543		
		Hosmer-Lemeshow	8.425		
			(0.393)		

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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E.III Estimation sample 2012 – 2015 (t-2)

Table 24 shows the coefficients of the models used in hypothesis 4, obtained from the estimation sample 2012 – 2015 with data from two fiscal years before bankruptcy. For this hypothesis, the models are estimated by their original econometric method.

Table 24 Coefficients of the models with sample 2012 – 2015(t-2)

Altman		**Ohlson**		**Zmijewski**	
MDA		Logit regression		Probit regression	
Intercept	-0.518	Intercept	-1.732	Intercept	-1.770***
			(0.183)		(0.000)
WC/TA	0.950	SIZE	-1.232***	NI/TA	-5.764***
			(0.000)		(0.000)
RE/TA	1.610	TL/TA	3.032***	TD/TA	1.176***
			(0.000)		(0.000)
EBIT/TA	6.017	WC/TA	-4.503***	CA/CL	-0.302***
			(0.001)		(0.006)
BVEQ/BVTD	-0.047	CL/CA	-1.715***		
			(0.007)		
SALES/TA	-0.217	OENEG	1.925***		
			(0.000)		
		NI/TA	-13.242***		
			(0.000)		
		FU/TL	-0.819		
			(0.603)		
		INTWO	0.320		
			(0.364)		
		CHNI	0.046		
			(0.824)		
N	1243	N	1243	N	1243
Eigenvalue	0.186	-2 Log likelihood	505.199	Log likelihood	-277.086
Wilks' lambda	0.843***	Cox and Snell R^2	0.184		
	(0.000)	Nagelkerke R^2	0.402		
		Hosmer-Lemeshow	4.668		
			(0.792)		

Note: Statistical significance indicated in parentheses. For MDA the dependent variable setup is: above the cut-off point = non-bankrupt and below the cut-off point = bankrupt. For logit and probit regression, the dependent variable setup is: 1 = bankrupt and 0 = non-bankrupt.

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