Forecasting European Corporate Bankruptcy

Patrick Schaap

Nijmegen, 30-11-2016

Colophon

Master's Thesis Economics

Author
Patrick Schaap
S4165950
Pjj.schaap@gmail.com
Master Corporate Finance and Control
Nijmegen School of Management
Radboud University Nijmegen

Supervisor
Dr. S. Zubair
Nijmegen School of Management
Department of Economics and Business Economic
Radboud University Nijmegen

Second reader
Dr. K. Burzynska
Nijmegen School of Management
Department of Economics and Business Economic
Radboud University Nijmegen

Nijmegen, November 30, 2016

Abstract

Recent research on bankruptcy prediction models has provided mixed results on the predictive performance of several econometric techniques with various sets of predictors, which include macroeconomic and industry specific predictors. This study re-estimates four econometric techniques, MDA, logit, probit, and Hazard models using European firms from three time periods that correspond with the pre-credit crisis period (2004-2006), credit crisis period (2007-2009), and sovereign debt crisis period (2010-2013). When assessing these models based on accuracy and information content the results were inconclusive regarding a best econometric technique or model for the prediction of bankruptcy in Europe. This study however found that macroeconomic factors can improve the performance of bankruptcy prediction models within the estimation sample. But these factors are non-stationary, in line with the accounting variables, leading to a loss of accuracy and information content over time. Industries do systematically differ in their likelihood of firm bankruptcy and this can be captured using both inter-industry and intra-industry models.

Table of contents

1. Introduction

The credit crisis of 2007-2009 and sovereign debt crisis of 2010-2013 have led to a higher number of bankruptcies in recent years. Data of Creditreform (2015) shows the high number of bankruptcies in Western Europe with 179,662 bankruptcies in 2014 (Creditreform, 2015). The highest number of bankruptcies could be seen in 2013, when Western Europe saw 189,855 bankruptcies (Creditreform, 2014). This is an increase of 6.5% over the pre-crisis year of 2009. These bankruptcies have a strong impact on a wide variety of stakeholders including the investors, employees, business partners of the firm, and society as a whole (Pastena & Ruland, 1986; Moulton & Thomas, 1993; Jackson & Wood, 2013).

Various authors have stated the high cost related to bankruptcy, up to 44% of a firm's pre-distress value (Ang et al., 1982; Pastena & Ruland, 1986; Lang and Stulz, 1992; Shleifer and Vishny, 1992; Branch, 2002). And this does not even take into account the possible contagion effects in which the bankruptcy of a firm can lead to the bankruptcy of more firms in its industry and other industries (Platt, 1989; Bhandari & Weiss, 1996). Due to the significant costs associated with bankruptcy, it has earned significant interest in the academic literature. A long line of research has attempted to create accurate models to predict bankruptcy beginning with the work of Beaver (1966), who used ratios from the financial reporting of firms to assess their financial health. Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and Hillegeist et al. (2004) created statistical models using different techniques, financial ratios, and other predictor variables. These bankruptcy prediction models (henceforth BPMs) are vital as bankruptcy is the result of a downward spiral in which early warning could bring around a turnover and warn investors of possible misallocation of funds (Hambrick & D'Aveni, 1988). Misclassification costs, the cost related to a model misclassifying a firm as either bankrupt or healthy, are however significant and are important when assessing the economic impact of the predictive power of BPMs (Bauer & Agarwal, 2014). The multivariate discriminate analysis (henceforth MDA) of Altman (1968), logit model of Ohlson (1980), probit model of Zmijewski (1984), the hazard model of Shumway (2001), and the distance to default model of Hillegeist et al. (2004) were created to predict bankruptcy more accurately than using a single financial ratio. Recent research has tested, extended, and compared these BPMs (Chava & Jarrow, 2004; Agarwal & Taffler, 2008; Wu et al., 2010; Tinoco & Wilson, 2013; Bauer & Agarwal, 2014). Yet, these studies have not provided a conclusive answer to which technique and which type of data provides the most accurate models for predicting bankruptcy (Agarwal & Taffler, 2008; Wu et al., 2010; Bauer & Agarwal, 2014). To this day, no model outperforms the others when predicting bankruptcy. While some found logistic regression models outperforming multivariate discriminant analysis models (Lennox, 1991; Begley et al., 1996), Collins and Green (1982) found no difference. Other researchers used time series data in a logistic model to attempt to create models with higher predictive power (Shumway, 2001; Chava & Jarrow, 2004). Hillegeist et al. (2004) created a model based on the option pricing theory of Merton (1974). Other researchers however argued that the outperformance might be more related to market data being used instead of accounting data (Agarwal and Taffler, 2008).

However, researchers concluded that BPMs need to be re-estimated for accurate results outside their particular industries and time as their predictors are not stable over time (Mensah, 1984; Begley et al., 1996; Grice & Ingram, 2001; Grice & Dugan, 2003; Agarwal & Taffler, 2007; Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). Other researchers have applied the insights from research streams such as industry evolution and valuation models to BPMs (Grice & Dugan, 2001; Grice & Ingram, 2001; Grice & Dugan, 2003; Chava & Jarrow, 2004). Research on industry evolution and valuation models have shown that industries differ systematically and therefore differ in their likelihood of bankruptcy (Sharpe, 1964; Cameron, 1983; Lester et al., 2003; Fama & French, 2004). Some researchers have consequently added industry classifications to BPMs and have found that this can improve the predictive ability of these models (Platt & Platt, 1990; Platt & Platt, 1991; Grice & Dugan, 2001; Chava & Jarrow, 2004). Others have argued that as predictors are not stable over time macroeconomic factors should be incorporated into models. These researchers found that incorporating these exogenous factors, adding to the risk of bankruptcy, improved their models (Platt et al., 1994; Nam et al., 2008; Tinoco & Wilson, 2013).

The importance of BPMs and inconclusive results of prior research provide interesting avenues for further research. Because the predictor variables of BPMs are not stable over time, these have to be re-estimated in order to provide accurate results in the near future. This study re-estimates BPMs using the techniques of Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001) in a European setting to assess which models outperforms the other models. These four models are chosen since they are often used to predict bankruptcy. A European setting is used as companies in this area were affected by both the credit and sovereign debt crisis, providing an interesting economic environment to test the predictive power of these models. Furthermore, the regulation in Europe is less suitable for reorganization when a business is in financial distress than the United States regulation, making bankruptcy prediction even more important (La Porta et al., 1998; Lee et al., 2011; Tarantino, 2013). The research question of this study therefore is:

Which bankruptcy prediction model outperforms the other models in predicting bankruptcy for European companies?

Three time periods are used corresponding with the pre-credit crisis period (2004-2006), credit crisis period (2007-2009), and sovereign debt crisis period (2011-2013). Samples of European firms belonging to the French civil law family will be drawn within these time periods to create one inter-industry sample and five intra-industry samples per time period. Only one legal family is chosen in order to avoid differences in the likelihood of bankruptcy as the result of legal differences. Data limitations prevent adding the other legal families by adding dummies in the BPMs. The French civil law family is chosen because this group includes many countries that suffered severe economic downturn during the credit crisis and the European sovereign debt crisis, which creates interesting macroeconomic circumstances (Claessens et al., 2010; De Haan et al., 2012).

As the availability of market data is only limited, only accounting data are used. The models account for the systematical differences between industries by adding this explicitly in the models using industry dummies. The three different period samples are used to test whether the predictor variables are stationary (e.g. if the magnitude and significance of the predictor variables are stable over time). This also provides a good opportunity to incorporate macroeconomic factors in the models, which is expected to improve the performance of the models. To test for this, the performance of models that include macroeconomic factors are compared to those that do not incorporate these factors using the hold-out samples.

The results of this research show that there is no single BPM that outperforms the others irrespective of the sample or set of predictors used for each econometric technique. They do however show that while it became harder to estimate accurate models in recent time periods, the predictors are indeed non-stationary, which results in BPMs losing accuracy and information content over time. Furthermore, while including macroeconomic factors as predictors improve the performance in the estimation sample, these factors reduce the performance in the hold-out samples. These factors thus have to be chosen carefully when they are added to a model. Intra-industry models do not necessary perform better than inter-industry models as these models did not perform better overall. By using a research design that accounts for different industry characteristics through adding dummies it is possible to create accurate BPMs that incorporate multiple industries. Creating inter-industry models is possible because these models did not underperform in comparison to the intra-industry models and because the industry dummies in the inter-industry models were often significant. A few industries did however benefit from intra-industry models, indicating that these models could be used to better capture industry characteristics for some economic sectors.

Re-estimating these four models increases our knowledge of bankruptcy prediction. As argued before, these models are already old and would have to be re-estimated in order to use them to predict bankruptcy outside their particular time periods and industries. This study adds to the literature by re-estimating the model for a recent time period (2004-2013) in a European setting. By doing so it improves on existing literature by introducing a few novelties. As most prior research focused on the United States, re-estimating the predictor variables for an European setting is important in order to use these BPMs. BPMs cannot be used across economic and institutional settings without taking these factors into account. Estimating within a European setting therefore allows the use of BPMs for bankruptcy prediction for European companies. Furthermore, by testing both intra- and inter-industry models, it assesses differences in bankruptcy prediction across industries. As industries differ systematically, it could be beneficial to create industry specific models. Prior research has shown differences in bankruptcy across industries, the study adds to the knowledge of the predictive ability of intra-industry BPM relative to inter-industry models. Prior research used either industry relative ratios (Platt & Platt, 1990: Platt & Platt, 1991), industry dummies (Grice & Dugan, 2001; Chava & Jarrow, 2004), or interaction effects of financial ratios with industry specific factors (Platt & Platt, 1990; Platt & Platt 1991; Grice & Dugan, 2001; Chava

& Jarrow, 2004). No prior research combined industry relative ratios and industry dummies to compare inter-industry and intra-industry models. Using both industry relative ratios and industry dummies is important because prior research has shown that these factors can improve the performance of BPMs (Platt & Platt, 1990: Platt & Platt, 1991; Grice & Dugan, 2001; Chava & Jarrow, 2004). This can improve the methods and create more accurate BPMs. The study also incorporates macroeconomic factors and has therefore provided additional insight how these factors influence the predictive ability of BPMs. The results of this study can be used for further research into BPMs.

Increasing our theoretical knowledge of bankruptcy prediction also has various practical implications. Default risk is very important for a wide variety of stakeholders of companies. Investors would have to be compensated for the default risk of a firm. They therefore need to have accurate insight into the financial health of firms. As prior research has mixed results if the investors are compensated for the additional default risk, it is very important to be able to accurately predict bankruptcy for their investment decisions (Dichev, 1998; Eberthart et al., 1999; Campbell et al., 2008; Da & Gao, 2010; George & Hwang, 2010). Investors, and other stakeholders can then use this additional information in their decision making. The results of this study suggest that many factors have to be taken into account if BPMs are made. Furthermore, the results suggest that practitioners, including firms, can create industry specific BPMs for some industries, increasing the bankruptcy forecasting potential. By taking these insights into consideration when creating BPMs, resources can be better allocated.

This study will be structured as follows. The second section provides a theoretical background of bankruptcy and literature review of BPMs. The third section describes the research design, including the data and models. The fourth section provides the results of this study. Finally, the last section provides a conclusion of this study including limitations and suggestions for further research.

2. Theoretical Background

Bankruptcy is often the result of a firm being in financial distress (Harhoff et al., 1998; Dyrberg, 2004). However, financial distress does not always lead to bankruptcy and bankruptcy does not only follow after financial distress (Gilson et al., 1990; Bhandari & Weiss, 1996; Harhoff et al., 1998; Li & Li, 1999; Dyrberg, 2004; Bris et al., 2006; Lee et al., 2011).

This section therefore first examines financial distress as one of the main causes of bankruptcy. Insights from the causes of financial distress are often applied to BPMs. Examining financial distress provides a theoretical background for macroeconomic factors and industry characteristics in BPMs. This analysis does not provide a comprehensive review regarding causes of financial distress but will only highlight a couple of the most important sources which are often incorporated in BPMs. The various modes of revival and exit of the firm are discussed second. This part highlights why financial distress often results in bankruptcy and will examine the costs of bankruptcy. It also explores why bankruptcy is a more prevalent result of financial distress in Europe than in the United States. The third subsection discusses the most widely used statistical BPMs and discuss how prior research incorporated various sources of financial distress in BPMs.

2.1 Bankruptcy

2.1.1 Corporate Financial Distress

Corporate financial distress is often defined as a state of firm insolvency in which the firm does not create sufficient cash flows to compensate the debt providers of the firm (Li & Li, 1999). Various measurements of corporate financial distress are used in academic literature to measure this construct. The measurements used include a sales decrease (Opler & Titman, 1994), persistent losses (DeAngelo et al., 1994), dividend reductions (DeAngelo et al., 1994), and investment returns (Altman & Hotchkiss, 2006). These are not exclusive and often multiple measurements are used. These measurements provide an indication of the performance and the value of the firm and bad performance will often lead to insolvency (Donaldson, 1978; Hambrick & D'Aveni, 1988). Karels and Prakash (1987) argued that declining financial performance will result in legal actions such as a declaration of bankruptcy. While financial distress if often measured in financial terms, bankruptcy is often defined in legal terms (Karels & Prakash, 1987; Balcaen & Ooghe, 2006).

It is important to look at causes of financial distress in order to gain insight into the early warning signs of bankruptcy. Financial distress can be caused by various events and problems, both endogenous sources and exogenous sources. A few of the most important factors leading to financial distress include high leverage, agency problems related to the capital structure, industry evolution, and macroeconomic events.

The activities of corporations are funded through debt and equity (Bhandari & Weiss, 1996). The existence of corporate debt, resulting in an obligation to make periodic payments, is one of the biggest factors contributing to the risk of financial distress (Bhandari

& Weiss, 1996). The greater the financial leverage, the higher the chance of financial distress and bankruptcy as periodic payments have to be made on the debt which are often not required for equity financing. This effect is worse in times of macroeconomic recession due to declining market conditions (Gilson et al., 1990). The capital structure (i.e. the mix of equity and debt) is therefore an important indicator of the risk of bankruptcy of the firm. According to Myers (1984), building on the trade-off theory, the optimal capital structure of the firm is determined by a trade-off of the costs and benefits of both debt and equity. Financing the operations of the firm with debt bonds can be cheaper than using external equity financing due to the tax advantages of debt, but too much debt financing increases the risk of bankruptcy (Walter, 1957; Myers, 1984; Altman, 1984; Myers, 2001). The risk associated with the cost of bankruptcy and the tax benefits of debt would therefore lead to an optimal capital structure of debt and equity (Altman, 1984).

The optimal capital structure is only maintained if the managers act within the interests of its capital providers (Myers, 2001). Due to agency problems related to conflicting interests between the managers and the capital providers, and between equity and debt providers, the optimal capital structure is often not achieved (Jensen & Meckling, 1976; Smith & Warner, 1979; Harris & Raviv, 1991). Agency problems between equity holders and debt holders include high risk projects, underinvestment, dividend payments which can be funded through new debt, asset substitution, and issuance of new debt leading to claim dilution (Smith & Warner, 1979; Healy & Palepu, 2001; Myers, 2001; Bryan et al., 2006; Gillan et al., 2006). The agency problems related to the financial structure of the firm can also lead to financial distress and possibly bankruptcy (Bhandari & Weiss, 1996). Due to information asymmetry, it is also difficult and expensive to monitor if the managers act according to the interests of the capital providers (Eisenhardt, 1989).

The industry in which the firm operates and the age of a firm also has an effect on the likelihood of business failure. Two theories on the evolution of industries are the models of Jovanic (1982) and Lambson (1991). The entry and exit of a firm is considered to have a bell-shaped relationship with time (Jovanovic, 1982; Dyrberg, 2004). A firm making its entry into a market will have to learn its place in the market and become efficient in order to become competitive and profitable. The theory of Jovanovic (1982) argues that the highest likelihood of corporate failure is during the firm’s early years. Firms that do not become efficient will exit the market (Quinn & Cameron, 1983; Lester et al., 2003; Morris, 1997). While some organizations become efficient and generate high returns, most will only generate marginal returns. Other firms might not become successful and are outcompeted in the market. These firms will not generate enough return, leading to firm exit (Lester et al., 2003). Quinn and Cameron (1983) stated that within one-and-a-half years about 54% of firms face corporate failure. Older firms that used to be successful might also lose their competitive advantage and get outperformed by their competitors in the industry. However, the risk of default is higher for younger firms. While the model of Jovanic (1982) is based on learning, other models use different forces for industry evolution. Lambson (1991) based industry evolution on the effect of changing market conditions. These industry evolution models therefore provide not only insight into the lifecycle of organizations and its relation with corporate failure, but also shows why the entry and exit of firms over time varies across industries (Jovanovic, 1982; Lambson, 1991). Sources of industry evolution, such as learning, changing market conditions, and macroeconomic events can have diverse effects on different industries, affecting the incumbent companies in different ways (Moulton & Thomas, 1993; Platt, 1989; Klein, 2000; Bhattacharjee et al., 2009). The risk of default can therefore differ significantly between industries. Data also shows that the number of bankruptcies differs across economic sectors Creditreform, 2015).

2.1.2 Revival or Exit of the Firm

Financial distress can lead to restructuring under bankruptcy law using an automatic stay of assets which prevents debtors from repossessing the assets of the firms during financial distress (Bhandari & Weiss, 1996; Li & Li, 1999; Bris et al., 2006; Lee et al., 2011), private restructuring outside bankruptcy laws (Gilson et al., 1990), and the modes of exit of a firm mergers and acquisitions (henceforth M&A) and bankruptcy (Harhoff et al., 1998; Dyrberg, 2004). Restructuring leads to a redistribution of wealth among the stakeholders of the firm (Pastena & Ruland, 1986; Moulton & Thomas, 1993). M&A activity is strongly pro-cyclical resulting in merger waves (Lambrecht, 2004; DePamPhilis, 2015). High M&A activity is often found during times of economic expansion and low M&A activity in times of financial recession (Lambrecht, 2004). This indicates that the likelihood of finding a buyer for a financial distressed firm, and therefore M&A as mode of exit, is also related to macroeconomic circumstances (Bhattacharjee et al., 2009). Voluntary liquidation is also possible as mode of exit, in which the debtors of the firm are paid and the residual value is distributed to the equity holders (Schary, 1991). This is more common for healthy firms.

The frequency of bankruptcy as result of financial distress is inefficient and could be seen as surprising, given the significant costs that are associated with filing bankruptcy such as haircuts on assets and administrative costs (Bulow & Shoven, 1978; Ang et al., 1982; Pastena & Ruland, 1986; Lee et al., 2011). This is related to the agency problems as a result of the various competing interests of the stakeholders of the firm regarding the different wealth distributions of the different modes of revival or exit of the firm (Pastena & Ruland, 1986; DePamphilis, 2015). Consequently, bankruptcy is a more attractive mode of exit for most firms due to these agency problems, even though the significant costs associated with it.

The possibilities and incentives to choose between these various modes of corporate revival and exit is affected by the legal framework of the country in which the firm operates. These laws differ in the leniency towards bankrupt entrepreneurs and protection of the capital providers (La Porta et al., 1998; Lee et al., 2011). There are vast differences in the legal environment between different countries, especially between the United States and most of the European countries. The United States and Great Britain have a common law system while the rest of Europe has a civil law system (La Porta et al., 1998). This is an important distinction since common law countries tend to provide stronger protection to the capital providers of the firm than civil law countries (La Porta et al., 1998). La Porta et al. (1998) noted that European civil law countries such as Germany do not have an automatic stay on assets which is a vital part of the reorganization bankruptcy law of the United States. Tarantino (2013) however argued that the recent convergence of the legal systems has made this distinction less evident as European countries are adopting more reorganization bankruptcy laws based on the United States chapter 11 bankruptcy code. This distinction indicates that reorganization is less likely to succeed in Europe, making bankruptcy a more expected result as result of financial distress.

According to Branch (2002), the costs related to the bankruptcy of firms are related to the real costs that are borne by the distressed firm, those borne directly by its claimants, the losses to the distressed firm that are offset by gains to other entities, and the real costs borne by parties other than the distressed firm or its claimants. These costs can be characterizes as direct cost and indirect costs. Direct costs relate to the administrative costs associated with the process of handling the bankruptcy (Ang et al., 1982). Indirect costs of bankruptcy are haircuts on the sale of assets, loss of tax credits of the firm (Ang et al., 1982; Pastena & Ruland, 1986).

Branch (2002) indicated that approximately 56% of the bankrupt firm's pre-distress value was recovered for the claimholders. Of the remaining 44%, 28% is lost in its entirety and 16% of the pre distress value is consumed by the managing of the bankruptcy. The findings indicate the huge loss of value for society if firms go bankrupt. Moulton and Thomas (1993) find that have to take a loss between 3% and 20% on their outstanding debt to the firm in the event of bankruptcy. Bhandari and Weiss (1996) also stressed the social cost of shock effects, or contagion, as the result of a single bankruptcy. A single bankruptcy can affect the performance, the value, and lead to the bankruptcy of its business partners and competitors. Shleifer and Vishny (1992) emphasized that the liquidation of assets as the result of a bankruptcy can lead to lower asset values for other firms in that industry, which can lead to a contagion effect of financial distress. Lang and Stulz (1992) found that bankruptcy announcement reduce the value of firms in the industry.

The social cost of bankruptcies can be seen when looking at the number of corporate insolvencies in Western Europe over the recent years, which is still higher than the pre-crisis level (Creditreform, 2015). In 2010 there were 174,463 bankruptcies in Western Europe, which grew to 189,855 in 2013 (Creditreform, 2015). In 2014 this number dropped down again to 179,662 bankruptcies (Creditreform, 2015). The substantial number of bankruptcies highlights the importance of being able to predict bankruptcy. Signs of bankruptcy would lead to increased distress risk and investors should therefore be able to expect higher returns. However, research is inconclusive if the higher returns related to the heightened distress risk can be earned (Dichev, 1998; Eberhart et al., 1999; Campbell et al., 2008; Da & Gao, 2010; George & Hwang, 2010, Boons, 2016).

2.2 Bankruptcy Prediction Models

2.2.1 An Overview

Hambrick and D'Aveni (1988) argued that an early slack in performance of a firm is a significant part of a downward spiral towards a state of financial distress of a firm. If a firm starts to underperform it could show early signs of financial distress. However, as corporate failure is a downwards spiral, early warning of financial distress could be used to revitalize the firm, especially for large firms that have a longer warning period (Hambrick & D'Aveni, 1988). Whitaker (1999) argued that early warning of slacking performance and financial distress can lead to managers taking corrective action, improving their performance. However signs of bankruptcy could also lead to a flight of capital, leading to the demise of the firm.

It is important for investors to use bankruptcy risk in their choice for investment. In order to make an appropriate investment decision the capital market should identify the default risk. High quality financial reporting is vital for efficient capital markets as it reduces the information asymmetry between managers and investors (Healy & Palepu, 2001; Bushman & Smith, 2001). A well-functioning financial system is important for efficient capital allocation as bankruptcy indicates a misallocation of capital (Aharony et al., 1980; La Porta et al., 2000; Myers, 2001). BPMs can use financial information to predict bankruptcy (Pastena & Ruland, 1986).

BPMs are vital tools for the prediction of financial distress and eventual bankruptcy of firms. According to Morris (1997) a distinction has to be made between models that identify bankruptcy and those that predict bankruptcy. Models that identify bankruptcy are based on one sample and work specifically on that particular sample of companies. These models are not very useful as they have no predictive value. Prediction models are created using a sample and used on several hold-out samples to assess whether a future bankruptcy is possible (Morris, 1997). These models can be very valuable as the information they provide can be used in the market for more efficient resource allocation. However it is important to take into account the misclassification costs of BPMs. According to Agarwal & Taffler (2008) classifying healthy firms as bankrupt firms will only lead to missed investment opportunities. On the other hand, Morris (1997) stated that if markets are efficient and a BPM is found to be very accurate, misclassification can lead to the demise of a healthy firm. Misclassified firms could go bankrupt as the market will no longer provide capital for the firm (Morris, 1997). It can therefore not only be a missed investment opportunity, but also a death sentence for a healthy firm. Classifying a bankrupt firm as healthy would lead to a loss of up to 100% of the investment (Agarwal & Taffler, 2008). It is therefore vital to create models with high accuracy and predictive power. Furthermore, Xiao et al. (2012) note that using the weighted results of multiple BPMs could provide superior predictive power.

Some of the earliest work on using financial ratios for bankruptcy prediction was conducted by Beaver (1966). Beaver (1966) conducted an empirical study to research the predictive ability of accounting data by comparing financial ratios across a selection of firms.

He based his research on prior studies using financial ratios to asses firm performance (Horrigan, 1968). The ratio analysis of Beaver (1966) is still limited as it is a univariate analysis which assessed the predictive value of each ratio separately. Beaver (1966) recognized this limitation and suggested future research to use multiple ratios at the same time. Various BPMs have been developed since Beaver's (1966) paper featuring a wide variety of techniques and data. These BPMs can be classified as either statistical or intelligent by design (Kumar & Ravi, 2007).

In their review of work on BPMs between 1968 and 2005, Kumar and Ravi (2007) found several intelligent techniques, which are characterized by artificial intelligence and soft computing. Examples of these models are neural networks, case-based reasoning, decision trees, and rule-based models (Kumar & Ravi, 2007; Zhang et al., 2013). Neural networks is the most used intelligent BPM (Demyank & Hasan, 2010). This technique uses computing to mimic the human neural network which is then used to process information. The neural network can therefore establish relationships between the variables used as input through a learning process to predict firm failure (Kumar & Ravi, 2007; Demyank & Hasan, 2010). Li and Sun (2008) argued that case-based reasoning can be used when financial information does not provide enough insight into the financial position of the firm. Case-based reasoning makes decisions on the financial position of firms based on human experience with similar cases (Li & Sun, 2008; Cho et al., 2010). Decision trees simulate a sequence of paths in which decisions have to be made. Through these decisions the total sample of firms can be divided between healthy and financially distressed firms (Cho et al., 2010). Zhang et al. (2013) used feature selection and a rule-based model, using a system of rules and constraints to determine if a firm goes bankrupt, to differentiate between healthy and bankrupt firms.

Statistical models can use accounting and financial market information to predict bankruptcy. Beaver et al. (2005, p. 93) argued that accounting data has "predictive power up to at least five years prior to the bankruptcy". Accounting information can be used because it provides objective ratios based on publically available data (Morris, 1997; Balcaen & Ooghe, 2006). This information is used based on the pretext that past performance can predict future performance (Trujilo-Ponce et al., 2013) These ratios can be used to assess the performance of a firm relative to its competitors (Morris, 1997). Financial ratios can therefore provide information on the long term position of the firm, its short term financial position, and the profitability and efficiency of the firm (Morris, 1997). Financial accounting ratios do have a few limitations: 1) restriction to large firms that have an obligation to publicly publish their financial situation, 2) they are prepared on a going-concern basis, and 3) it limits the models to only financial information which might not contain all relevant factors that may lead to bankruptcy (Morris, 1997; Hillegeist et al., 2004; Balcaen & Ooghe, 2006). Most importantly financial reporting quality can be lower for financially distressed firms or even unavailable (DeAngelo et al., 1994; Frost, 1997; Rosner, 2003; Burgstahler et al., 2006; Charitou et al., 2007; Al-Attar et al., 2008).

Market data can also provide valuable insight into the financial status of a firm. Beaver et al. (2005) and Agarwal and Taffler (2008) argued that market data can valuable to bankruptcy prediction as it combines information from all available sources where accounting information is based on the financial statements of the firm. Market data might therefore provide more information on the future performance of the firm (Hillegeist et al., 2004). Furthermore, market data is more timely, incorporates market values for assets, it provides an indication of the volatility of the value and returns on investments in the firm, and it is less prone to the manipulation of management (Hillegeist et al., 2004; Beaver et al., 2005; Agarwal & Taffler, 2008; Trujilo-Ponce et al., 2013). Hillegeist et al. (2004) argued that market data based BPMs performs better than the accounting BPMs. Agarwal and Taffler (2008) compared the performance of BPM that used accounting data and those that incorporated market data. They argued that the predictive ability of those models do not differ. Hillegeist (2004) and Agarwal and Taffler (2008) hence argued that BPMs best use both types of data as each type captures different aspects of bankruptcy. It should however be noted that comparing the Altman (1968) z-score as accounting BPM and a distance to default model as market BPM does not only measure the usefulness and predictive power of the data that is used, but also the performance of the techniques.

Statistical techniques include the multivariate discriminate analysis (MDA) of Altman (1968), logistic regression of Ohlson (1980), probit model of Zmijewski (1984), the hazard model of Shumway (2001), and a Black-Scholes probability model of Hillegeist et al. (2004) (Kumar & Ravi, 2007; Wu et al., 2010). This study focuses on statistical models as these models relate closely to the field of economics while the intelligent models use various other techniques.

Research based on these techniques have used the original methods and variables suggested by the authors, and expanded on these with their own techniques and variables (Shumway, 2001). It is therefore important to review the five main statistical techniques and the used (table 1).

[Insert table 1 here]

It is important to take into account the limitations of BPM. According to Balcaen and Ooghe (2006) most BPMs, including the five BPMs named in table 1, only include financial ratios. The literature review above has shown that financial distress and bankruptcy can be caused by a broader selection of factors (Jovanovic, 1982; Moulton & Thomas, 1993; Platt, 1989; Klein, 2000; Dyrberg, 2004; Bhattacharjee et al., 2009). Some recent BPM research has taken into account industry factors and macroeconomic circumstances (Mensaa, 1984; Grice & Dugan, 2001; Chava & Jarrow, 2004). Market based data also indirectly incorporates broader aspects of bankruptcy in their valuation, mitigating this limitation (Hillegeist et al., 2004; Agarwal & Taffler, 2008).

A second limitation is that every BPM research uses its own definition of bankruptcy which makes comparisons of results difficult. Most recent research does however use a legal definition of bankruptcy, which makes comparison easier. This exact definition used depends on the sample and database used in the research.

Furthermore, it is important to use a correct sample of firms. Zmijewski (1984) mentioned two common problems of BPMs research that can lead to biased model parameters and in accurate probabilities of default. The first is choice-based sample bias of including too many bankrupt companies. These companies are over-represented in the research compared to the frequency of bankruptcy in the real economy (Grice & Ingram, 2001). The second problem is the unavailability of data for bankrupted firms. However, in present days getting accounting data is comparatively easy compared to 1984. Gathering market data for bankrupt firms still proves to be a limitation.

2.2.2 Altman's Multivariate Discriminate Analysis

Altman (1968) introduced a MDA model, which makes a distinction between healthy firms and financial distressed firms based on financial ratios. This is important as single financial ratios do not provide a good measure of the financial situation of a company. Using combined ratios (equation 1) as firm characteristics, the MDA attempts to derive a linear combination of the variables in order to create groupings to classify firms as healthy or bankrupt. The technique creates the group dispersion by minimizing the variance within each group while maximizing the variance between the two groups. The coefficients therefore do not indicate the effect of each variable. Balcaen and Ooghe (2006) argued that quadratic MDA has also been used in research, but to a lesser extent. A single discriminant score (Z-score) is created to classify the firms using equation 1.

The outcome of this model is not directly a dichotomous variable. A value between 0 and 1 would be ideal as it facilitates an easy interpretation of the probability of default. The MDA however ranks the firms and uses a cutoff point for the joint effect of all the ratios (Balcaen & Ooghe, 2006). A lower Altman (1968) Z-score (the discriminant score) indicates a higher potential for bankruptcy. The results of this study showed that a Z-score of 2.675 was seen as the critical value best discriminating between bankrupt and non-bankrupt firms. However, determining the critical values this way is rather arbitrary. Wu et al. (2010) stated that the MDA technique uses strict assumptions, which are more relaxed in bankruptcy prediction research studies following Altman (1968). The assumptions of MDA are:

1. The data used in MDA should be jointly normally distributed. According to Balcaen and Ooghe (2006) this assumption of multivariate normality is often violated which produces inaccurate results. According to Lo (1986) multivariate normality can be tested using a Shapiro-Wilks test. Rejecting multivariate normality is problematic as there are no good remedies (Lo, 1986; Balcaen & Ooghe, 2006). Approximating normality through univariate normality is also problematic (Balcaen & Ooghe, 2006). Therefore rejection of multivariate normality is often ignored when using MDA as the only alternative is using a logit or probit model (Lo, 1986).
2. Another assumption of MDA is that the variance-covariance matrices, the group dispersion, is equal for the healthy and failing firms (Collins & Green, 1982; Karels &

Equation 1 – MDA model

Model	Variables
$Z = v_1x_1+v_2x_2 + \cdots + v_nx_n$	$x_1 = \frac{Net\ working\ capital}{Total\ assets}$
$v_1, v_2, \dots v_n = discriminant\ coefficients$	$x_2 = \frac{Retained\ earnings}{Total\ assets}$
$x_1, x_2, \dots x_n = independent\ variables$	$x_3 = \frac{EBIT}{Total\ assets}$
	$x_4 = \frac{Market\ capitalization}{Book\ value\ of\ total\ liabilities}$
	$x_5 = \frac{Sales}{Total\ assets}$

Prakash, 1987; Morris, 1997; Balcaen & Ooghe, 2006). This assumption is also often violated, indicating that quadratic MDA should be used. However quadratic MDA performs worse than linear MDA when predicting bankruptcy (Collins & Green, 1982; Balcaen & Ooghe, 2006). Quadratic MDA is especially problematic when a lot of independent variables are used (Balcaen & Ooghe, 2006). Therefore the rejection of this assumption is also often ignored.

3. Balcaen and Ooghe (2006) stated that multicollinearity could decrease the accuracy of the model. Multicollinearity can especially be a problem when using financial ratios due to the high interrelations (Morris, 1997). However, the absence of multicollinearity is not a necessary requirement of MDA (Eisenbeis, 1977).
4. Lennox (1999) stressed that a specific problem of MDA is that the sample is assumed to be randomly drawn. However, often the healthy firms in the sample are matched based on criteria such as industry sector, industry sector, or year of failure which makes the sample not random anymore. This matching problem could lead to variables not being significant and a biased estimation.

Altman (1968), using type I and type II errors, found his model to be 95% accurate. Type I error represents classifying a firm in financial distress as healthy (false negative). The type II error means classifying a healthy firm as bankrupt (false positive). However, the predictive power declined with each additional year prior to bankruptcy. Deakin (1972) compared the models of Beaver (1966) with the MDA technique used by Altman (1968) using the sample of the original Beaver (1966) paper. He found that the MDA technique was useful to predict bankruptcy up to three year prior to bankruptcy. However, due to a significant failure rate related to type I and type II errors, Deakin (1972) stressed that the results of the MDA BPMs should be used as further evidence of failure and not as sole proof on itself. Edmister (1972) found the MDA technique to be useful for small firm failure. Altman et al. (1977) used the original model to create a ZETA model. They found that their model predicts bankruptcy with over 90% accuracy the year prior to corporate failure and that their linear model outperforms the quadratic alternative.

2.2.3 Ohlson's Logit Model

Ohlson (1980) used a logit model (equation 2), which is a logistic regression model that calculates the natural logarithm of the odds. The logit probability distribution of the Ohlson (1980) model between 0 and 1 provides a clearer interpretations than the linear Z-score and is better suitable to bankruptcy prediction (Collins & Green, 1982; Shumway, 2001; Balcaen & Ooghe, 2006). Contrary to the MDA, the coefficients of logit, probit, and hazard models can be interpreted as the relative importance of the variable in the absence of multicollinearity (Balcaen & Ooghe, 2006).

While the MDA has a strict assumption of normality of the data used, the logit model of Ohlson (1980) is less strict as it does not require multivariate normality or equal dispersion matrices (Collins & Green, 1982; Lo, 1986; Balcaen & Ooghe, 2006). Extreme deviations from normality do however influence the accuracy of the model (Mcleay & Omar, 2000). The logit model also avoids the matching problem, related to prior probabilities of bankruptcy, of MDA. In this way, the Ohlson (1980) model provides a clearer answer to the log odds of a specific firm failing within a pre-specified period of time if it falls within a specific population of firms. The only important assumptions of the logit model, aside from using correctly collected and measured data, is that there is no multicollinearity between the independent variables (Collins & Green, 1982; Balcaen & Ooghe, 2006). Some authors mention that there can be a heteroskedasticity problem when determining the effect of independent variables on the probability of bankruptcy due to omitted variables (Davidson & MacKinnon, 1984; Lennox, 1999). However, while it is possible to test for heteroskedasticity as there is no good solution for this problem it is often not taken into account (Davidson & MacKinnon, 1984; Lennox, 1999).

2.2.4 Zmijewski's Probit Model

Zmijewski (1984) used a probit model which is a logistic regression model that calculates the likelihood of a firm being bankrupt based upon a cumulative distribution function of the normal distribution (Φ in equation 3).

Zmijewski (1984) used a limited set of variables including a ratio for return on assets, financial leverage, and liquidity. Using only three ratios could be seen a limitation of this model. However these variables cover three of the four important dimensions of the financial position of the firm (Pompe & Bilderbeek, 2005). The model therefore only lacks an activity ratio since the other three ratios regarding financial position (e.g. profitability, solvency, and liquidity ratios) are included in the model.

The biggest contributions of Zmijewski (1984) are the probit model, which slightly differs in interpretation from the logit model of Ohlson (1980), and highlighting the

Equation 2 – Logit model

Model	Variables
$P = \frac{1}{1 + e^{(-\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$	$x_1 = \frac{Log(Total\ assets)}{GNP\ price\ level\ index}$
	$x_2 = \frac{Total\ liabilities}{Total\ assets}$
	$x_3 = \frac{Working\ capital}{Total\ assets}$
	$x_4 = \frac{Current\ liabilities}{Current\ assets}$
	$x_5 = Dummy\ with\ a\ value\ of\ 1\ if\ total\ liabilities > total\ assets$
	$x_6 = \frac{Net\ income}{Total\ assets}$
	$x_7 = \frac{Income\ from\ operations - depreciation}{Total\ liabilities}$
	$x_8 = Dummy\ with\ a\ value\ of\ 1\ if\ net\ income\ was\ negative\ for\ 2\ years$
	$x_9 = Relative\ change\ in\ net\ income$

Equation 3 – Probit model

Model	Variables
$P = \Phi(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)$	$x_1 = \frac{Net\ income}{Total\ assets}$
	$x_2 = \frac{Total\ liabilities}{Total\ assets}$
	$x_3 = \frac{Current\ assets}{Current\ liabilities}$

importance of a representative sample. However, due to the additional computation required by using this normal distribution there have not been many studies choosing this model over the logit model (Balcaen & Ooghe, 2006). The probit uses the same assumptions as the logit model of Ohlson (1980).

2.2.5 Shumway's Discrete-Time Hazard Model

The discrete-time hazard model of Shumway (2001) predicts the chance of a firm surviving in a particular time (e.g. time t) on the condition that it has survived up until that time (e.g. time t-1)(Shumway, 2001; Beaver et al., 2005). This model differs from the static logistic model of Ohlson (1980) because it can include panel data (Wu et al., 2010). In essence, the hazard model is a panel-logit model (Shumway, 2001). Using data from multiple points in time possibly increases the explanatory power of BPMs over the static models, since it takes into account the changing operations of the firm and the environment in which it operates (Balcaen & Ooghe, 2006). Beaver et al. (2005) argued that the hazard model could have higher predictive power due to the multicollinearity problem of the static models. The model itself (equation 4) is very similar to the model of Ohlson (1980). However, where the model of Ohlson (1980) uses a set of variables from one point in time (equation 2), the model of Shumway (2001) allows for data, the covariates that affect the hazard rate, from multiple years. The 'P' in the model resembles the hazard rate, the risk of bankruptcy of the firm (Beaver et al., 2005). The 'a' variable resembles the baseline hazard rate (Beaver et al., 2005).

Shumway (2001) argued that the static models can produce biased and inconsistent estimates of bankruptcy probabilities. By incorporating multiple sets of variables the hazard model is more consistent. He further argues that variables that might be significant for the prediction of bankruptcy might differ for a discrete-time model compared to a static model. Based on this, Shumway (2001) included more market variables. Market data is however harder to gather than accounting data, which limits the uses of those variables. The assumptions of the hazard model are:

1. Can be estimated roughly the same as the logit model but it has to use the number of firms instead of the number of firm years as it has multiple observations for each firm (Shumway, 2001). If the hazard model is estimated using a sequence of logit models the researcher has to take into account the lack of independence between the firm-year observations (Shumway, 2001).
2. Hazard models are sensitive to non-informative censoring. This implies that the underlying factors behind the censoring, when data of a firm is available in time t but not in t+1, have to be related to bankruptcy.
3. The hazard model of Shumway (2001) is based on the Cox Model of Cox and Snell (1968). One important assumption of this model is that the hazard rate is proportional over time depending on the set of covariates. Shumway (2001) however stated that this assumption does not hold for bankruptcy survival analysis.

Equation 4 – Hazard model

Model	Variables
$P = \frac{1}{1 + e^{(y_{i,t})}}$	$x_1 = \frac{Net\ income}{Total\ liabilities}$
$y_{i,t} = a + \beta X_{i,t-1} = \beta \begin{pmatrix} X_{1,t-1} & \cdots & X_{1,t-j} \\ \vdots & \ddots & \vdots \\ X_{n,t-1} & \cdots & X_{n,t-j} \end{pmatrix}$	$x_2 = \frac{Total\ liabilities}{Total\ assets}$
	$x_3 = \frac{Log(Market\ capitalization)}{Total\ market\ value\ of\ debt\ and\ equity}$
	$x_4 = Cumulative\ annual\ return\ in\ year\ t_{-1} - the\ return\ of\ the\ relevant\ major\ index\ in\ year\ t_{-1}$
	$x_5 = Standard\ deviation\ of\ the\ residual\ derived\ from\ regressing\ monthly\ stock$

2.2.6 Distance to Default Model of Hillegeist, Keating, Cram, and Lundstedt

Hillegeist et al. (2004) created a Black-Scholes probability model (equation 5) based on the Black–Scholes–Merton option-pricing model (Black & Scholes, 1973; Merton, 1974). Kumar & Ravi (2007) and Agarwal and Taffler (2008) stressed that a limitation of most BPMs is that they are not based on explicit theory. Most BPMs use variables that have been selected through empirical research (Balcaen & Ooghe, 2006). The distance to default (or contingent claims model) model of Hillegeist et al. (2004) is an exception (Bauer & Agarwal, 2014). This model incorporates market data (Wu et al., 2010). Financial statements are based on past performance based on an ongoing-concern principle. The information value of these statements might be less than market data, which includes expectations of future performance (Hillegeist et al., 2004). Hillegeist et al. (2004) found that their model outperforms the models of Altman (1968) and Ohlson (1980). The model uses equity as a call option on the assets of the firm to derive the probability that the value of equity is negative at maturity (Agarwal & Taffler, 2008; Barath & Shumway, 2008). If this value is negative, the value of the assets is equal or lower than the value of debt, then the firm will be bankrupt (Trujilo-Ponce et al., 2013; Buaer & Agarwal, 2014).

As the distance to default model is based on the work of Black & Sholes (1973) and Merton (1974) it uses some strict assumptions and is therefore subject to limitations:

1. A few variables in the models, including the market value of assets, are not directly observable and would need to be estimated by the researcher (Agarwal & Taffler, 2008).
2. Market values are volatile but are set as fixed input for the entire time period. This means that the model does not fully use the advantage that market data provides, namely using timely data and accurate volatility of the firm. However, the data is

Equation 5 – Distance to default model

Model	Variables
$P = N - \left(\dfrac{\ln\left(\frac{V_A}{X}\right) + (\mu - \delta - 0.5\sigma_A^2)t}{\sigma_A \sqrt{t}} \right)$	$V_E = Current\ market\ value\ of\ equity$
	$V_A = Current\ market\ value\ of\ assets$
	$X = Face\ value\ of\ debt\ maturing\ at\ time\ T$
	$\delta = Continous\ dividend\ rate\ expressed\ in\ terms\ of\ V_a$
	$\sigma_A = \dfrac{\sigma_E V_E}{V_E + X}$
	$\mu = Continously\ compounded\ expected\ return\ on\ assets$
	$t = Debt\ maturity, set\ as\ 1\ year$

often more timely than accounting data (Agarwal & Taffler, 2008; Buaer & Agarwal, 2014).

3. The model cannot differentiate between different types of debt since it uses one zero-coupon bond with one maturity for all the debt (Agarwal & Taffler, 2008).
4. As the model uses a set maturity the model assumes that the firm cannot go bankrupt before maturity of the bonds used in the model (Trujilo-Ponce et al., 2013).
5. As the model sees equity as a call option the asset it assumes that there is only residual value if all debt has been paid (Agarwal & Taffler, 2008). However, this absolute priority rule does not always hold (Trujilo-Ponce et al., 2013).

2.3 Assessing Bankruptcy Prediction Models

These statistical BPMs are usually assessed based on their information content and accuracy (Bauer & Agarwal, 2014). The information content assesses the incremental information about bankruptcy that is captured by a BPM (Hillegeist et al., 2004; Bharatzh & Shumway, 2008; Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). Bauer and Agarwal (2014) assessed the information content of BPMs by using the ex-ante likelihood of bankruptcy from each BPM, either bankrupt or healthy, as independent variable in a hazard model together with the baseline hazard rate. A model provides information content if the ex-ante bankruptcy score is significant. In order to use the results of MDA in the hazard model Bauer and Agarwal (2014) first transformed the score into logit variables (equation 6) in line with Hillegeist et al. (2004).

$$\text{Ex} - \text{ante likelihood} = \frac{e^{\text{score}}}{1 + e^{\text{score}}} \quad \textbf{(6)}$$

The accuracy is often assessed based upon type I and type II errors (Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). However this approach has its limitations and might therefore be classified as outdated. The model of Altman (1968) and the logistic regression models of Ohlson (1980), Zmijewski (1984), and Shumway (2001) produce a result, either the z-score or a probability between 0 and 1 for the bankruptcy of firms. The actual cut-off point for bankrupt or healthy is then arbitrarily chosen by the researcher. This makes it hard to generalize. Bauer and Agarwal (2014) suggested using receiver operating characteristics (henceforth ROC) based upon the work of Sobehart and Keenan (2001). The area under the ROC-curve (henceforth AUC) gives an indication of the predictive ability of the model as it shows the relationship between the hit rate (percentage of bankrupt firms predicted as bankrupt) and the false alarm rate (percentage of healthy firms predicted as bankrupt). It therefore provides a good indication of the accuracy of the model. Furthermore, because it does not require a subjective cut-off point it is a unbiased estimator (Agarwall & Taffler, 2008). This offers an estimation of the accuracy of the model which can be compared with other BPMs.

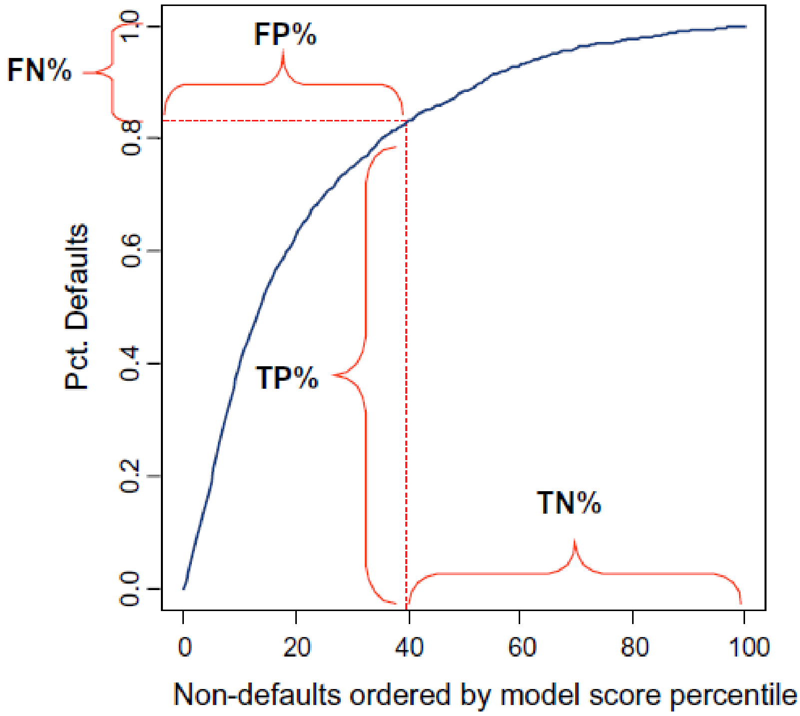
The paper of Stein (2005) provides a good explanaton of the ROC curve (figure 1). Figure 1 shows how the ROC curve plots the false negatives (FN), false positives (FP), true positives (TP), and true negatives (TN). The X-axis of the figure indicates the amount of healthy firms in the sample. The Y-axis provides the amount of bankrupt firms correctly predicted by the model given a X value. The curve therefore provides a clearer indication of the accuracy of the model without making a subjective cut-off point. Stein (2005) and Blöchlinger and Leippold (2006) used the ROC curve to create a profit-maximizing cut-off point for loan prices. This optimal cut-off point depends on the costs associated with FN and FP. Figure 1 shows the optimal cut-off point of Stein (2005), which is found at 40% on the X-axis. Due to the ambiguity associated with the costs of bankruptcy it is however difficult to create an optimal cut-off point for the BPMs (Agarwall & Taffler, 2008). Consequently, the costs of bankruptcy are usually not included when comparing BPM (Bauer & Agarwal, 2014).

The accuracy of BPMs is therefore assessed based on AUC-statistic. The AUC-statistic can be generated using Wilcoxon statistic (Hanley & McNeil, 1982; Sobehart & Keenan, 2001; Agarwall & Taffler, 2008; Bauer & Agarwal, 2014). Sobehart and Keenan (2001) noted that the AUC-statistic must have a value between 0 and 1. A value of 1 indicates a complete accuracy, while a value of 0.5 means that the model has no discriminatory power (Sobehart & Keenan, 2001; Engelmann et al., 2003).

Engelmann et al. (2003), Agarwal and Taffler (2008), and Bauer and Agarwal (2014) showed that the accuracy ratio (henceforth AR) can be derived by:

$$AR = 2(A - 0.5) \quad \textbf{(7)}$$

Figure 1 – Receiver operating characteristics curve



Source: Stein (2005, p. 1216).

Bauer and Agarwal (2014) provided further equations on how to calculate the standard error of the AUC-statistic (se(A)) which can be used together with the AUC-statistic to derive the z-statistic. The z-statistic can be used to compare different models based on their accuracy (Agarwal & Taffler, 2007):

$$z = \frac{A_1 - A_2}{\sqrt{(se(A_1))^2 + (se(A_2))^2}} \tag{8}$$

The standard error of the AUC-statistic can be derived using equation 9 (Hanley & McNeil, 1982; Bauer & Agarwal, 2014). This equation takes into account the AUC-statistic and the size of the sample used. While the AUC-statistic determined the direction of the z-statistic, the sample size used by both models determines its size with larger samples leading to larger z-statistics.

Equation 9 – Standard error of the AUC-statistic

Model	Variables
$se(A) = \sqrt{\frac{A(1-A) + \left(N_f - 1\right)(Q_1 - A^2) + \left(N_{nf} - 1\right)(Q_2 - A^2)}{N_f N_{hf}}}$	$A = AUC\ statistic$ $N_f = Number\ of\ bankrupt\ firms$ $N_{hf} = Number\ of\ healthy\ firms$ $Q_1 = \frac{A}{2-A}$ $Q_2 = \frac{2A^2}{1+A}$

2.4 Methodological Issues

Various research has been conducted using BPMs after the research of Altman (1968). Besides the research that developed well-known models, various authors have tested, extended, and compared BPMs. Additionally, as industries systematically differ and macroeconomic developments are an important exogenous factor contributing to the risk of bankruptcy, it is interesting to see which studies used industry and macroeconomic factors in their BPMs. Through making a review of recent research regarding methodological development the current state of BPM research is assessed on which this study can built.

2.4.1 Performance of Econometric Techniques

Prior research has found mixed results on the performance of various BPM. Press and Wilson (1978) used several samples to compare MDA and a logistic model. They found that both models produced roughly similar results, with the logistic model only slightly outperforming the MDA.

Collins and Green (1982) conducted a study to compare MDA and logit models. They found their performance to be roughly the same, with logit models only producing slightly less type I errors. Furthermore they argue that MDA models are approximately similar to linear probability models, which is based on Ordinary Least Squares (OLS).

Lennox (1991) performed a study to re-estimate the MDA, logit, and probit model using a sample of 949 firms from the United Kingdom. He argued that prior studies, such as Press and Wilson (1978) and Collins and Green (1982), tended to avoid the heteroskedasticity problem of MDA. When taking this problem into account, he found that logit and probit models outperform MDA models.

Grice and Ingram (2001) re-estimated the MDA model of Altman (1968) to assess its predictive ability over time, as the predictors of MDA often are not stationary. This means that the magnitude and significance of the predictor are not stable over time (Grice & Ingram, 2001). Furthermore they evaluated the performance of the model outside the original manufacturing industry. Grice and Ingram (2001) used one sample to re-estimate the model from years 1985-1987 and one hold-out sample from 1988-1991. These samples included both manufacturing firms and non-manufacturing firms. They found that the performance of the MDA model declined using a recent sample and outside its particular industry. Grice and Ingram (2001) also argued that the MDA model can be used to predict other types of financial distressed positions.

Grice and Dugan (2003) evaluated the logit model of Ohlson (1980) and the probit model of Zmijewski (1984) to assess if the predictors are stationary over time and thus keep high predictive value. They used a big samples to re-estimate the models of 1,048 and 1,059 firms and two hold-out samples of 1,024 and 1,043 firms from the United States. They found that the coefficients of these models need to be re-estimated in order to keep high predictive accuracy

Mensah (1984) conducted a research to assess if predictor variables are stationary over time. He argued that different economic environments create significant differences between time periods that need to be taken into account. Using four samples of United States firms belonging to different time periods between 1972 and 1980 he found that the accuracy and structure of models, relating to their significance and size of the coefficients, differed between these time periods.

Begley et al. (1996) re-estimated the models of Altman (1968) and Ohlson (1980) and found that their re-estimated models performed worse than the models in their original time period. Furthermore, they found that the logit model outperformed the MDA.

Hillegeist et al. (2004) created the distance to default model as reaction to the heavy reliance of accounting based variables of the MDA, logit, and probit models. Building their model on option pricing theory and including only market data they found that their model outperformed the previous models. Furthermore, they found industry classifications to have significant impact.

Agarwal and Taffler (2008) tested the Altman (1968) model and the model of Hillegeist (2004). They found that in terms of predictive ability there is little difference between BPMs using accounting-based or market-based data and that both carry unique information about bankruptcy. They claim that the lack of greater predictive ability of the distance to default model might be due to two limitations of these models: 1) misspecifications related to restrictive assumptions of the mode, such as being unable to differ between factors such as asset classes and maturity dates, and 2) measurement errors, such as the value and volatility of assets being unobservable (Hillegeist et al., 2004; Agarwal & Taffler, 2008).

Wu et al. (2010) argued that an integrated model of accounting data, market data, and firm characteristics, such as size and corporate diversification, is most likely to be accurate. They found that the ROC score of the MDA (0.861) was lower than the score of the logit model (0.887), but higher than the score of the probit model (0.852) using a sample of roughly 50,000 United States firms. The hazard model (0.906) and the distance to default model (0.929) both performed better than these three models. They created a new model using various elements on the old models and compared the model to re-estimated models of Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001) and Hillegeist et al. (2004). They found that their model outperformed these models. They included a factor for the degree of diversification in their model which was found to be significantly negatively associated with the risk of bankruptcy. They also argued that size is a firm characteristic that might help to predict future bankruptcy (Wu et al., 2010).

Bauer and Agarwal (2014) compared a hazard model with the model of Altman (1968) and a distance to default model using a database of firms from the United Kingdom. They found that their hazard model outperformed these two other models.

2.4.2 Industry Specification in Bankruptcy Prediction Models

Several authors have applied an industry specification to BPM research. Platt and Platt (1990) argued that most models, MDA, logit, and probit, produce similar results in their estimation sample and low scores in their hold-out sample. They therefore suggested that the models need to be re-estimated because the predictors are not stationary over time, but they also argue that industry characteristics could have an effect. Building on the work of Lev (1969), they argued that firms adjust their financial ratios to mimic the industry average. They found that industry-relative ratios provide greater accuracy, in the estimation and hold-out sample, and are more stable over time using a sample of 114 firms from the United States.

Platt and Platt (1991) compared unadjusted and industry-relative financial ratios for bankruptcy prediction. Using two samples, both taken from Platt and Platt (1990), they verified the conclusion of Platt and Platt (1990) that industry-relative ratios provide stronger results.

Grice and Dugan (2001) used various large samples of United States firms from various industries between 1988-1991 and 1992-1999 to evaluate the models of Ohlson (1980) and Zmijewski (1984). They found that the models are less accurate outside their original sample, indicating that predictor variables might not be stationary over time and would need to be re-estimated. They also found that the probit model was significantly more accurate than the logit model due to the higher sensitivity of the logit model to macroeconomic factors and industry classifications.

Chava and Jarrow (2004) applied a hazard model with industry effects to a large sample of United States firms over the period 1962-1999. They found the hazard model to be superior to the models of Altman (1968) and Zmijewski (1984). Furthermore, they found that adding industry classifications are significant when added to the model. They also found that using monthly data improves the predictive ability of hazard models over using only yearly data.

2.4.3 Macroeconomic Factors in Bankruptcy Prediction Models

Because predictor variables are often not stationary over time several researchers have tested the accuracy of the models across several time periods (Mensah, 1984; Begley et al., 1996; Grice & Ingram, 2001; Grice & Dugan, 2003). Some authors have also explicitly incorporated macroeconomic factors in their models to examine if these variables improve the accuracy of BPMs.

Platt et al. (1994) used a sample of 124 oil and gas firms from the United States between 1982 and 1988. They studied if temporal distortion, related to industry and macroeconomic events, had an effect on the accuracy of BPMs. They found that including these factors improved the accuracy of BPMs.

Nam et al. (2008) argued that prior studies found models to perform poorly out of sample as they failed to incorporate macroeconomic dependencies in the models. They used three different models, original model of Shumway (2001), the hazard model re-estimated, and the hazard model extended by constructing a baseline hazard rate with macroeconomic factors. Using a estimation sample between 1991 and 1997 and hold-out sample between 1998 and 2000 consisting of Korean firms they found that the models with time-varying covariates, re-estimated variables, performed better than the static Shumway (2001) model. Furthermore, they found that the model using macroeconomic factors outperformed both other models.

Tinoco and Wilson (2013) used a big sample of 3020 firms from the United Kingdom with financial information between 1980 and 2011. They created a hazard model using accounting, market, and macroeconomic data. Tinoco and and Wilson (2013) found that both market data and macroeconomic factors add to the predictive power of their model.

2.5 Bankruptcy Prediction Models Reexamined

The predictive ability of these BPMs varies over time, suggesting that different data and techniques could capture different aspects of bankruptcy and that predictors are not stationary over time due to changing relationships between variables and ratios moving out of their historical range (Platt & Platt, 1990; Grice & Dugan, 2001; Wu et al., 2010). The techniques of Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and Hillegeist (2004) vary in effectiveness over time, but the predictive value of this group of BPMs is often still very robust and significant over a large time period (Beaver et al., 2005). BPMs do therefore offer valuable insight into the financial health of companies next to other factors, such as auditor signaling rates (McKee, 2003). In order to keep strong predictive ability however, some BPMs would need to be re-estimated since applying BPMs models outside their original time periods and specific industries might lead to a decrease in accuracy (Mensah, 1984; Grice & Dugan, 2001; Balcaen & Ooghe, 2006). Most prior research on BPMs has been conducted in an United States setting (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Platt et al., 1994; Shumway, 2001; Grice & Dugan, 2001; Grice & Dugan, 2003; Chava & Jarrow, 2004; Hillegeist et al., 2004). It would therefore be interesting to re-estimate the models in a European setting under contemporary conditions and controlling for industry classification to analyze their predictive power and information content. This is especially interesting as Europe was subject to both economics crises and because the continental European legislation leads more often to bankruptcy. This leads to the following research question:

Which bankruptcy prediction model outperforms the other models in predicting bankruptcy for European companies?

The hypothesis are formulated below to answer this research question.

Accounting and market information both have their own benefits. Accounting data can provide objective financial information that has predictive power to predict bankruptcy with high accuracy years before the eventual bankruptcy (Morris, 1997; Beaver et al., 2005; Balcaen & Ooghe, 2006). However others have argued that accounting data has its limitations (Morris, 1997; Hillegeist et al., 2004; Balcaen & Ooghe, 2006). Other authors have argued in favor of using market data as it combines various sources of information (Hillegeist et al., 2004; Beaver et al., 2005; Agarwal & Taffler, 2008; Trujilo-Ponce et al., 2013). Research incorporating these sources of data in their BPMs found contrasting results. Agarwal and Taffler (2008) argued that there is little difference in the predictive ability of models using accounting and market data. Due to the limited data availability of market data this research will focus mainly on models using accounting data. The study will look at the predictive ability of the models of Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001). The distance to default model will therefore be excluded as it relies entirely on market data. This is a limitation of this research, as the distance to default model is the only BPM that is based on theory and has shown to perform well.

The hazard model of Shumway (2001) might be superior to the other models as it combines using a logistic regression with panel data. Bauer and Agarwal (2014) have found that hazard models are superior to these other models. Due to data limitations it is however impossible to use the technique of Shumway (2001) with his original variables. Shumway (2001) included a lot of market variables for which the data is likely to be unavailable. This study therefore uses the technique of Shumway, namely a logit model with panel data, with the variables of the normal logit model of Ohlson (1980). As the technique of Shumway (2001) uses logistic regression with panal data it is likely to be the superior model (Chava & Jarrow, 2004; Bauer & Agarwal 2014). The first hypothesis therefore is:

H1a: A bankruptcy prediction model using the technique of Shumway (2001) is more accurate than the other bankruptcy prediction models tested.

H1b: A bankruptcy prediction model using the technique of Shumway (2001) contains more incremental information than the other bankruptcy prediction models tested.

Prior research has shown that macroeconomic events have an impact on the likely of bankruptcy (Moulton & Thomas, 1993; Platt, 1989; Gilson et al., 1990; Bhattacharjee et al., 2009). These factors also affect the incumbent firms of different industries in different ways. The research of Platt et al. (1994), Nam et al. (2008), and Tinoco and Wilson (2013) has shown that incorporating variables based on macroeconomic factors can improve the predictive power of the models. This study therefore incorporates macroeconomic factors in the model as it is expected that including these factors improves the quality of the models. The second hypothesis therefore is:

H2a: Bankruptcy prediction models containing macroeconomic factors are more accurate than models that do not incorporate these factors.

H2b: Bankruptcy prediction models containing macroeconomic factors contain more incremental information than models that do not incorporate these factors.

Grice and Dugan (2001) argued that researchers best control for industry classification when applying BPMs outside their original settings. This is in line with Hillegeist et al. (2004), Chava and Jarrow (2004), and Wu et al. (2010) who suggested industry classification as an important firm characteristic. Industry evolution and valuation model literature has also shown that industries differ systematically. Some industries are inherently more risky than others and could show more bankruptcies (Opler & Titman, 1994; Maksimovic & Phillips, 1998).

Most of the research on BPMs is conducted using samples consisting of firms from single industries. Platt and Platt (1991) and Platt et al. (1994) suggest using industry-relative ratios when using samples with more than one industry. As industries differ in their nature, such as different production factors and competitive structure, ratios might be similar intra-industry but differ a lot inter-industry (Platt & Platt, 1990; Chava & Jarrow, 2004). Combining multiple industries into a single model using the normal ratios might therefore bias the results. Using industry-relative ratios has a few advantages: 1) more stable financial ratios, 2) more stable coefficient estimates, and 3) more accuracy and therefore more predictive power (Platt & Platt, 1991). In addition, Chava and Jarrow (2004) suggested also including an intercept dummy for each industry included in the model.

It is interesting to see if it is possible to create models that have great predictive power for more than a single industry. This study therefore creates separate models for a few industries and a single model using all these industries with industry-relative ratios. However as this inter-industry combines firms from multiple industries it might be harder to estimate a model with great predictive value. Intra-industry models would only need to take into account the characteristics of a single industry and are therefore likely to be more accurate and have greater predictive power. The third hypothesis therefore is:

H3a: Intra-industry bankruptcy prediction models are more accurate than inter-industry models.

H3b: Intra-industry bankruptcy prediction models contain more incremental information than inter-industry models

Finally, as prior research has stated that the predictors of BPMs are not stationary over time, leading to a decrease in the accuracy and information content, and therefore decreased predictive ability of these models (Mensah, 1984; Begley et al., 1996; Grice & Ingram, 2001; Grice & Dugan, 2003; Agarwal & Taffler, 2007; Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). Therefore it is expected that the performance of the models is lower in the hold-out samples than in the estimation samples. The fourth hypothesis therefore is:

H4a: Bankruptcy prediction models lose their accuracy over time.

H4b: Bankruptcy prediction models lose their information content over time.

3. Research Method

In order to conduct the research several methodological choices have to be made. These choices and related limitations are discussed below.

3.1 Sample Description

A dataset is created in order to study the performance of the BPMs. Data is gathered from European countries. La Porta (1998) stated that the European legal framework could be seen as a patchwork of legal families. Commercial law, including bankruptcy law, is either based on common law or civil law. La Porta (1998) further divided civil law in French, German, and Scandinavian civil law. These differences in legal frameworks have influence on the likelihood of bankruptcy due to different levels of investor protection. In order to use a European sample it is important to either take countries belonging to one of these families or use dummy variables to account for the legal differences. In order to focus on the effect of industry and macroeconomic factors, this study uses only one legal family as sample. Furthermore, as the legal framework of Europe and the United States is converging, the legal differences are of increasingly less importance (Tarantino, 2013). The French civil law family is chosen as this group includes many countries that suffered severe economic downturn during the credit crisis (2007-2009) and the European sovereign debt crisis (2010-2013), which creates interesting macroeconomic circumstances (Claessens et al., 2010; De Haan et al., 2012).

[Insert table 2 here]

As the macro economy of Europe in the recent decade was characterized by the credit crisis and European sovereign debt crisis the time periods used for the samples are designed around these macroeconomic events. This study uses three time periods: a pre-credit crisis period (2004-2006), credit crisis period (2007-2009), and sovereign debt crisis period (2011-2013).

Data is gathered using ORBIS, a database of Bureau van Dijk. This database has an advantage that it contains vast financial information of firm using one accounting convention which facilitates comparison between firms. Data limitations prevent the creation of models incorporating multiple legal families with dummies to account for these differences. Orbis does not have complete information on sufficient bankrupt firms from these two other legal families for these to be incorporated into the models. Furthermore, the database does not have sufficient data for private firms that went bankrupt. The study therefore focuses on public firms in line with prior research (Chava & Jarrow, 2004; Tinoco & Wilson, 2013). Lastly, the start of the sovereign debt crisis, 2010, cannot be included in the models as Orbis does not provide complete information on sufficient bankrupt firms. The number of bankrupt firms in this year would be too low, due to necessary data missing for some variables. This would cause the ratio of bankrupt to healthy firms to be unrealistic which can cause problems when using BPMs (Zmijewski, 1984; Grice & Ingram, 2001; Balcaen & Ooghe, 2006). The bankrupt firms are selected based on the following criteria, taking into account differences in Orbis versions:

1. Listed in ORBIS as status 'Bankruptcy' with either a 'Last available year' in the period 2004-2009 or as 'Inactive since' in the period 2005-2010 for the first two time periods. Or listed as 'Dissolved (bankruptcy)' with either 'Status date' or 'Status updated in Orbis' in the period 2012-2014 for the third time period.
2. The firm was located in a country belonging to the French-origin civil law family: Belgium, France, Greece, Italy, the Netherlands, Portugal, or Spain (table 2).
3. The firm belongs to one of the following industries using BvD major sectors: 'Construction', 'Machinery, equipment, furniture, recycling', 'Metals & metal products', 'Other services', or 'Wholesale & retail trade'. Further details regarding the samples is provided in sections 4.1.1, 4.2.1, and 4.3.1.
4. The firm was publically listed during the time periods in order to facilitate the data gathering.
5. All the required data for the models (appendix A) is available for the firm, with exception of the market capitalization (see 3.2.1).

Using a representative sample of firms in which the ratio of healthy and bankrupt firms is equal to that of the whole population is important for estimating reliable coefficients (Zmijewski, 1984; Grice & Ingram, 2001; Balcaen & Ooghe, 2006). It would normally be ideal to use the annual default rate (ADR) of European firms to create the correct ratio between healthy and bankrupt firms. There are however problems related to using the ADR as ratio. The ADR is usually relatively low, which would create datasets with only a few bankrupt firms relative to the healthy firms. In line with prior research (Grice & Ingram, 2001; Balcaen & Ooghe, 2006) the ADR is found to be too low to use as ratio, and a ratio of 1:10 (bankrupt to healthy firms) is chosen. The number of healthy firms is selected based on the number of bankruptcies after the first year. This ratio might therefore differ in the other years of the same time period. Using the last year to create the ratios would lead to an unrealistically high number of bankrupt firms. Furthermore, a lot more data would be required for the first year, which might not be available. A minimum of 200 healthy firms is always used in order to create sufficiently large datasets.

The number of years included in each period has been limited to three due to the data limitations and the assumption of absence of non-informative censoring. This implies that the bankrupt firms first have to filtered for complete information in year one of each period. The firms that go bankrupt after either the second or third year would also need complete information for the second year or entire period respectively. By only using bankrupt firms with complete information these firms can only leave the sample due to their bankruptcy and no due to data limitations. Through satisfying the assumption of absence of non-informative censoring the dataset is suitable for the hazard models at the expense of the number of bankrupt firms in the sample.

These healthy companies are selected based on the following criteria:

1. Listed in ORBIS as ‘Active’.
2. The firm is active during one of the three sample periods. The active firms are active during all the years of a period. Firms that are active for part of a period and go bankrupt during the period are classified as healthy during the years period to bankruptcy.
3. The firm was located in a country belonging to the French-origin civil law family: Belgium, France, Greece, Italy, the Netherlands, Portugal, or Spain (table 2).
4. The firm belongs to one of the following industries using BvD major sectors: ‘Construction’, ‘Machinery, equipment, furniture, recycling’, ‘Metals & metal products’, ‘Other services’, or ‘Wholesale & retail trade’.
5. The firm was publically listed during the time periods in order to facilitate the data gathering.
6. All the required data for the models (appendix A) is available for the firm, with exception of the market capitalization (see 3.2.1).

3.2 Statistical Models

This study uses two separate groups of models, intra-industry models and inter-industry models. These different groups are used to asses if the systematic differences between industries can be incorporated within a single BPM while still having high accuracy.

3.2.1 Intra-Industry Models

The models used in this study are based on the work of Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001) and can be found in table 3. A few changes are made to these models. The model of Altman (1968) uses the variable market capitalization. It can be hard to find data for sufficient companies for this variable. Francis and Schipper (1999) suggested using a proxy to estimate the market capitalization. They estimated the market value of equity in two ways: (1) as a function of the book values of assets and liabilities (equation 12), and (2) as a function of the book value of total assets and earnings (equation 13).

$$Market\ capitalization_t = \beta_1 Total\ assets_t + \beta_2 Total\ liabilities_t \qquad \textbf{(12)}$$

$$Market\ capitalization_t = \beta_1 Total\ assets_t + \beta_2 Earnings_t \qquad \textbf{(13)}$$

Francis and Schipper (1999) evaluated their proxies based on the adjusted r-squared acquired from Ordinary Least Squares (OLS) using a sample of exchange-listed and Nasdaq firms from the period 1952-1994. They found that a proxy using total assets and earnings outperformed the alternative proxy as it had the highest average adjusted r-squared over a 42 year period. Furthermore, the adjusted r-squared increased over the sample period and showed the least variance of all proxies. The coefficients related to the highest adjusted r-squared across the sample is found near the end of the time period. As these coefficients explain the most variance in market capitalization and this proxy is found to have increasing explanatory value over time, this study uses the proxy Book Value & Earnings Relation of Francis and Schipper (1999) with their coefficients related to the highest adjusted r-squared to make an estimation of the market capitalization of the firms with these coefficients:

$$Market\ capitalization_t = 0.73 * Total\ assets_t + 3.77 * Earnings_t \qquad \textbf{(14)}$$

The SIZE variable that Ohlson (1980) incorporated in his logit model divided the natural logarithm of the total assets of the firm by the Gross National Product (GNP) price level index with a base of 100 in 1968. The GNP is therefore used as a measure of inflation. The World Bank now uses the Gross National Income (GNI) indicator as a measure of inflation, replacing GNP (OECD, 2003; World Bank, 2016). This study replaces the GNP with the GNI, Atlas method (current US$).

The hazard model uses the technique of Shumway (2001) but the variables of Ohlson (1980) due to the limited availability of market data in Orbis. A significant amount of bankrupt firms were rather small and the database therefore lacked sufficient market data for these firms. Gathering market data from different sources could lead to matching issues and is too time-consuming given the time span of the research. The baseline hazard, which is the baseline default rate when the time varying covariates of the model are set to zero, rate of this model will be the annual default rate of European firms (Hillegeist et al., 2001; Nam et al., 2008). This rate provides the percentage of total bankruptcies over the entire population of firms, both healthy and bankrupt firms (Standard & Poors, 2015). This baseline hazard rate provides the additional benefit that it indirectly incorporates macroeconomic factors as these factors influence the number of bankruptcies in a given time period. Nam et al. (2008) have shown that this can increase the quality of the model.

Finally, Mensah (1984) stated that researchers should account for the underlying economic developments when using financial ratios. The models used in this study include macroeconomic factors. Prior research has incorporated (changes in) prime interest rates (Platt et al., 1994; Hillegeist et al., 2001; Nam et al., 2008), price of important raw materials such as oil (Platt et al., 1994), volatility of foreign exchange rates (Nam et al., 2008), retail price index (Tinoco & Wilson, 2013), and real short term treasury bill rate (Tinoco & Wilson, 2013). This study uses changes in prime interest rates for firms as macroeconomic variable as it effects the market value of long-term debt and therefore the true indebtedness of the firm. Euribor cannot be used as proxy for prime interest rate as this rate is the same for all the countries in the sample. Including Euribor would lead to estimation errors, including collinearity and a singular sample covariance matrix for multivariate discriminate analysis. The 10 year T-bills of the respective countries is used as this provides a country specific indication of the prime lending rate. Furthermore, the credit and sovereign debt crisis had a big impact on the economic growth of the countries in this sample, which has an effect on the likelihood of bankruptcy (Claessens & Klapper, 2005; Claessens et al., 2010). The models use the change in gross domestic product (GDP) as second macroeconomic variable.

[Insert table 3 here]

3.2.2 Inter-Industry Models

Platt and Platt (1990), Platt and Platt (1991), Grice and Dugan (2001), and Chava and Jarrow (2004) are among the pioneers of using industry classification in BPM research. The inter-industry models are based on their work. Platt and Platt (1991) and Platt et al. (1994) suggested a solution for the problems related with incorporating various systematically different industries in a single BPM. They suggested using financial ratios that are adjusted to the industry average and have found these to provide superior results. These ratios are calculated as follows (Platt & Platt, 1990):

$$Industry\ relative\ ratio = \frac{Firm\ ratio}{Mean\ ratio\ industry * 100} \quad \textbf{(15)}$$

Platt and Platt (1990) noted that the mean of the industry is multiplied by 100 in order to acquire ratios that have a mean of 0.1. This coding provides industry relative ratios that have less variance than the variance of the unadjusted ratio (Platt & Platt, 1990). These are scalar ratios that are adjusted each year by that year's industry average. Taking these relative ratios ensures that the ratios of firms from different industries can be used in one BPM. In line with Platt and Platt (1991), the average of the firms belonging to a single industry in the sample is taken as the industry average. This average is computed using the sample as actual industry averages are hard to obtain and are often obtained from different data sources and because using a sample with a correct ratio of healthy and bankrupt firms, based on the annual default rate of European firms, makes it possible to generate a industry average (Platt & Platt, 1990; Platt & Platt, 1991).

Chava and Jarrow (2004) suggested using intercept and slope coefficient dummies to capture the unique variance of each industry. They argued for slope coefficient dummies as industries differ in their competition and might therefore have different accounting conventions, resulting in different balance sheets. Chava and Jarrow (2004) found their coefficient dummies to add to the power of the model. This study does not use coefficient dummies for two reasons. First, adding a coefficient dummy that makes each industry interact with each variable would create very large model. This would lower the degrees of freedom and make the results very hard to interpret. Furthermore, in this study we are not necessarily interested in the interaction of each industry with each variable, but only in the total industry effect. Second, it is expected that the industry relative ratios correct for the different balance sheet conventions. This would make adding these industry coefficient dummies redundant. The inter-industry models will however include intercept dummies to capture any additional industry effects. These intercept dummies will be added using regular dummy coding. A full overview of the type of models that are used can be found in table 4.

[Insert table 4 here]

3.3 Empirical Analysis

The second section has already introduced a set of assumptions for each model and the performance evaluation tools for BPMs. In addition this study follows Dichev (1998) by using a winsorized mean. As the datasets are relatively small the extreme values, the top and bottom 5% of all accounting variables are set to the values associated with the 5^{th} and 95^{th} percentile respectively to limit the influence of extreme outliers. As the market capitalization variable is created using accounting data this variable is also winsorized. For the intra-industry models, these variables are winsorized per industry and per time period. The inter-industry models only winsorize per time period.

3.3.1 Assumptions of Statistical Models

The second section has provided a list of assumptions for each statistical technique used to create BPMs. Therefore, in order to non-biased model parameters and accurate probabilities of default, the during the statistical analysis the assumptions related to each model will be assessed and corrective measures will be taken where needed.

3.3.2 Evaluation of the Models

The models are assessed for their predictive value based upon their information content and on the ROC curve in order to capture a broad indication of their quality. The information content is determined using a hazard model as explained in the second chapter of this study. The accuracy of the BPMs is determined using the AUC-statistic. The equation of Agarwall & Taffler (2007) is used to compare the AUC-statistics of multiple models.

As various researchers have shown that the predictors of BPMs are not stationary over time this study uses various hold-out samples to verify the quality of the models. This is important to ensure that the model accurately captures the financial consequences of the underlying causes of corporate failure (Morris, 1997). Each model is first re-estimated using a sample between 2004 and 2006. The hold-out samples used in this research relate to the time periods 2007-2009 and 2011-2014.

It is important to take into account three criticisms of Grice and Ingram (2001) regarding the use of hold-out samples for proper evaluation of BPMs. First, they argued that the estimation and hold-out sample need to be substantially different. This study uses a different set of firms for each of the three time periods. Their second criticism is using a hold-out sample from the same industry as the estimation sample. As this study explicitly tries to compare inter- and intra-industry models, it is in the research design that the industry is the same for the inter-industry model and that the intra-industry model uses the same industries in order to compare these models. This should also not be a problem as the inter-industry models are specifically estimated for one industry and the intra-industry model uses a wider selection of industries. Third, the hold-out samples have to be sufficiently large with an amount of bankrupt firms that is proportional to the actual default rate. As stated at the sample description, a proper ratio is used.

4. Results

4.1 Estimating Inter-Industry Models

4.1.1 Descriptive Statistics.

The inter-industry models are created using a sample of the financial data of 1,991 firms from various industries in the period 2004-2006 (table 5). As can be seen the healthy firms have been randomly selected with a ratio of 1:10 (bankrupt to healthy) firms in the first year of the period as we have 163 bankrupt and 1630 healthy firms.

[Insert table 5 here]

A full overview of all the independent variables of the first inter-industry sample can be found in table 4. This table shows that the accounting based non-dummy firm ratios have been divided by the average industry ratio in order to acquire the industry relative ratios with a mean of 0.1. The industry dummies have been excluded from this overview as table 6 provides a better overview of the types of firm in the sample.

[Insert table 6 here]

4.1.2 Testing Assumptions

The MDA models are subject to three important assumptions. The first assumption of multivariate normality is tested using the Doornik-Hansen (2008) omnibus test for normality which assesses both skewness and kurtosis. This test was significant, rejecting the null hypothesis of multivariate normality, in line with prior research (Lo, 1986; Balcaen and Ooghe, 2006). The Box's M statistic found the assumption of equality of variance-covariance matrices to be violated. This is in line with prior research and therefore not a problem for re-estimating BPMs (Collins & Green, 1982; Karels & Prakash, 1987; Morris, 1997; Balcaen & Ooghe, 2006). The third assumption of absence of multicollinearity is tested using the variance inflation factor (henceforth VIF). The highest VIF score of 2.67 is below the critical value of 10 which indicates that there is no significant multicollinearity (Hair et al., 2010).

The logit and probit models are subjected only to the assumption of absence of multicollinearity, which holds with maximum VIF scores of 2.53 and 2.24 respectively. The highest VIF score of the hazard models is 2.24. Using a sample of three year in which firms only leave the sample through bankruptcy ensures that the dataset holds for the time data and absence of non-informative censoring assumption of hazard models. The third assumption of hazard models assumes that the hazard rate is proportional over time depending on the set of covariates. However as this assumption does not hold for bankruptcy analysis (Shumway, 2001), this assumption is not tested for.

4.1.3 Model Coefficients and Performance

The models have been estimated based on their specifications found in table 3. The hazard models were first estimated using the Cox hazard model in line with Shumway (2001). All predictors with the exception of ADR were included in the model as time-varying covariates. Half of these predictors were significant. This is in line with Shumway (2001), who found that most of the variables used by static models are not significant in dynamic models. The rest of the hazard models were estimated using simple logistic regression, which Shumway (2001) proved to provide similar outcomes. Estimating a hazard function using logistic regression requires correcting the biased t statistic (Wald statistic in logistic regression). This bias is the result of the logit model incorporating each observation as a separate firm within one time period instead of multiple firm observations over a period of time (Shumway, 2001). This results in the model overestimating the sample size by failing to take into account the dependence between observations and therefore underestimating the standard errors. In order to correct for this bias the standard error of each coefficient is divided by the average number of firm observations (Shumway, 2001).

[Insert table 7 here]

Table 7 shows the results of each of the eight models. The table shows that most variables that are significant for the logit model are not significant for the hazard model, in line with Shumway (2001). The strength of the influence of indicator variables is also important. Looking at the coefficients we can see that the coefficients of the SIZE (total assets divided by GNI price level index) and TLTA (total liabilities divided by total assets) variables are high. The size of the firm and solvency are therefore important financial dimensions for predicting bankruptcy. Looking at the macroeconomic variables we can see that the GDP growth has more influence than change in interest rate. This could be attributed to GDP growth incorporating many other macroeconomic factors indirectly.

Furthermore, the table shows that in all models most industries differ significantly in their inherent bankruptcy risk as the industry dummies are often significant. This could indicate that intra-industry models can provide a better fit. These models only incorporate the financial data of firms from a single industry. This can provide superior results as industries are inherently different. The firms in different industries use different financial structures and are often best analyzed relative to its competitors within the industry when assessing performance and financial health. For example, firms in one industry can use a more highly leveraged financial structure than firms in a different industry, while still being healthy. Intra-industry models would also provide with coefficients that show the relative importance of each financial ratio when assessing financial health. For MDA

For the MDA models the unstandardized canonical discriminant function coefficients are shown as these are used in hold-out samples (Altman, 1968). The standard error of these coefficients are not shown as these cannot be estimated and the model is evaluated based on the significance of each discriminant dimension. In order to asses which ratios contribute most to the discrimination between the two groups (either healthy or bankrupt) we need to assess the standardized canonical coefficients (table 8). This table shows that retained earnings divided by total assets (RETA) and EBIT divided by total assets (EBITTA) are two variables that contribute a lot to the discrimination between the groups. As firms go either bankrupt or stay healthy, there is only 1 discriminant dimension which is significant for both MDA models. This indicates that there is a significant difference between the two groups. These standardized canonical coefficients are only estimated for the first sample as the other two samples are not used for re-estimation and have the same coefficients.

[Insert table 8 here]

The canonical correlation of both MDA models, without and with macroeconomic variables, is .3946 and .4198 respectively, indicating that there is a reasonable association between the discriminant function and the groups.

In order to assess the performance of these models the AUC-statistic and the information content has been determined (table 9). The goodness of fit is measured with the adjusted R-squared for MDA and pseudo R-squared for logit, probit, and hazard models. Due to the various limitations and ways to calculate the pseudo R-squared this measure is not taken into account for assessing the performance of the models. Alternative, the Lemeshow and Hosmer (1982) test could be used for logistical models to assess the fit of the model. However data limitations and the nature of bankruptcy, which ensures all failures fall into one group which have to be arbitrarily chosen, causes for low sample sizes and big differences in the group sizes which could cause biased results as type I and type II errors would heavily influence the statistic. Consequently this statistic is not used and the goodness of fit is not used to assess the performance of these BPMs.

[Insert table 9 here]

Table 9 shows the AUC-statistic which is based on the ex-ante bankruptcy score and the information content of this score for each model. The ex-ante bankruptcy score is significant at the 1% level for each model, indicating that these models provide information content that help predict bankruptcy over the annual default rate. The z-statistic of Agarwal and Taffler (2007) is used in tables 9 and 10 to assess the relative performance of these models based on their accuracy (AUC) and the standard deviation of the AUC-statistic (Hanley & McNeil, 1982; Agarwal & Taffler, 2007; Bauer & Agarwal, 2014). The z-statistic shows that for this estimation sample the MDA model outperforms the other 3 models which is surprising due to the econometric limitations of the technique used (table 10). The logit models outperform both the probit and hazard models. The underperformance of the hazard model is worse due to the higher standard deviation of the AUC-statistic as result of the bigger sample size by including three years instead of only one. It is interesting if these results also hold for the intra-industry models.

[Insert table 10 here]

Each model performs better if macroeconomic factors are included as predictors (table 9). This indicates that these variables capture an unique aspect of bankruptcy not captured by the accounting-based variables which allows the models to better discriminate between healthy and bankrupt firms.

4.2 Estimating Intra-Industry Models

4.2.1 Descriptive Statistics

The intra-industry models were created using a sample of financial data of firms in the period 2004-2006 again seeding with a 1:10 ratio (table 11). The industry dummies have been excluded from this overview as table 11 provides a better overview of the types of firms in the samples. Table 11 shows that, in line with the inter-industry models, the firms are divided over 5 industries. There are enough firms for each industry. This sample does however have a relative high number of firms from the Machinery, equipment, furniture, recycling industry compared to the inter-industry sample. However, as these models are generated per industry this should not impact the analysis.

A full overview of all the independent variables of the first intra-industry samples can be found in tables 12-16. These tables show that the ratios do not have a mean of 1 as these models do not use industry relative ratios. Furthermore, winsorized means are used to correct for extreme values.

[Insert tables 11-16 here]

4.2.2 Testing Assumptions

For the MDA models the assumptions of multivariate normality and equality of variance-covariance matrices hold for none of the models. The assumption of absence of multicollinearity holds for all ten MDA models, even when using a VIF of 6 in order to account for the smaller data samples (Hair et al., 2010). This assumption also holds for most of the logit, probit, and hazard models. All five intra-industry samples have also been gathered and coded correctly in order satisfy the absence of non-informative censoring assumption of hazard models. The final assumption of hazard model of a proportional hazard rate depending on the set of covariates is again not tested for in line with Shumway (2001).

4.2.3 Model Coefficients and Performance

The models have been estimated based on their specifications found in table 3. The coefficients and significance of variables of these models can be found in tables 17-21. The size of the coefficients for GDP growth is still large compared to the change in interest rate in line with the inter-industry models. The SIZE and TLTA predictor variables are a lot smaller in size compared to the inter-industry models. Using only one industry in a BPM reduces the influence of these predictors. In the inter-industry models the size of the effect is a lot bigger, but the bankruptcy risk is also affected by the industry in which the firms operates through the industry dummy. The intra-industry models might reduce the size of the effect by only taking into account the characteristics of a single industry.

[Insert tables 17-21 here]

Table 22 shows that in line with the models from the inter-industry sample, the models that incorporated macroeconomic factors outperformed their counterparts on accuracy. Furthermore, all the models again provide significant information content on the likelihood of bankruptcy.

[Insert table 22 here]

Looking at the accuracy of the models using the AUC-statistic we can see that every model has high accuracy with no model having a AUC-statistic lower than 0.80, which corresponds with an accuracy of 60% (Engelmann et al., 2003; Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). Table 23 shows the relative performance of each techniques on accuracy for each sample. Using the z-statistic of Agarwal and Taffler (2007) we can see that the logit models outperform the other techniques in all but three samples. This technique only underperforms relative to MDA but also outperforms this technique 7 out of 10 times. The other three techniques show mixed results. The hazard models only outperforms the other techniques 4 out of 30 times. This performance is worse than the probit technique, outperformance 10 out of 30 times, and MDA technique with an outperformance 18 out of 30 models. The underperformance of the hazard models is in line with the inter-industry model. Hypothesis 1a, which stated that a BPM using the technique of Shumway (2001) is the most accurate of the BPMs tested, is therefore rejected. Part of this rejection could be attributed to the larger sample size of the hazard models which result in larger standard deviations of the AUC-statistic. This leads to them to perform worse on the z-statistic of Agarwal and Taffler (2007). However the sample size can only increase of reduce the size of the z-statistic as the AUC-statistic determines which model has higher accuracy. Furthermore, the value of BPMs is often determined by their predictive power out of sample. Thus when assessing the stationarity of predictor variables the hazard models could still outperform the other models. As every model provided significant information content in every sample, both for the inter-industry model and the intra-industry models, no model clearly outperforms the other models. However the logit model outperforms the other models on all but three models, twice having a lower accuracy than the MDA model and ones than the probit model. Thus while not outperforming all the other models in all samples, it is the best performing model for these intra-industry samples. This contradicts the earlier findings of the inter-industry analysis which found the MDA model to predict bankruptcy best. The most interesting finding of both the inter-industry sample and the intra-industry samples is the underperformance of the hazard models. In the inter-industry sample the hazard models were outperformed by all other models. In these intra-industry samples the hazard models underperformed their counterparts 26 out of 30 times. As the hazard model does not outperform the other models on information content, hypothesis 1b is also rejected.

[Insert table 23 here]

Tables 9 and 22 clearly show that BPMs that incorporate macroeconomic factors as predictors outperformed their counterparts every time. Hypothesis 2a, which stated that models containing macroeconomic factors are more accurate than models that do not incorporate these factors, is accepted. Ones again, as every model provides significant information content in every sample, hypothesis 2b has to be rejected.

Taking a closer look at the relative performance of inter-industry versus intra-industry models (table 24), we can see that intra-industry models outperform their inter-industry counterpart 22 out of 40 models. The performance of the intra industry models is worst for the MDA models, 4 out of 10 models underperform, and probit, 5 out of 10 models underperform. The hazard and logit intra-industry models perform relatively well with 6 out of 10 and 7 out of 10 out performances compared to the inter-industry models respectively. Different industries also show contrasting results. For the industries 'Metals & metal products' and 'Wholesale & retail trade' all eight models outperform the inter-industry model. The other industries perform worse with 'Construction' 4 out of 8, 'Machinery, equipment, furniture, recycling' 2 out of 8, and 'Other services' with 0 out of 8 models outperforming the inter-industry models. As appendix B also shows that these industries often significantly differ in their risk of bankruptcy as predicted by the variables this could indicate that industries indeed differ systematically in their risk of bankruptcy and that for some industries it could be beneficial to estimate industry specific BPMs. However this does not hold for all industries. Due to these mixed results hypothesis 3a, intra-industry models are more accurate than inter-industry models, cannot be supported. The disappointing performance of the intra-industry models could be related to their lower sample size, which could make it harder for the models to estimate the coefficients. However this lower sample size also results in lower standard deviations of the AUC-statistic, which improves their relative under or over performance. The good performance of the inter-industry model could also be attributed to the industry-relative ratios and added industry dummies which were significant for most models. It could be possible that the industry-relative ratios and industry dummies are sufficient to capture the industry specific bankruptcy risk if one is interested in a broad range of firms belonging to different economic sectors. As all models perform well on information content hypothesis 3b, intra-industry models contain more incremental information than inter-industry models, is also rejected.

[Insert table 24 here]

4.3 Stationarity of Predictor Variables

4.3.1 Descriptive Statistics

The stationarity of predictor variables is tested using two inter-industry hold-out samples, 2007-2009 and 2011-2013, and ten intra-industry samples using the same time periods as the inter-industry models and the same industries as in the estimation sample. As the number of bankruptcies differs per industry the amount of total firms in each sample differs as seen the healthy firms have been randomly selected with a ratio of 1:10 (bankrupt to healthy) firms in the first year of the period with a minimum of 200 healthy firms in order to acquire a sizable sample size. Table 25 provides an overview of each sample. The same procedures that have been applied to the first samples have been applied to these samples.

[Insert table 25 here]

4.3.2 Model Performance

Each model has been applied to both hold-out samples using the coefficients that have been estimated using the 2004-2006 estimation sample. Tables 26 and 27 provide an overview of the accuracy, using the AUC-statistic, and the information content of these out of sample models. Table 26, providing an overview of the performance of the models in the 2007-2009 hold-out sample, shows that most models still perform relatively well. While the models underperform their estimation sample counterparts 45 out of 48 times, their accuracy is higher than 50% for 40 out of 48 models and higher than 60% 27 out of 48 times. Looking at the AUC-statistic, we can see that models that incorporate macroeconomic factors almost always perform worse on accuracy than the models that do not include these factors as predictors. Only 6 times do these models outperform their counterpart, each time when incorporated in a hazard model. These models seem to perform better when incorporating macroeconomic factors as predictors. The size of the z-statistic of the macroeconomic models higher for all but 5 models, indicating that these models underperform more relative to their estimation models than models that do not incorporate macroeconomic factors are predictors. All 5 models that underperformed less were hazard models. This is interesting as these models did perform better in the estimation sample. This means that the decline in accuracy is worse if models incorporate macroeconomic factors, suggesting that these predictors are less stationarity than firm specific accounting variables. The non-stationarity of these predictors has a severe negative effect on the predictive power of the models. Looking at the information content of the models in this hold-out sample we can see that every model still provides significant information to predict bankruptcy.

[Insert table 26 here]

[Insert table 27 here]

The results of the second hold-out sample (table 27) show that the models perform poorly. Every model underperforms compared to its estimation sample counterpart and the models have no discriminative power (AUC $\leq$ .5) 16 out of 48 times. No model has an accuracy higher than 50%. Looking at the z-statistic we can again see that models that incorporate macroeconomic variables underperform more relative to those that do not use these factors to predict bankruptcy. Their accuracy is also lower for all but one logit model. Especially hazard models underperform severely compared to the estimation sample. These models seem very sensitive to changes in the predictor variables, especially the baseline hazard rate and macroeconomic factors. Where most models only use the annual default rate to assess the information content, hazard models also incorporate it as a predictor variable. As the annual default rate is influenced by many factors, including macroeconomic factors, the hazard models are extra sensitive to changes in the macroeconomic environment. These results however conflict with the first hold-out sample, which found macroeconomic hazard models performing better than hazard models that did not incorporate macroeconomic factors as predictors. When looking at the multicollinearity of ADR, INT, and GDP for all three samples (table 28) we can see that only the second sample, in which the models performed better, shows high collinearity between ADR and GDP. This corresponds to collinearity during the credit crisis period but not during the sovereign debt crisis period. These results indicate that different macroeconomic environments could require different macroeconomic factors as predictors in BPMs in order to produce highly accurate models. As macroeconomic variables are not stationary over time, these factors that could help the model to predict bankruptcy could lead to underperformance if not chosen carefully.

[Insert table 28 here]

When assessing the information content of the models in the second hold-out sample we can see that 28 out of 48 models do not provide significant information content at 95% confidence level. This signals that the models perform very poorly as the ex-ante probability of bankruptcy as predicted by these models does not provide significant predictive power. These results confirm both hypothesis 4a and 4b as BPMs lose both their accuracy and information content over time.

4.4 Robustness Test

4.4.1 Robustness to Sample

It is important that the results of the models in these hold-out samples are not sample specific and the predictors are genuinely not stationary. To test for this the hold-out samples of the inter-industry model are used to re-estimate the eight models. The performance of these models are then compared to the performance of the hold-out models from the same sample (table 29). If the predictors are stationary over time then these re-estimated models would perform similar on accuracy and information content as the hold-out models.

[Insert table 29 here]

As we are looking at BPMs that predict and not only identify bankruptcy we are looking for strong performance on accuracy and information content in hold-out samples from different time periods. Splitting up the 2004-2006 inter-industry sample into different subsamples would not allow us to further test the performance of these models as we would test in exactly the same time period which would provide ideal circumstances for maximum performance. We test the robustness of the results to the samples used by using the three different sample periods, which provides an more realistic performance measure.

For these models the first two assumptions of MDA again do not hold. The assumption of absence of multicollinearity holds for all but one model. The macroeconomic hazard model in period 2007-2009 shows significant collinearity between ADR (VIF = 13.31) and GDP (VIF = 12.40). GDP was removed as a variable in order to obtain more reliable estimators. After removing GDP the VIF of ADR dropped to 1.66. Again, the assumptions of the hazard model hold.

Table 29 includes two z- statistics. The first provides an performance measure of the re-estimated model relative to the estimated model in period 2004-2006. Only 3 out of 16 models perform better in accuracy than their counterpart in the first sample. These three models all belong to the 2007-2009 sample. This provides an indication that it became harder in more recent times for statistical BPMs to accurately predict bankruptcy. The information content is still significant for all models.

The second z-statistic displays the performance on accuracy relative to the hold-out model of the same sample. For the two hold-out samples all the re-estimated models performed better than their hold-out models. The underperformance of the hold-out models was worst for the 2011-2013 sample. This indicates that for all models, especially those from the second hold-out sample, it is beneficial to re-estimate them. Especially for the second hold-out sample it is clear that while the re-estimated models underperform to the estimation models of the estimation sample, they outperform the hold-out samples drastically. Thus while it is harder to estimate accurate models in recent time periods, these models still outperform older estimated models that are used out of sample. This indicates that the predictor variables are indeed not stationary over time as their relationship with the likelihood of bankruptcy changes.

4.4.2 Robustness to set of Predictors

As mentioned in the theoretical framework it is hard to test and compare the efficiency of different econometric techniques as each uses different variables. In order to verify the previous results the 2004-2006 inter-industry models are re-estimated using one set of variables that is used in each model. In order to capture all the aspects of bankruptcy it is important to use a variable that can measure the financial health of each dimension used by Pompe and Bilderbeek (2005). These models used the set of predictors used by Zmijewski (1984) in order to capture the profitability, solvency, and liquidity of the firms. The predictor 'sales divided by total assets' (STA) is added as this total asset turnover ratio functions as activity ratio. The annual default ratio (ADR) is again added to the hazard models in order to function as baseline hazard rate.

The results (table 30) shows to relative performance on accuracy of each of these models using the same set of predictors. These results shows that the MDA technique underperforms relative to all the other techniques when using the same set of predictors. This is surprising as this technique performed best in the 2004-2006 estimation sample when all models used their own set of predictors. The hazard models again perform poorly, only performing well on accuracy compared to the MDA models. The probit and logit models perform best.

[Insert table 30 here]

Table 31 shows the performance on accuracy of these models related to their counterpart that does include macroeconomic factors as predictors (z-statistic M.), the performance relative to the original models (z-statistic Or.), and for the hold-out samples the relative performance compared to the 2004-2006 sample model using the same set of predictors. The results show that the models that incorporate macroeconomic factors as predictors again perform better in the estimation sample and often worse in the hold-out samples. The performance of the techniques using the alternative set of predictors compared to using the original set shows mixed results. The performance of the hazard technique does not clearly improve using a different set of predictors. Furthermore, the table shows that the predictors are again non-stationary. The underperformance relative to the estimation sample is again more severe for models that incorporate macroeconomic predictors. This does not hold for the MDA models, but these models perform very poorly overall in this robustness test.

[Insert table 31 here]

5. Conclusion

Prior research studying the performance of BPMs that incorporate different variables in order to assess the different dimensions of the financial state of firms, has found mixed results. This body of research tested, extended, and compared the models of Altman (1968), Ohlson (1980), Zmijewski (1984), and Hillegeist et al. (2010) and found no model clearly outperforming the alternative models (Collins & Green, 1982; Lennox, 1991; Grice & Ingram, 2001; Pompe & BilderBeek, 2005; Agarwal & Taffler, 2008; Bauer & Agarwal, 2014). These researchers did however find that predictors are not stationary over time due to changing relationships between variables and ratios moving out of their historical range (Mensah, 1984; Platt & Platt, 1990; Grice & Dugan, 2001; Grice & Dugan, 2003; Wu et al., 2010).

Other researchers, such as Platt and Platt (1991), Grice and Dugan (2001), and Chava and Jarrow (2004) incorporated different sources of financial distress in their models in order to increase the predictive ability. Research on industry evolution and valuation models has also shown that industries differ systematically and therefore differ in their likelihood of bankruptcy (Sharpe, 1964; Cameron, 1983; Lester et al., 2003; Fama & French, 2004). Some researchers therefore incorporated industry effects in their models (Platt & Platt, 1990; Platt & Platt, 1991; Grice & Dugan, 2001; Chava & Jarrow, 2004). These researchers have shown that industry-relative financial ratios and industry dummies can increase the performance of BPMs. In addition, macroeconomic events can have diverse effects on different industries, affecting companies in different ways (Moulton & Thomas, 1993; Platt, 1989; Klein, 2000; Bhattacharjee et al., 2009). Some researchers included macroeconomic factors as predictors in BPMs (Nam et al., 2008; Tinoco & Wilson, 2013). They found that adding these factors as predictors adds to the predictive power of BPMs.

Most of the prior researches have been conducted in an United States setting (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Platt et al., 1994; Shumway, 2001; Grice & Dugan, 2001; Grice & Dugan, 2003; Chava & Jarrow, 2004; Hillegeist et al., 2004). Because the legal differences between the US and continental Europe, bankruptcy in Europe is more likely to be the result of financial distress than in the US (La Porta et al., 1998; Lee et al., 2011; Tarantino, 2013). The reason being that civil law, which is predominant in continental Europe in contrast to common law in the UK and the US, makes reorganization of firms less likely to succeed. Additionally, Europe, in contrast to the US, was hit by both the financial crisis of 2007-2009 and the sovereign debt crisis of 2010-2013. This makes it more interesting to study BPMs in Europe. This study therefore addressed the following research question:

Which bankruptcy prediction model outperforms the other models in predicting bankruptcy for European companies?

In order to use BPMs to predict bankruptcy in Europe, three time periods have been selected corresponding with the pre-credit crisis period (2004-2006), credit crisis period (2007-2009), and sovereign debt crisis period (2011-2013). The start of the sovereign debt crisis, 2010, was not included in the models as there was not enough complete information on sufficient bankrupt firms for this year. Samples of European firms belonging to the French civil law were drawn within these time periods to create one inter-industry sample and five intra-industry samples per time period. The MDA, logit, and probit models were used with their original set of predictors. The technique of Shumway (2001) was used with the variables of Ohlson (1980) due to data limitations. The four tested models were tested with inter-industry and intra-industry data, of which the extreme outliers were winsorized at 5% in each tail. The models in the inter-industry sample incorporated industry-relative ratios and industry dummies. These models were estimated with and without macroeconomic predictors. The models were assessed for their predictive value based upon their information content and on the receiver operating characteristics curve in order to capture a broad indication of their quality. The information content is determined using a hazard model and the accuracy of the BPMs is determined using the area under the AUC-statistic. The equation of Agarwall & Taffler (2007) was used to compare the AUC-statistics of multiple models.

As the hazard model of Shumway (2001) combines a logistic regression with panel data it was hypothesized that this model would lead to superior performance on both accuracy and information content. The results show that within the estimation sample the hazard models underperform relative to the other three models based on accuracy and perform equally well on information content. Especially the MDA and logit models performed well. This results holds when using an alternative set of predictors. This had led to a rejection of hypothesis 1a and 1b which stated that a BPM using the technique of Shumway (2001) is both more accurate and contain more incremental information than the other bankruptcy prediction models tested. This rejection is in line with prior research. For example, Agarwal and Taffler (2007) and Agarwal and Taffler (2008) noted that despite the econometric and theoretical limitations of MDA models, this technique often still creates robust models with high predictive value. The same result was found in other research as well (Collins & Green, 1982). The better performance of the logit and probit models relative to the MDA model in the intra-industry sample and hold-out samples is in line with Lennox (1991) and Begley et al. (1996).

The underperformance of the hazard model could be related to the non-stationarity of predictor variables. Because this technique uses multiple years to estimate the model the changes this non-stationarity could result in lower quality predictors if the economic environment is volatile as was the case in this research. The strong performance of this model in the reviewed literature could, therefore, be related to the different samples that were used. A different explanation of the difference in results between the current study and others studies, could be due to the use of market variables in other research. Market variables generally carry broader and more timely information.

Each model in the estimation sample, both inter-industry and intra-industry improved on accuracy if macroeconomic factors were added as predictors. This effect holds when an alternative set of predictors is used. Hypothesis 2a was therefore accepted. This result is in line with Nam et al. (2008) and Tinoco and Wilson (2013). The information content of these models was significant with and without macroeconomic variables, leading to a rejection of hypothesis 2b. The significant information content is in line prior research (Wu et al., 2010; Bauer & Agarwal, 2014).

The intra-industry models are expected to outperform their inter-industry counterparts on accuracy and information content since these models would only need to take into account the characteristics of a single industry. The results were inconclusive since only 22 out of 40 intra-industry models performed better on accuracy. The results however differed per type of model and type of industry. The industry dummies in the inter-industry models were often significant, indicating that industries indeed differ systematically in their risk of bankruptcy. This means that for some industries this could be beneficial to estimate industry specific BPMs. However, due to the relatively good performance of the inter-industry model, it could also be possible to create BPMs with multiple industries if industry-relative ratios and industry dummies are added. This is in line with Grice and Dugan (2001) who found that their model was not sensitive to industry classifications. The performance of the inter-industry models likely benefitted from the inclusion of industry dummies and industry-relative ratios, which is in line with Platt and Platt (1991) and Chava and Jarrow (2004). Due to these mixed results hypothesis 3a and 3b, which stated that intra-industry bankruptcy prediction models are more accurate and contain more incremental information than inter-industry models, were rejected.

The results of this research have clearly shown that predictor variables are not stationary over time. While it became harder to estimate accurate models in recent time periods, BPMs still lose their predictive accuracy and information content over time. This effect is worse for models that incorporate macroeconomic factors as predictors. Thus while macroeconomic factors could help the model to predict bankruptcy better, they could lead to underperformance if not chosen carefully. A robustness test verified that the accuracy and information content of BPMs also decreases with an alternative set of predictors. As economic conditions change it would be beneficial to re-estimate the models every few years to more accurately reflect current conditions. Hypothesis 4a and 4b are therefore accepted as BPMs lose both their accuracy and information content over time in line with prior research (Mensah, 1984; Begley et al., 1996; Grice & Ingram, 2001; Grice & Dugan, 2003).

The economic and social value of BPMs is assessed based on its ability to predict bankruptcy out of sample (Morris, 1997). If these models are found to be accurate they can be used for efficient resource allocation. It is therefore vital to be critical when determining the best BPM for European companies. The results of this research are mixed and therefore no conclusive answer can be given to this research question. Both within sample and out of sample the results are varied and have provided several interesting theoretical and practical implications. However, no BPM clearly outperforms the other models and has emerged as the most accurate model. This study has however shown that macroeconomic predictors can be used to more accurately predict bankruptcy if BPMs are re-estimated often as they can then capture a broader set of economic factors. This re-estimation has to be every few years in as the predictors are not stationary. Furthermore intra-industry can be used for some industries to more accurately predict bankruptcy.

This research is subject to several limitations. Firstly, the definition used for bankrupt firms is based on a legal definition of bankruptcy. However, legal bankruptcy is not only the result of bad financial performance. This implies that BPMs do not only measure the relationship between financial health and bankruptcy as result of poor financial performance, but between financial healthy and all cases of bankruptcy. However voluntary liquidation as exit mode of the firm should reduce the amounts of non-financial bankruptcies incorporated in the samples as this mode of exit is often more beneficial to the stakeholders of the firm. This study used the legal definition in line with prior research, but future research could use a combination of multiple financial proxies of financial distress (Grice & Dugan, 2001). However this is of course also not without limitations as not all financial distressed firms end up in bankruptcy.

Secondly, this study could only use a limited set of firms which resulted in low sample sizes for the intra-industry samples. This limitation is the result of using Orbis. Using Orbis to collect the data is justified since Orbis facilitates broad selection of firms across countries with a single accounting convention. As a result of this limitation the ratio between bankrupt and healthy firms varied between the different samples. Future research could incorporate a broader selection of firms by increasing the number of countries and number of industries. If more countries are added within Europe a dummy that measures the unique variance related to institutional differences might be required. The models would then incorporate a dummy for each legal family included in the models. Institutional differences could then be used to help explain the risk of bankruptcy (La Porta et al., 1998; Lee et al., 2011).

Thirdly, the research focused on four econometric methods as market data was hard to acquire. The market capitalization of the firms therefore had to be estimated as a function of the total assets and earnings of the firm. This measure will never be as precise as the real market value of the equity. This study also used a different predictor set for the model of Shumway (2001) than the original research. As prior research suggests that different types of data can capture different aspects of bankruptcy it could be beneficial to add market variables to the models if data can be gathered. While the robustness test suggests that the underperformance of the hazard model is not related to the set of predictors used, it could be that the model performs better if it can incorporate market data as the original model of Shumway (2001) did incorporate these variables. Furthermore, while this study used four variables in the robustness test to capture all four dimensions of the financial status of the firm it might be possible to gather a stronger set of variables using exploratory factor analysis. Future research could even add more non-financial predictors to the BPMs, including agency factors. These data limitations and changed predictor variables make the comparison of results with other studies more difficult.

Finally, the models were assessed on their accuracy using the AUC-statistic which did not take into account the costs associated with type I and type II misclassifications as these are hard to determine for bankruptcies due to the various different aspects of bankruptcy and possible contagion effects. Misclassification can lead to both an missed investment opportunity and the death sentence of a healthy firm if the model is regarded as accurate. Future research should therefore try to incorporate the costs and benefits of BPMs.

References

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*, vol. 37(4), pp. 285-300.

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

Aharony, J., Jones, C. P., and Swary, I. (1980). An Analysis of Risk and Return Characteristics of Corporate Bankruptcy Using Capital Market Data. *The Journal of Finance*, vol. 35(4), pp. 1001-1016.

Al-Attar, Al., Hussain, S., and Zuo, L. Y. (2008). Earnings quality, bankruptcy risk and future cash flows. *Accounting and Business Research*, vol. 38(1), pp. 5-20.

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, vol. 23(4), pp. 589-609.

Altman, E. I. (1984). A Further Empirical Investigation of the Bankruptcy Cost Question. *The Journal of Finance*, vol. 39(4), pp. 1067-1089.

Altman, E. I. & Hotchkiss, E. (2006). *Corporate Financial Distress and Bankruptcy.* New Jersey, United States of America: John Wiley & Sons.

Altman, E. I., Haldeman, R. G., and Narayanan, P. (1977). ZETA Analaysis. A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance*, vol. 1, pp. 29-54.

Ang, J. S., Chua, J. H., and McConnell, J. J. (1982). The Administrative Costs of Corporate Bankruptcy: A Note. *The Journal of Finance*, vol. 37(1), pp. 219-226.

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*, vol. 38, pp. 63-93.

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

Davidson, R. & MacKinnon, J. G. (1984). Convenient specification tests for logit and probit models. *Journal of Econometrics*, vol. 25, pp. 241-262.

Beaver, W. H. (1966). Financial Ratios As Predictors of Failure. *Journal of Accounting Research*, vol. 4, pp. 71-111

Beaver, W. H., McNichols, M. F., and Rhie, J. W. (2005). Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy. *Review of Accounting Studies*, vol. 10, pp. 93-122.

Begley, J., Ming, J, and Watts, S. (1996). Bankruptcy Classification Errors in the 1980s: An Empirical Analysis of Altman's and Ohlson's Models. *Review of Accounting Studies*, vol. 1, pp. 267-284.

Bhandari, J. S. & Weiss, L. A. (1996). *Corporate Bankruptcy. Economic and Legal Perspectives.* New York, United States of America: Cambridge University Press.

Bharath, S. T. & Shumway, T. (2008). Forecasting Default with the Merton Distance to Default Model. *The Review of Financial Studies*, vol. 21(3), pp. 1339-1369.

Bhattacharjee, A., Higson, C., Holly, S., and Kattuman, P. (2009). Macroeconomic Instability and Corporate Failure: The Role of the Legal System. *Review of Law & Economics*, vol. 5(1), pp. 1-32.

Black, F. & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, vol. 81(3), pp. 637-654.

Blöchlinger, A. & Leippold, M. (2006). Economic benefit of powerful credit scoring. *Journal of Banking and Finance*, vol. 30, pp. 851-873.

Boons, M. (2016). State variables, macroeconomic activity, and the cross section of individual stocks. *Journal of Financial Economics*, vol. 199, pp. 489-511.

Branch, B. (2002). The costs of bankruptcy. A review. *International Review of Financial Analysis*, vol. 11, pp. 39-57.

Bris, A., Welch, I., and Zhu, N. (2006). The Costs of Bankruptcy: Chapter 7 Liquidation versus Chapter 11 Reorganization. *The Journal of Finance*, vol. 61(3), pp. 1253-1303.

Bryan, S., Nash, R., and Patel, A. (2006). Can the agency costs of debt and equity explain the changes in executive compensation during the 1990s? *Journal of Corporate Finance*, vol. 12, pp. 516-535.

Bulow, J. I. & Shoven, J. B. (1978). The Bankruptcy Decision. *The Bell Journal of Economics*, vol. 9(2), pp. 437-456.

Burgstahler, D. C., Hail, L., and Leuz, C. (2006). The Importance of Reporting Incentives: Earnings Management in European Private and Public Firms. *The Accounting Review*, vol. 81(5), pp. 983-1016.

Bushman, R. M. & Smith, A. J. (2001). Financial accounting information and corporate governance. *Journal of Accounting and Economics*, vol. 32, pp. 237-333.

Campbell, J. Y., Hilscher, J., and Szilagyi, J. (2008). In Search of Distress Risk. *The Journal of Finance*, vol. 63(6), pp. 2899-2939.

CBS (2016). *Aantal faillissementen stijgt.* Retrieved from (12-03-2016): http://www.cbs.nl/nl-NL/menu/themas/bedrijven/publicaties/artikelen/archief/2016/2016-03-09-m07.htm

Charitou, A., Lambertides, N., and Trigeorgis, L. (2007). Earnings Behaviour of Financially Distressed Firms: The Role of Institutional Ownership. *Abacus*, vol. 43(3), pp. 271-296.

Chava, S. & Jarrow, R. (2004). Bankruptcy Prediction with Industry Effects. *Review of Finance*, vol. 8, pp. 537-569.

Cho, S., Hong, H., and Ha, B-C. (2010). A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance: For bankruptcy prediction. *Expert Systems with Applications*, vol. 37, pp. 3482-3488.

Claessens, S., Dell'Ariccia, G., Igan, D., and Laeven, L. (2010). Cross-country experiences and policy implications from the global financial crisis. *Economic Policy*, vol. 25(62), pp. 267-293.

Claessens, S. & Klapper, L. F. (2005). Bankruptcy around the World: Explanations of Its Relative Use. *American Law and Economics Review*, vol. 7(1), pp. 253-283.

Collins, R. A. & Green, R. D. (1982). Statistical Methods for Bankruptcy Forecasting. *Journal of Economics and Business*, vol. 34, pp. 349-354.

Cox, D. R. & Snell, E. J. (1968). A General Definition of Residuals. *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 30(2), pp. 248-275.

Creditreform (2015). *Corporate insolvencies in Europe, 2014/15*. Retrieved from (28-04-2016): http://www.creditreform.lt/fileadmin/user_upload/CR-International/local_documents/lt/Documents/Corporate_insolvencies_in_Europe_2014-15_EN.pdf

Creditreform (2014). *Corporate insolvencies in Europe, 2013/14*. Retrieved from (16-11-2016): http://www.businesscreditreports.com/documents/analysis_corporate_insolvencies_in_europe_2013-14.pdf

Da, Z. & Gao, P. (2010). Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks. *Journal of Financial and Quantitative Analysis*, vol. 45(1), pp. 27-48.

Deakin, E. B. (1972). A Discriminant Analysis of Predictors of Business Failure. *Journal of Accounting Research*, vol. 10, pp. 167-179.

DeAngelo, L. E. (1988). Managerial competition, information costs, and corporate governance: The Use of Accounting Performance Measures in Proxy contests. *Journal of Accounting and Economics*, vol. 10, pp. 3-36.

DeAngelo, H., DeAngelo, L., and Skinner, D. J. (1994). Accounting choice in troubled companies. *Journal of Accounting and Economics*, vol., 17, pp. 113-143.

De Haan, J., Oosterloo, S., and Schoenmaker, D. (2012). *Financial Markets and Institutions: A European perspective*. Cambridge, United Kingdom: Cambridge University Press.

DePamphilis, D. M. (2015). *Mergers, Acquisitions, and Other Restructuring Activities.* Cambridge, United States of America: Academic Press.

Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance*, vol. 53(3), pp. 1131-1147.

Donaldson, G. (1978). New framework for corporate debt policy. *Harvard Business Review*, vol. 56(5), pp. 149-164.

Doornik, J. & Hansen, H. (2008). An Omnibus Test for Univariate and Multivariate Normality. *Oxford Bulletin of Economics and Statistics*, vol. 70(1), pp. 927-939.

Dyrberg, A. (2004). *Firms in Financial Distress: An Exploratory Analysis*. Danmarks Nationalbank Working Papers, no. 17, pp. 1-68.

Eberthart, A. C., Altman, E. I., and Aggarwal, R. (1999). The Equity Performance of Firms Emerging from Bankruptcy. *The Journal of Finance*, vol. 54(5), pp. 1855-1868.

Edmister, R. O. (1972). An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. *Journal of Financial and Quantitative Analysis*, vol. 7(2), pp. 1477-1493.

Eisenbeis, R. A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *The Journal of Finance*, vol. 32(3), pp. 875-900.

Eisenhardt, K. M. (1989). Agency Theory: An Assessment and Review. *Academy of Management Review*, vol. 14(1), pp. 57-74.

Engelmann, B., Hayden, E., and Tasche, D. (2003). Testing rate accuracy. *Risk*, vol 16, pp. 82-86.

Fama, E. F. & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, vol. 18(3), pp. 25-46.

Francis, J. & Schipper, K. (1999). Have Financial Statements Lost Their Relevance?. *Journal of Accounting Research*, vol. 37(2), pp. 319-352.

Frost, C. A. (1997). Disclosure policy choices of UK firms receiving modified audit reports. *Journal of Accounting and Economics*, vol. 23, pp. 163-187.

George, T. J. & Hwang, C-Y. (2010). A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics*, vol. 96, pp. 56-79.

Gillan, S. L. (2006). Recent Developments in Corporate Governance: An Overview. *Journal of Corporate Finance*, vol. 12, pp. 381-402.

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

Grice, J. S. & Dugan, M. T. (2001). The Limitations of Bankruptcy Prediction Models: Some Cautions for the Researcher. *Review of Quantitative Finance and Accounting*, vol. 17, pp. 151-166.

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

Grice, J. S. & Dugan, M. T. (2003). Re-estimation of the Zmijewski and Ohlson Bankruptcy Prediction Models. *Advances in Accounting*, vol. 20, pp. 77-93.

Gruber, M. J. & Warner, J. B. (1977). Bankruptcy Costs: Some Evidence. *The Journal of Finance*, vol. 32(2), pp. 337-347.

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). *Multivariate Data Analysis*. New Jersey, United States of America: Pearson Prentice Hall.

Hambrick, D. C. & D'Aveni, R. A. (1988). Large Corporate Failures as Downward Spirals. *Administrative Science Quarterly*, vol. 33, pp. 1-23.

Hanley, J. A. & McNeil, B. J. (1982). The Meaning and Use of the Area under a Receiver Operating Characteristic (ROC) Curve. *Radiology*, vol. 143(1), pp. 29-36.

Harhoff, D., Stahl, K., Woywode, M. (1998). Legal form, growth and exit of West German firms – Emperical results for manufacturing, constructing, trade and service industries. *The Journal of Industrial Economics*, vol. 46(4), pp. 453-488.

Harris, M. & Raviv, A. (1991). The Theory of Capital Structure. *The Journal of Finance*, vol. 46(1), pp. 297-355.

Healy, P. M. & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, vol. 31, pp. 405-440.

Hillegeist, S. A., Keating, E. K., Cram, D. P., and Lundstedt, K. G. (2004). Assessing the Probability of Bankruptcy. *Review of Accounting Studies*, vol. 9, pp. 5-34.

Horrigan, J. O. (1968). A Short History of Financial Ratio Analysis. *The Accounting Review*, vol. 43(2), pp. 284-294.

Jackson, R. H. G. & Wood, A. (2013). The performance of insolvency prediction and credit risk models in the UK: A comparative study. *The British Accounting Review*, vol. 45, pp. 183-202.

Jensen, M. C. & Meckling, W. H. (1976). Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics*, vol. 3, pp. 305-360.

Jovanovic, B. (1982). Selection and the Evolution of Industry. *Econometrica*, vol. 50(3), pp. 649-670.

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

Klein, J. I. (2000). *Corporate failure by design. Why organizations are built to fail.* Westport, United States of America: Quorum Books.

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

Lambson, V. E. (1991). Industry evolution with sunk costs and uncertain market conditions. *International Journal of Industrial Organization*, vol. 9, pp. 171-196.

La Porta, R. & Lopez-de-Silanes, F. (1998). Law and Finance. *Journal of Political Economy*, vol. 106(6), pp. 1113-1155.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. (2000). Investor protection and corporate governance. *Journal of Financial Economics*, vol. 58, pp. 3-27.

Lambrecht, B. M. (2004). The timing and terms of mergers motivated by economies of scale. *Journal of Financial Economics*, vol. 72, pp. 41-62.

Lang, L. H. P. & Stulz, R. M. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements. *Journal of Financial Economics*, vol. 32, pp. 45-60.

Lee, S-H., Yamakawa, Y., Peng, M. W., and Barney, J. B. (2011). How do bankruptcy laws affect entrepreneurship development around the world? *Journal of Business Venturing*, vol. 26, pp. 505-520.

Lemeshow, S. & Hosmer, D. W. (1982). A review of goodness of fit statistics for use in the development of logistic regression models. *American Journal of Epidemiology*, vol. 115(1), pp. 92-106.

Lennox, C. (1999). Identifying Failing Companies: A Re-evaluation of the Logit, Probit and DA Approaches. *Journal of Economics and Business*, vol. 51, pp. 347-364.

Lester, D. L., Parnell, J. A., and Carraher, S. (2003). Organizational life cycle: A five-stage empirical scale. *The International Journal of Organizational Analysis*, vol. 11(4), pp. 339-354.

Lev, B. (1969). Industry Averages as Targets for Financial Ratios. *Journal of Accounting Research*, vol. 7(2), pp. 290-299.

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

Li, H. & Sun, J. (2008). Ranking-order case-based reasoning for financial distress prediction. *Knowledge-Based Systems*, vol. 21, pp. 868-878.

Lo, A. W. (1986). Logit Versus Discriminant Analysis. *Journal of Econometrics*, vol. 31, pp. 151-178.

Maksimovic, V. & Phillips, G. (1998). Asset Efficiency and Reallocation Decisions of Bankrupt

Firms. *The Journal of Finance*, vol. 49(3), pp. 1495-1532.
McKee, T. E. (2003). Rough Sets Bankruptcy Prediction Models versus Auditor Signalling Rates. *Journal of Forecasting*, vol. 22, pp. 569-586.
McLeay, S. & Omar, A. (2000). The sensitivity of prediction models to the non-normality of bounded and unbounded financial ratios. *British Accounting Review*, vol. 32, pp. 213-230.
Mensah, Y. M. (1984). An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study. *Journal of Accounting Research*, vol. 22(1), pp. 380-395.
Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance*, vol. 29(2), pp. 449-470.
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.
Moulton, W. N. & Thomas, H. (1993). Bankruptcy as a Deliberate Strategy: Theoretical Considerations and Empirical Evidence. *Strategic Management Journal*, vol. 14(2), pp. 125-135.
Myers, S. C. (1984). The Capital Structure Puzzle. *The Journal of Finance*, vol. 39(3), pp. 575-592.
Myers, S. C. (2001). Capital Structure. *Journal of Economic Perspectives*, vol. 15(2), pp. 81-102.
Nam, C. W., Kim, T. S., Park, N. J., and Lee, H. K. (2008). Bankruptcy Prediction Using a Discrete-Time Duration Model Incorporating Temporal and Macroeconomic Dependencies. *Journal of Forecasting*, vol. 27, pp. 493-506.
OECD. (2003). Gross National Income (GNI). Retrieved from (29-06-2016): https://stats.oecd.org/glossary/detail.asp?ID=1176
Ohlson, J. A. (1980). Financial Ratios and the Probability Prediction of Bankruptcy. *Journal of Accounting Research*, vol. 18(1), pp. 109-131.
Opler, T. C. & Titman, S. (1994). Financial Distress and Corporate Performance. *The Journal of Finance*, vol. 44(3), pp. 1015-1040.
Pastena, V. & Ruland, W. (1986). The Merger/Bankruptcy Alternative. *The Accounting Review*, vol. 61(2), pp. 288-301.
Platt, H. D. (1989). The Determinants of Interindustry Failure. *Journal of Economics and Business*, vol. 41(2), pp. 107-126.
Platt, H. D. & Platt, M. B. (1990). Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction. *Journal of Business Finance and Accounting*, vol. 17(1), pp. 31-51.
Platt, H. D. & Platt, M. B. (1991). A note on the use of industry-relative ratios in bankruptcy prediction. *Journal of Banking and Finance*, vol. 15, pp. 1183-1194.
Platt, H. D. & Platt, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias. *Journal of Economics and Finance*, vol. 26(2), pp 184-199.
Platt, H. D., Platt, M. B., and Pedersen, J. G. (1994). Bankruptcy Discrimination with Real

Variables. *Journal of Business Finance and Accounting*, vol. 21(4), pp. 491-510.
Pompe, P. P. M. & Bilderbeek, J. (2005). The prediction of bankruptcy of small- and medium-sized industrial firms. *Journal of Business Venturing*, vol. 20, pp. 847-868.
Press, S. J. & Wilson, S. (1978). Choosing Between Logistic Regression and Discriminant Analysis. *Journal of the American Statistical Association*, vol. 73, pp. 699-705.
Quinn, R. E. & Cameron, K. (1983). Organizational life cycles and shifting criteria of effectiveness: Some preliminary evidence. *Management Science*, vol. 29(1), pp. 33-51.
Rosner, R. L. (2003). Earnings Manipulation in Failing Firms. *Contemporary Accounting Research*, vol. 20(2), pp. 361-408.
Ross, S. A. (1977). The Determination of Financial Structure: The Incentive-Signalling Approach. *The Bell Journal of Economics*, vol. 8(1), pp. 23-40.
Schary, M. A. (1991). The probability of exit. *RAND Journal of Economics*, vol. 22(3), pp. 339-353.
Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *Journal of Business*, vol. 74(1), pp. 101-124.
Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, vol. 19(3), pp. 425-442.
Shleifer, A. & Vishny, R. (1992). Liquidation Values and Debt Capacity: A Market Equilibrium Approach. *The Journal of Finance*, vol. 47(4), pp. 1343-1366.
Sobehart, J. & Keenan, S. (2001). Measuring Default Accurately. *Risk*, no. March, pp. 31-33.
Standard & Poors (2015). Default, Transition, and Recovery:2014 Annual European Corporate Default Study And Rating Transitions. Retrieved from (29-05-2016): https://www.agefi.com/uploads/media/2014_Annual_European_Corporate_Default_Study_And_Rating_Transitions_19-05-2015.pdf
Stein, R. M. (2005). The relationship between default prediction and lending profits: integrating ROC analysis and loan pricing. *Journal of Banking and Finance*, vol. 29, pp. 1213-1236.
Tarantino, E. (2013). Bankruptcy law and corporate investment decisions. *Journal of Banking and Finance*, vol. 37, pp. 2490-2500.
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*, vol. 30, pp. 394-419.
Walter, J. E. (1957). Determination of Technical Solvency. *The Journal of Business*, vol. 30(1), pp. 30-43.
Whitaker, R. B. (1999). The Early Stages of Financial Distress. *Journal of Economics and Finance*, vol. 23(2), pp. 123-133.
World Bank. (2016). GNI, Atlas method (current US$). Retrieved from (29-06-2016): http://data.worldbank.org/indicator/NY.GNP.ATLS.CD
Wu, Y. Gaunt, C., and Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, vol. 6(1), pp. 34-45
Xiao, Z., Yang, X., Pang, Y., and Dang, X. (2012). The prediction for listed companies' financial

distress by using multiple prediction methods with rough set and Dempster–Shafer evidence theory. *Knowledge-Based Systems*, vol. 26, pp. 196-206.

Zhang, Y., Wang, S., and Ji, G. (2013). A Rule-Based Model for Bankruptcy Prediction Based on an Improved Genetic Ant Colony Algorithm. *Mathematical Problems in Engineering*, pp. 1-10.

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, vol. 22, pp. 59-82.

Appendix

Table 1 – Overview statistical models

Model	Method	Type of data used
Altman (1968)	Multivariate discriminate analysis	Accounting and market data
Ohlson (1980)	Logistic regression (Logit)	Accounting data
Zmijewski (1984)	Logistic regression (Probit)	Accounting data
Shumway (2001)	Discrete-time hazard model	Accounting and market data
Hillegeist et al. (2004)	Distance to default model	Market data

Source: Wu et al. (2010) and the five original papers.

Table 2 – European legal families

French-origin	German-origin	Scandinavian-origin
Belgium	Austria	Denmark
France	Germany	Finland
Greece	Switzerland	Norway
Italy		Sweden
Netherlands		
Portugal		
Spain		

Note: This table provides an overview of the European legal families. Source: La Porta (1998).

Table 3 – Overview models used					
Group	Technique	Equation	Variables	Tag	Description
Intra industry	MDA	$Z = v_1 x_1 + v_2 x_2 + \cdots + v_n x_n$	x_1	WCTA	Working capital divided by total assets.
			x_2	RETA	Retained earnings divided by total assets.
			x_3	EBITTA	EBIT divided by total assets.
			x_4	MCBVTL	Market capitalization divided by book value of total liabilities.
			x_5	STA	Sales divided by total assets.
			x_6	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
			x_7	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
	Logit	$P = \frac{1}{1 + e^{(-\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$	x_1	SIZE	Log(total assets) divided by GNI price level index. Index base value of 100 in 1968.
			x_2	TLTA	Total liabilities divided by total assets.
			x_3	WCTA	Working capital divided by total assets.
			x_4	CLCA	Current liabilities divided by current assets.
			x_5	DTLTA	Dummy with a value of 1 if total liabilities exceed total assets.
			x_6	NITA	Net income divided by total assets.
			x_7	FUTL	Income from operations minus depreciation divided by total liabilities.
			x_8	NIN	Dummy with a value of 1 if net income was negative for two prior years.
			x_9	CINI	Relative change in net income, calculated by adding $Net\ income_t$ with $Net\ income_{t-1}$ and dividing this figure by the sum of the absolute value of $Net\ income_t$ and absolute value of $Net\ income_{t-1}$

		x_{10}	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
		x_{11}	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
Probit	$P = \Phi(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)$	x_1	NITA	Net income divided by total assets.
		x_2	TLTA	Total liabilities divided by total assets.
		x_3	CACL	Current assets divided by current liabilities.
		x_4	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
		x_5	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
Hazard	$P = \frac{1}{1 + e^{(y_{i,t})}}$	x_1	ADR	Annual default rate.
		x_2	SIZE	Log(total assets) divided by GNI price level index. Index base value of 100 in 1968.
	$y_{i,t} = a + \beta X_{i,t-1} = \beta \begin{pmatrix} X_{1,t-1} & \cdots & X_{1,t-j} \\ \vdots & \ddots & \vdots \\ X_{n,t-1} & \cdots & X_{n,t-j} \end{pmatrix}$	x_3	TLTA	Total liabilities divided by total assets.
		x_4	WCTA	Working capital divided by total assets.
		x_5	CLCA	Current liabilities divided by current assets.
		x_6	DTLTA	Dummy with a value of 1 if total liabilities exceed total assets.
		x_7	NITA	Net income divided by total assets.
		x_8	FUTL	Income from operations minus depreciation divided by total liabilities.
		x_9	NIN	Dummy with a value of 1 if net income was negative for two prior years.
		x_{10}	CINI	Relative change in net income, calculated by adding $Net\ income_t$ with $Net\ income_{t-1}$ and dividing this figure by the sum of the absolute value of $Net\ income_t$ and absolute

					value of $Net\ income_{t-1}$
			x_{11}	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
			x_{12}	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
Inter industry	MDA	$Z = v_1x_1 + v_2x_2 + \cdots + v_nx_n$	x_1	WCTA	Working capital divided by total assets.
			x_2	RETA	Retained earnings divided by total assets.
			x_3	EBITTA	EBIT divided by total assets.
			x_4	MCBVTL	Market capitalization divided by book value of total liabilities.
			x_5	STA	Sales divided by total assets.
			x_6	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
			x_7	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
			$x_8 - x_{11}$	IND	Industry dummies.
	Logit	$P = \frac{1}{1 + e^{(-\beta_1x_1 + \beta_2x_2 + \ldots + \beta_nx_n)}}$	x_1	SIZE	Log(total assets) divided by GNI price level index. Index base value of 100 in 1968.
			x_2	TLTA	Total liabilities divided by total assets.
			x_3	WCTA	Working capital divided by total assets.
			x_4	CLCA	Current liabilities divided by current assets.
			x_5	DTLTA	Dummy with a value of 1 if total liabilities exceed total assets.
			x_6	NITA	Net income divided by total assets.
			x_7	FUTL	Income from operations minus depreciation divided by total liabilities.
			x_8	NIN	Dummy with a value of 1 if net income was negative for two

				prior years.
		x_9	CINI	Relative change in net income, calculated by dividing adding $Net\ income_t$ with $Net\ income_{t-1}$ and dividing this figure by the sum of the absolute value of $Net\ income_t$ and absolute value of $Net\ income_{t-1}$
		x_{10}	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
		x_{11}	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
		$x_{12} - x_n$	IND	Industry dummies.
Probit	$P = \Phi(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)$	x_1	NITA	Net income divided by total assets.
		x_2	TLTA	Total liabilities divided by total assets.
		x_3	CACL	Current assets divided by current liabilities.
		x_4	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
		x_5	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
		$x_6 - x_n$	IND	Industry dummies.

Hazard	$P = \frac{1}{1 + e^{(y_{i,t})}}$	x_1	ADR	Annual default rate.
		x_2	SIZE	Log(total assets) divided by GNI price level index. Index base value of 100 in 1968.
	$y_{i,t} = a + \beta X_{i,t-1}$	x_3	TLTA	Total liabilities divided by total assets.
	$= \beta \begin{pmatrix} X_{1,t-1} & \cdots & X_{1,t-j} \\ \vdots & \ddots & \vdots \\ X_{n,t-1} & \cdots & X_{n,t-j} \end{pmatrix}$	x_4	WCTA	Working capital divided by total assets.
			CLCA	Current liabilities divided by current assets.
		x_5	DTLTA	Dummy with a value of 1 if total liabilities exceed total assets.
		x_6	NITA	Net income divided by total assets.
		x_7		
		x_8	FUTL	Income from operations minus depreciation divided by total liabilities.
		x_9	NIN	Dummy with a value of 1 if net income was negative for two prior years.
		x_{10}	CINI	Relative change in net income, calculated by dividing adding $Net\ income_t$ with $Net\ income_{t-1}$ and dividing this figure by the sum of the absolute value of $Net\ income_t$ and absolute value of $Net\ income_{t-1}$
		x_{11}	INT	Change in prime interest rate. Measured by Int_t minus Int_{t-1} and dividing this number by Int_{t-1}
		x_{12}	GDP	GDP growth. Measured by GDP_t minus GDP_{t-1} and dividing this number by GDP_{t-1}
		$x_{13} - x_n$	IND	Industry dummies.

Table 4 – Summary of research design

		Estimation Sample	Hold-out Samples	
		2004-2006	2007-2009	2011-2013
Inter-Industry				
	Industry dummies & No Macroeconomic	Altman (1968) Ohlson (1980) Zmijewski (1984) Shumway (2001)	Models using estimated predictor variables	
	Industry dummies & Macroeconomic	Altman (1968) Ohlson (1980) Zmijewski (1984) Shumway (2001)	Models using estimated predictor variables	
Intra-Industry				
	No Macroeconomic	Altman (1968) Ohlson (1980) Zmijewski (1984) Shumway (2001)	Models using estimated predictor variables	
	Macroeconomic	Altman (1968) Ohlson (1980) Zmijewski (1984) Shumway (2001)	Models using estimated predictor variables	

Table 5 – Industry classifications and bankruptcies inter-industry models 2004-2006

Bankruptcy	Industry					Total
	Construction	Machinery, equipment, furniture, recycling	Metals & metal products	Other services	Wholesale & retail trade	
No	212	187	115	443	673	1,630
	(13.00)	(11.47)	(7.06)	(27.18)	(41.92)	
2005	20	44	20	35	44	163
	(12.27)	(26.99)	(12.27)	(21.47)	(26.99)	
2006	6	29	10	29	35	109
	(5.50)	(26.61)	(9.17)	(26.61)	(32.11)	
2007	14	20	15	20	20	89
	(15.73)	(22.47)	(16.85)	(22.47)	(22.47)	
Total	252	280	160	527	772	1,991
	(12.66)	(14.06)	(8.04)	(26.47)	(38.77)	

Note: This table provides an overview of the industry classifications and number of bankruptcies specified by year of the inter-industry estimation sample 2004-2006. The first row of figures provides the absolute number of firms, the second row provides row percentages.

Table 6 – Descriptive statistics inter-industry models 2004-2006

Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.1	.1	.1	.1	-.0116	.0272	.0061	.1	.1
Std. Dev.	.0130	.0169	.0072	.0063	.1251	.0120	.0012	.0032	.0032
Min.	-.0278	-.0536	-.0034	.0005	-.1780	.0060	.0048	.0047	.0028
Max.	.0401	.0662	.0471	.0296	.1990	.0570	.0078	.0181	.0183
Obs.	5,538								

Variable	WCTA	CLCA	DTLTA	NITA	FUTL	NIN	CINI	CACL
Mean	.1	.1	.0614	.1	.1	.1004	.1	.1
Std. Dev.	.0080	.0052	.2401	.0289	.0072	.3006	.0127	.0056
Min.	-.0057	.0023	0	-.1286	.0005	0	-.0170	.0023
Max.	.0274	.0339	1	.0984	.0339	1	.0170	.0347
Obs.	5,538							

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the inter-industry estimation sample 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 7 – Estimated models inter-industry models 2004-2006								
Variable	MDA		Logit		Probit		Hazard	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-20.9363	-9.3928	-25.4434	-18.2707			-.1131	.9577
			(19.8639)	(21.5848)			(26.2099)	(26.86001)
RETA	-68.0442	-62.7316						
EBITTA	-42.8191	-41.7269						
MCBVTL	69.2345	71.9408						
STA	44.2426	43.8183						
SIZE			117.5665**	-188.5845**			167.8718**	108.8847
			(56.4587)	(86.4706)			(74.5915195)	(82.6024)
TLTA			358.7093***	346.4434***	180.0372***	158.784***	210.6893**	195.5043**
			(87.9772)	(93.8925)	(37.4000)	(41.0286)	(98.2452604)	(99.6552)
CLCA			24.1706	25.1848			24.41202	26.6978
			(29.7164)	(33.3159)			(39.6138063)	(40.8897)
DTLTA			.9221**	1.0137**			.4644019	.5558
			(.4134545)	(.4558)			(.600861874)	(.6170)
NITA			-24.2642***	-22.9860***	-17.3604***	-17.2635***	-19.24641**	-18.4881**
			(8.1376)	(8.3795)	(2.7241)	(2.9091)	(7.87779248)	(7.9479)
FUTL			44.4153*	49.3986*			31.691	42.5881
			(24.9761)	(26.2536)			(33.3004585)	(34.0635)
NIN			-1.0476***	-.98040**			-.565921	-.5277
			(.3893)	(.4118)			(.484987221)	(.4890)
CINI			-27.9212**	-28.0167**			-35.59107**	-36.5154**

			(13.5342)	(13.6547)			(17.1171402)	(17.1842)
CACL					-40.4877*	-49.9998*		
					(23.1949)	(25.6122)		
INT		2.8380		4.3668*		.1752		2.5017
				(2.3914)		(1.0542)		(2.0934)
GDP		-32.3755		-142.676***		-54.3023***		-58.5596**
				(26.5088)		(11.035)		(23.8059)
ADR							-111.2849	120.2507
							(155.8538)	(210.7078)
Industry1	.7224	.6503	1.7014***	1.8584	.6418***	.6609***	.4691	.5856
			(.4368)	(.4613)	(.1924)	(.2064)	(.6273)	(.6379)
Industry2	1.0702	.8312	2.1593***	1.9200	.8464***	.7162***	1.0725	.9523
			(.4321)	(.4533)	(.1912)	(.2067)	(.5251)	(.5318)
Industry3	1.1204	.9433	1.4176***	1.3448	.6053***	.4844*	.3322	.2912
			(.5174)	(.5328)	(.2319)	(.2489)	(.6738)	(.6761)
Industry4	.3382	.2492	.7636*	.9450	.3409**	.2821	.0657	.1227
			(.3921)	(.4077)	(.1712)	(.1816)	(.5108)	(.5175)
Constant	-.1019	.4256	-9.5144***	-3.4428**	-3.7529***	-1.9984***	-7.0067***	-6.4453**
			(1.3147)	(1.6026)	(.5493)	(.6675)	(1.6361)	(1.7737)

Note: This table provides an overview of the estimated models of the inter-industry estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), industry: Construction (Industry1), industry: Machinery, equipment, furniture, and recycling (Industry2), industry: Metals & metal products (Industry3), and industry: Other services (Industry4). The fifth industry, Wholesale & retail trade is excluded as reference category. The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 8 – Standardized canonical coefficients inter-industry models 2004-2006		
Variable	MDA macroeconomic	MDA no macroeconomic
WCTA	-.1686	-.0756
RETA	-.8104	-.7471
EBITTA	-.6616	-.6447
MCBVTL	.5470	.5684
STA	.2689	.2663
INT		.1499
GDP		-.3832
Industry1	.2442	.2198
Industry2	.3476	.2699
Industry3	.2954	.2487
Industry4	.1501	.1106

Note: This table provides an overview of the estimated standardized canonical coefficients of the MDA models of the inter-industry estimation sample 2004-2006. The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), industry: Construction (Industry1), industry: Machinery, equipment, furniture, and recycling (Industry2), industry: Metals & metal products (Industry3), and industry: Other services (Industry4). The fifth industry, Wholesale & retail trade is excluded as reference category.

Table 9 – Model performance inter-industry models 2004-2006

Measure	MDA	MDA macro	Logit	Logit macro
AUC	.8945***	.9236***	.8903***	.9196***
	(.0170)	(.0128)	(.0192)	(.0139)
Information content	6.7668***	6.4398***	3.6381***	3.7347***
	(.3187)	(.2885)	(.1384)	(.1398)
Goodness of fit	.1513	.1710	. 3670	. 4275
z-statistic	-.9752	.9752	-0.9636	0.9636

Measure	Probit	Probit macro	Hazard	Hazard macro
AUC	.8800***	.9120***	.8823***	.8922***
	(.0208)	(.0152)	(.0090)	(.0081)
Information content	3.8967***	4.0949***	4.4698***	4.5139**
	(.1506)	(.1506)	(.1641)	(.1615)
Goodness of fit	.3170	.3794	.3116	.3317
z-statistic	-1.0135	1.0135	-.6088	.6088

Note: This table provides an overview of the performance measures of the estimated models of the inter-industry estimation sample 2004-2006. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The goodness of fit measure for MDA is the adjusted R-squared and for logit, probit, and hazard models the Pseudo R-squared. The z-statistic compares each model with the same model that incorporated macroeconomic variables and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. The significance is given at 10% (*), 5% (**), and 1% (***).

Table 10 – Relative performance inter-industry models 2004-2006				
Model	MDA	Logit	Probit	Hazard
MDA		.13090	.44347	.48096
Logit	-.1309		.31260	.31139
Probit	-.4435	-.31260		-.08696
Hazard	-.4810	-.31139	-.08696	
Model	MDA macro	Logit macro	Probit macro	Hazard macro
MDA macro		.1427	.4055	1.3885
Logit macro	-.1427		.2629	1.1913
Probit macro	-.4055	-.2629		.8354
Hazard macro	-1.3885	-1.1913	-.8354	

Note: This table provides an overview of the z-statistic of the estimated models of the inter-industry estimation sample 2004-2006. The z-statistic compares each model with the same other models and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. For example, the 0.13090 indicates that the MDA model without macroeconomic variables outperforms the logit model without macroeconomic factors on accuracy.

Table 11 – Industry classifications and bankruptcies intra-industry models 2004-2006

Bankruptcy	Industry					Total
	Construction	Machinery, equipment, furniture, recycling	Metals & metal products	Other services	Wholesale & retail trade	
No	200	440	200	350	440	1,630
	(12.27)	(26.99)	(12.27)	(21.47)	(26.99)	
2005	20	44	20	35	44	163
	(12.27)	(26.99)	(12.27)	(21.47)	(26.99)	
2006	6	29	10	29	35	109
	(5.50)	(26.61)	(9.17)	(26.61)	(32.11)	
2007	14	20	15	20	20	79
	(17.72)	(25.32)	(18.99)	(25.32)	(25.32)	
Total	240	533	245	434	539	1,991
	(12.05)	(26.77)	(12.31)	(21.80)	(27.07)	

Note: This table provides an overview of the industry classifications and number of bankruptcies specified by year of the intra-industry estimation samples 2004-2006. The first row of figures provides the absolute number of firms, the second row provides row percentages.

Table 12 – Descriptive statistics intra-industry model Construction 2004-2006

Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.1785	.0555	1.3343	1.2237	-.0190955	.0285134	.0061442	.4032965	.7270781
Std. Dev.	.1920	.0686	.6540	.7791	.1200652	.0108858	.0012341	.1267919	.1955935
Min.	-.4506	-.1281	.1846	.0858	-.1731707	.006	.0048	.2096962	.3306829
Max.	.5701	.2277	3.1656	2.9156	.1989986	.057	.0078	.6790885	1.2907
Obs.	674								

Variable	WCTA	CLCA	DTLTA	NITA	FUTL	NIN	CINI	CACL
Mean	.4235917	.7579491	.0519288	.0338	1.8008	.0371	.7349	1.5430
Std. Dev.	.2612364	.2750325	.2220481	.0521	1.1789	.1891	.5893	.7079
Min.	.0006486	.2647344	0	-.1249	.1430	0	-1	.6340
Max.	.9162696	1.577278	1	.1705	4.4478	1	1	3.7774
Obs.	674							

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the intra-industry estimation sample Construction 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 13 – Descriptive statistics intra-industry model Machinery, equipment, furniture, recycling 2004-2006									
Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.2087	.0524	1.5533	1.2994	-.0093	.0239	.0063	.4527	.6509
Std. Dev.	.2227	.0847	1.0038	.5751	.1269	.0116	.00124	.1312	.2070
Min.	-.3216	-.1997	.0848	.4193	-.1780	.0060	.0048	.2170	.2422
Max.	.6535	.2235	4.5881	2.6455	.1990	.0570	.0078	.7497	1.0001
Obs.	1,482								
Variable	WCTA	CLCA	DTLTA	NITA	FUTL	NIN	CINI	CACL	
Mean	.3502	.7235	.0472	. 0249	2.2360	.1113	.5401	1.6697	
Std. Dev.	.1968	.3056	.2122	.0671	1.2013	.3147	.7741	.7836	
Min.	-.0174	.2521	0	-.1747	.5888	0	-1	.6458	
Max.	.7207	1.5486	1	.1525	5.3733	1	1	3.9672	
Obs.	1,482								

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the intra-industry estimation sample Machinery, equipment, furniture, recycling 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 14 – Descriptive statistics intra-industry model Metals & metal products 2004-2006									
Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.2244	.0485	1.5788	1.2472	-.0088	.0255	.0063	.4289	.6570
Std. Dev.	.2503	.07659	1.1499	.5095	.1273	.0124	.0012	.1241	.2258
Min.	-.3447	-.1617	.0608	.5182	-.1731	.0060	.0048	.2098	.2033
Max.	.7295	.2062	5.1929	2.3697	. 1990	.0570	.0078	.6746	1.1169
Obs.	685								
Variable	WCTA	CLCA	DTLTA	NITA	FUTL	NIN	CINI	CACL	
Mean	.3367	.7903	.0599	.0205	2.1118	.1109	.5082	1.5546	
Std. Dev.	.1857	.3346	.2374	.0640	1.1515	.3143	.7837	.7953	
Min.	-.0164	.2546	0	-.1718	.6177	0	-1	.6211	
Max.	.7030	1.6101	1	.1371	4.9528	1	1	3.9284	
Obs.	685								

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the intra-industry estimation sample Metals & metal products 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 15 – Descriptive statistics intra-industry model Other services 2004-2006

Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.1707	.0569	1.8587	1.3584	-.0192	.0267	.0063	. 4427	.6760
Std. Dev.	.2989	.1136	1.8269	.9677	.1212	.0112	.0012	.1488	.2725
Min.	-.7725	-.2571	-.4982	.0740	-.1780	.0060	.0048	.2003	.1630
Max.	.7502	.3143	7.8461	3.5629	.1990	. 0570	.0078	.7870	1.3150
Obs.	1,203								

Variable	WCTA	CLCA	DTLTA	NITA	FUTL	NIN	CINI	CACL
Mean	.2311	.9581	.0840	.0294	2.2807	.1106	.5618	1.5689
Std. Dev.	.2556	.6347	.2774	.1038	1.7662	.3137	.7522	1.1339
Min.	-.2104	.1845	0	-.3734	.1194	0	-1	.3408
Max.	.7797	2.9346	1	.2247	6.7107	1	1	5.4194
Obs.	1,203							

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the intra-industry estimation sample Other services 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 16 – Descriptive statistics intra-industry model Wholesale & retail trade 2004-2006

Variable	RETA	EBITTA	MCBVTL	STA	INT	GDP	ADR	SIZE	TLTA
Mean	.1823	.0499	1.4508	2.0006	-.0187	.0291	.0063	.3998	.7059
Std. Dev.	.2376	.0783	.9360	1.1105	.1228	.01271	.0012	.1299	.2263
Min.	-.4393	-.1482	.01214	.5404	-.1732	.0060	.0048	.2035	.2621
Max.	.6623	.2234	4.1527	4.8953	.1990	.0570	.0078	.6796	1.2329
Obs.	1,494								

Variable									
Mean	.3707	.8057	.0710	.0274	3.1472	. 0917	.6347	1.4412	
Std. Dev.	.2625	.2972	.2568	.0672	1.9347	.2887	.7176	.6122	
Min.	-.1103	.3124	0	-.1903	.7444	0	-1	.6364	
Max.	.8444	1.5713	1	.1765	8.1703	1	1	3.2014	
Obs.	1,494								

Note: This table provides an overview of the descriptive statistics, the mean, standard deviation, minimum, maximum, and amount of observations per variable, of the intra-industry estimation sample Wholesale & retail trade 2004-2006. It covers the following variables: retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), change in prime interest rate (INT), GDP growth (GDP), annual default rate (ADR), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), working capital divided by total assets (WCTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities, dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), and current assets divided by current liabilities (CACL).

Table 17 – Estimated models intra-industry model Construction 2004-2006

Variable	MDA		Logit		Probit		Hazard	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-.9249	-.6432	.2900	1.3116			.3561	.5373
			(1.7299)	(2.4224)			(2.5611)	(2.8201)
RETA	-6.2705	-5.6492						
EBITTA	-9.8365	-9.8999						
MCBVTL	1.2616	1.2642						
STA	.8096	.7459						
SIZE			8.0836*	-1.4392			8.3454	6.2073
			(4.1353)	(7.0571)			(6.4199)	(8.0583)
TLTA			8.0643*	8.2933	2.4885*	3.3633*	6.7195	5.77437
			(4.7344)	(5.7915)	(1.4716)	(1.9723)	(5.8403)	(5.9562)
CLCA			1.7699	2.0971			.5276	.7070
			(2.8956)	(3.2729)			(2.9822)	(3.0848)
DTLTA			.6509	1.9417			.3449	.6688
			(1.3439)	(1.8131)			(2.1161)	(2.3124)
NITA			2.0504	8.3152	-1.6083	.1799	-4.0343	-2.4666
			(10.3546)	(11.3536)	(4.3321)	(4.9121)	(12.5909)	(12.9098)
FUTL			1.0562*	1.4234**			.5323	.7965
			(.3826)	(.5521)			(.6162)	(.7423)
NIN			3.4127**	6.2825			1.1076	1.1542
			(1.7195)	(5.1980)			(1.9656)	(2.0822)
CINI			-.6059	-.83993			-.5903	-.8135

			(.7346)	(.8624)			(.9951)	(1.0541)
CACL					-.8422	-.7770		
					(.5474)	(.5809)		
INT		3.2522		10.6026		-1.0138		8.5441
				(8.4193)		(2.5799)		(8.8838)
GDP		-34.6317		-340.7471**		-66.0952***		-128.2116
				(147.27)		(23.7735)		(116.9129)
ADR							-598.1414	33.5365
							(572.6851)	(813.1911)
Constant	-.4945	.0806	-16.071***	-6.9279	-2.3305	-1.2300	-9.8588	-9.8565
			(4.8796)	(6.0670)	(1.5899)	(2.0101)	(6.2998)	(7.1989)

Note: This table provides an overview of the estimated models of the intra-industry Construction estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by current assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), and annual default rate (ADR). The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 18 – Estimated models intra -industry model Machinery, equipment, furniture, recycling 2004-2006								
Variable	MDA		Logit		Probit		Hazard	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-1.1352	-.7211	.4326	.5826			.0461	.1591
			(.4326)	(1.7524)			(2.0186)	(2.0603)
RETA	-3.6437	-3.4174						
EBITTA	-9.2987	-9.5759						
MCBVTL	.3362	.3981						
STA	.0241	.0380						
SIZE			5.7234*	3.9534			2.4465	1.6280
			(3.2612)	(3.8412)			(3.5378)	(3.8073)
TLTA			4.2440	3.6065	2.5168**	2.1780*	4.3221	3.9766
			(3.1026)	(3.2332)	(1.1660)	(1.2940)	(3.3860)	(3.3964)
CLCA			2.2447	2.3932			1.0487	1.2146
			(1.4052)	(1.4878)			(1.5339)	(1.5641)
DTLTA			-1.042529	-.82294			-.2451	-.0978
			(.8470)	(.8759)			(1.0712)	(1.1044)
NITA			-12.1780**	-12.0333*	-7.5654***	-7.5939***	-8.5546	-8.7296
			(6.6402)	(6.7078)	(2.2268)	(2.3473)	(6.8222)	(6.9947)
FUTL			-.1781	-.0907			.0858	.1575
			(.3800)	(.3923)			(.3895)	(.4002)
NIN			-.7480	-.6555			-.3629	-.2914
			(.6849)	(.6926)			(.8653)	(.8721)
CINI			-.4266	-.3966			-.4074	-.3915
			(.4475)	(.4481)			(.5728)	(.5733)

CACL					-.1696	-.2432		
					(.2928)	(.3070)		
INT		2.0177		1.6468		.6478		3.3839
				(5.1121)		(2.2818)		(4.4846)
GDP		-23.0467		-69.1293		-43.5971		-42.5716
				(65.7657)		(26.6047)		(48.7334)
ADR							98.3873	388.6173
							(305.6568)	(462.1515)
Constant	1.2253	1.2870	-10.5484***	-8.2497**	-3.4501***	-2.1517	-8.8607**	-9.5003**
			(3.0441)	(3.6001)	(1.1786)	(1.4021)	(3.5005)	(3.9294)

Note: This table provides an overview of the estimated models of the intra-industry Machinery, equipment, furniture, recycling estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), and annual default rate (ADR). The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 19 – Estimated models intra -industry model Metals & metal products 2004-2006								
Variable	MDA		Logit		Probit		Hazard	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-2.5308	-2.2134	-1.5142	1.9128			.5838	.7401
			(4.8545)	(5.6700)			(4.2522)	(4.3284)
RETA	-4.4792	-4.4751						
EBITTA	-11.3519	-11.4448						
MCBVTL	.7134	.7369						
STA	.4739	. 4533						
SIZE			12.4203*	8.7519			6.0116	4.7647
			(7.3744)	(10.3208)			(7.2288)	(7.8258)
TLTA			-5.0010	-9.4897	-.2867	-3.6595	-3.3943	-4.13301
			(5.2140)	(6.3614)	(1.5736)	(2.5893)	(5.3707)	(5.5159)
CLCA			7.0338**	10.9129**			2.0338	2.2311
			(3.0489)	(4.7057)			(2.7626)	(2.8051)
DTLTA			2.4502	5.5815*			1.8453	2.0831
			(2.2945)	(3.3131)			(2.0198)	(2.1161)
NITA			-46.20678	-51.5002**	-18.7956***	-23.9314***	-16.8335	-17.7629
			(20.3383)	(22.6978)	(4.96245)	(6.9277)	(13.1058)	(13.2572)
FUTL			-.1656	.8714			-.2456	-.2420
			(.8414)	(1.2005)			(.8752)	(.9278)
NIN			-.8478	-.0145			-.5100	-.5075
			(2.1427)	(2.7377)			(1.4384)	(1.4609)
CINI			1.3195	2.0645			-.5379	-.5504
			(1.3453)	(1.6944)			(1.1166)	(1.1105)

CACL					-2.8245***	-4.5599***		
					(1.0207)	(1.6619)		
INT		.9214		47.3955		.7989		5.7678
				(36.7393)		(4.3895)		(7.2577)
GDP		-11.5578				-151.129*		-40.2846
						(78.5014)		(85.1175)
ADR							-331.2579	85.2018
							(582.5374)	(775.1496)
Constant	.8596	.9603	-11.5213	-22.0146*	1.4705	9.2929**	-3.1873	-4.1198
			(6.143165)	(11.32681)	(1.832495)	(4.530531)	(5.7617)	(6.1511)

Note: This table provides an overview of the estimated models of the intra-industry Metals & metal products estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), and annual default rate (ADR). The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 20 – Estimated models intra -industry model Other services 2004-2006								
Variable	MDA		Logit		Probit		Hazard	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-.9861	-.67392	-1.5450	-2.14223*			-.5104	-.3623
			(1.1628)	(1.2817)			(1.5030)	(1.5640)
RETA	-3.0988	-2.6616						
EBITTA	-5.8441	-5.5643						
MCBVTL	.2487	.2548						
STA	.4274	.4624						
SIZE			-.3908	-9.3271**			.4648	-1.4315
			(2.3485)	(4.0303)			(3.0697)	(3.6485)
TLTA			5.5820**	6.9112***	2.1950***	2.0733**	3.0982	3.0701
			(2.2422)	(2.5282)	(.8132)	(.8527)	(2.3589)	(2.4743)
CLCA			-.1491	-.4252			.1390	.1277
			(.5129)	(.5551)			(.6225)	(.6441)
DTLTA			-.0585	-.6064			-.8872	-.7181
			(.9330)	(1.0578)			(1.3222)	(1.3656)
NITA			-5.2436	-4.8887	-3.0648*	-2.7963	-4.5331	-4.0007
			(5.3812)	(5.5378)	(1.6801)	(1.7477)	(3.8308)	(3.9534)
FUTL			.0974757	.1256252			.0671	.1189396
			(.2028)	(.2319)			(.2742)	(.296106254)
NIN			-.7898	-.8092			-1.2353	-1.2830
			(.8541)	(.9385)			(1.0076)	(1.0416)
CINI			-.2013	-.0624			-.8506	-.8473
			(.5208)	(.5473)			(.5465)	(.5552)

CACL					-.2777	-.28433		
					(.2869)	(.2948)		
INT		4.2642		6.1200		1.6374		2.0043
				(4.4410)		(2.3572)		(4.0311)
GDP		-33.8546		-170.092***		-53.1571**		-86.5934*
				(49.8552)		(24.5673)		(48.4896)
ADR							-91.9962	125.1984
							(307.4227)	(405.6006)
Constant	.2157	.4786	-6.70222***	-.0496	-2.9948***	-1.7296	-4.4276	-3.0525
			(2.294632)	(3.011806)	(.8568715)	(1.107567)	(2.8814)	(3.3683)

Note: This table provides an overview of the estimated models of the intra-industry Other services estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), and annual default rate (ADR). The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 21 – Estimated models intra -industry model Wholesale & retail trade 2004-2006								
Variable	MDA		Logit		Probit		Hazard	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WCTA	-.3788	.0628	-.2144	-.4226			.3374	.2658
			(1.5255)	(1.6125)			(1.6899)	(1.7044)
RETA	-4.2755	-4.0473						
EBITTA	-11.0046	-10.2700						
MCBVTL	.6736	.6663						
STA	.2125	.1655						
SIZE			5.6331	-1.9123			7.0669*	5.9684
			(3.4298)	(4.9633)			(3.8286)	(4.0694)
TLTA			5.1156*	4.4509	2.8171**	2.2836	1.7644	1.6470
			(2.7873)	(2.7946)	(1.0938)	(1.1395)	(2.7391)	(2.7456)
CLCA			-1.0469	-.8303			.6348	.6071
			(1.5127)	(1.5547)			(1.5789)	(1.5884)
DTLTA			1.4506	1.2788			.3038	.2481
			(.9963)	(1.0599)			(1.2373)	(1.2528)
NITA			-20.7494*	-17.8992*	-11.4294***	-10.8348***	-14.9933*	-15.2231
			(10.7502)	(10.6676)	(2.9161)	(3.0753)	(7.7076)	(8.1328)
FUTL			.1135	.1267			.0634	.0757
			(.1961)	(.2047)			(.2064)	(.2093)
NIN			-3.0314**	-2.9217**			-1.1057	-1.0263
			(1.2020)	(1.2520)			(1.0286)	(1.0358)
CINI			-.4837	-.5454			-.4098	-.3811
			(.5274)	(.5345)			(.5887)	(.5945)

CACL					.2225	.1093		
					(.3703)	(.3897)		
INT		4.1979		7.2902		2.2431		3.1075
				(5.5809)		(2.2606)		(4.1437)
GDP		-33.6907		-119.5059**		-55.4951***		-38.7805
				(52.7580)		(21.1738)		(42.6673)
ADR							-137.3163	96.9476
							(327.2090)	(408.9247)
Constant	.2097	.6756	-8.5563***	-2.8831	-4.1862***	-2.3850*	-7.2235*	-7.1388
			(2.9532)	(3.6526)	(1.1512)	(1.3756)	(3.2160)	(3.4354)

Note: This table provides an overview of the estimated models of the intra-industry Wholesale & retail trade estimation sample 2004-2006. For the MDA models the unstandardized canonical discriminant function coefficients are shown. No standard errors are estimated for these coefficients. For the logit, probit, and hazard models the coefficients and standard errors are shown. The coefficients of the hazard models have been estimated with logit analysis. The standard errors of these coefficients have been modified in line with Shumway (2001). The table covers the following variables: working capital divided by total assets (WCTA), retained earnings divided by total assets (RETA), EBIT divided by total assets (EBITTA), market capitalization divided by book value of total liabilities (MCBVTL), sales divided by total assets (STA), log(total assets) divided by GNI price level index with a base value of 100 in 1968 (SIZE), total liabilities divided by total assets (TLTA), current liabilities divided by current assets (CLCA), dummy with a value of 1 if total liabilities exceed total assets (DTLTA), net income divided by total assets (NITA), income from operations minus depreciation divided by total liabilities (FUTL), dummy with a value of 1 if net income was negative for two prior years (NIN), relative change in net income (CINI), current assets divided by current liabilities (CACL), change in prime interest rate (INT), GDP growth (GDP), and annual default rate (ADR). The significance of coefficients is given at 10% (*), 5% (**), and 1% (***).

Table 22 – Model performance intra-industry models 2004-2006								
Construction								
Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8511***	.8961***	.9186***	.9489***	.8234***	.8896***	.9124***	.9358***
	(.0595)	(.0451)	(.0338)	(.0250)	(.0675)	(.0432)	(.0204)	(.0157)
Information	5.6921***	6.1383***	3.6538***	3.5716***	5.9395***	5.5464***	4.6147***	4.5659***
content	(.8483)	(.8332)	(.3982)	(.3627)	(.7777)	(.7108)	(.4948)	(.4703)
z-statistic	-.5209	.5209	-.4619	. 4619	-.7317	.7317	-.5679	.5679
Machinery, equipment, furniture, recycling								
Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8890***	.9008***	.9176***	.9195***	.8893***	.8990***	.8784***	.8808***
	(.0341)	(0306)	(.0251)	(.0245)	(.0307)	(.0275)	(.0176)	(.0174)
Information	6.9941***	6.5964***	4.1779***	4.4199***	6.1269***	5.7023***	5.8209***	5.6097***
content	(.6493)	(.5911)	(.3306)	(.3359)	(.4932)	(.4626)	(.4490)	(.4184)
z-statistic	-.1761	. 1761	-.0316	. 0316	-.1443	. 1443	-.0729	.0729
Metals & metal products								
Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.9583***	.9647***	.9893***	.9910***	.9727***	.9893***	.9446***	.9489***
	(.0204)	(.0173)	(.0058)	(.0051)	(.0152)	(.0057)	(.0143)	(.0138)
Information	8.4079***	8.2846***	3.6635***	3.4379***	3.7939***	3.5857***	4.6463***	4.3916***
content	(1.0647)	(1.0440)	(.3671)	(.3766)	(.3669)	(.3639)	(.4157)	(.3914)
z-statistic	-.1295	. 1295	-.06662	. 06662	-.4726	. 4726	-.1297	.1297

Other services

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8688***	.9000***	.8529***	.9093***	.8509***	.8863***	.8444***	.8761***
	(.0390)	(.0291)	(.0465)	(.0337)	(.0431)	(.0315)	(.0210)	(.0169)
Information	5.5801***	4.8185***	3.6137***	3.4436***	3.8469***	4.2674***	5.2947***	4.9327***
content	(.5774)	(.4786)	(.3714)	(.3614)	(.4126)	(.4000)	(.4705)	(.3994)
z-statistic	-.4478	.4478	-.8033	.8033	-.4829	.4829	-.8637	.8637

Wholesale & retail trade

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.9297***	.9534***	.9086***	.9435***	.8871***	.9295***	.9059***	.9113***
	(.0237)	(.0172)	(.0447)	(.0258)	(.0516)	(.0310)	(.0164)	(.0148)
Information	6.2420***	5.3884***	3.5353***	3.6197***	3.6434***	4.1319***	4.7473***	4.7404***
content	(.5531)	(.4611)	(.2519)	(.2658)	(.2799)	(.3106)	(.3317)	(.3251)
z-statistic	-.4579	.4579	-.6075	.6075	-.6726	.6726	-.1898	.1898

Note: This table provides an overview of the performance measures of the estimated models of the intra-industry estimation sample 2004-2006. A ‘M’ indicates that the model incorporates macroeconomic factors as predictor variables. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The goodness of fit measure for MDA is the adjusted R-squared and for logit, probit, and hazard models the Pseudo R-squared. The z-statistic compares each model with the same model that incorporated macroeconomic variables and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. For example, the -.44779 indicates that the MDA model underperforms relative to the MDA model that incorporates macroeconomic predictors on accuracy. The significance of the AUC statistic and information content is given at 10% (*), 5% (**), and 1% (***).

Table 23 – Relative performance intra-industry models 2004-2006

Construction

Model	MDA	Logit	Probit	Hazard
MDA		-.8150	.2906	-.8478
Logit	.8150		1.1054	.1039
Probit	-.2907	-1.1054		-1.1701
Hazard	.8478	-.1039	1.1701	

Model	MDA M	Logit M	Probit M	Hazard M
MDA M		-.7537	.0802	-.6330
Logit M	.7537		.5426	.2653
Probit M	-.0802	-.5426		-.7216
Hazard M	.6330	-.2653	.7216	

Machinery, equipment, furniture, recycling

Model	MDA	Logit	Probit	Hazard
MDA		-.44262	-.00438	.19701
Logit	.44262		.43825	.80492
Probit	.00438	-.43825		.20276
Hazard	-.19701	-.80492	-.20276	

Model	MDA M	Logit M	Probit M	Hazard M
MDA M		-.29832	.02741	.38653
Logit M	.29832		.32569	.80238
Probit M	-.02741	-.32569		.34963
Hazard M	-.38653	-.80238	-.34963	

Metals & metal products

Model	MDA	Logit	Probit	Hazard
MDA		-.7583	-.3071	.3153
Logit	.7583		.4726	1.4711
Probit	.3071	-.4726		.7378
Hazard	-.3153	-1.4711	-.7378	

Model	MDA M	Logit M	Probit M	Hazard M
MDA M		-.6970	-.6396	.3884
Logit M	.6970		.0666	1.4640
Probit M	.6396	-.0666		1.3601
Hazard M	-.3884	-1.4640	-1.3601	

Other services

Model	MDA	Logit	Probit	Hazard
MDA		.2118	.2378	.4168
Logit	-.2118		.0260	.1403
Probit	-.2378	-.0260		.1068
Hazard	-.4168	-.1403	-.1068	

Model	MDA M	Logit M	Probit M	Hazard M
MDA M		-.1444	.2028	.4537
Logit M	.1444		.3471	.6507
Probit M	-.2028	-.3471		.1857
Hazard M	-.4537	-.6507	-.1857	

Wholesale & retail trade

Model	MDA	Logit	Probit	Hazard
MDA		.3524	.6761	.5319
Logit	-.3524		.3249	.0550
Probit	-.6761	-.3249		-.3554
Hazard	-.5319	-.0550	.3554	

Model	MDA M	Logit M	Probit M	Hazard M
MDA M		.2023	.4614	1.0924
Logit M	-.2023		.2602	.7815
Probit M	-.4614	-.2602		.4084
Hazard M	-1.0924	-.7815	-.4084	

Note: This table provides an overview of the z-statistic of the estimated models of the intra-industry estimation sample 2004-2006. A 'M' indicates that the model incorporates macroeconomic factors as predictor variables. The z-statistic compares each model with the same model that incorporated macroeconomic variables and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. For example, the -.81498 indicates that the MDA model without macroeconomic variables performs worse than the logit model without macroeconomic predictors on accuracy.

Table 24 – Relative performance of intra-industry models compared to its inter-industry counterpart

Model	MDA	MDA M	Logit	Logit M
Construction	-.6285	-.4593	.5066	.6382
Machinery, equipment, furniture, recycling	-.1029	-.4538	.5633	-.0021
Metals & metal products	1.4854	1.0537	3.303	2.6757
Other services	-.4543	-.4679	-.6355	-.2107
Wholesale & retail trade	.7692	.7759	.3646	.5788

Model	Probit	Probit M	Hazard	Hazard M
Construction	-.7715	-.3633	.9068	1.4865
Machinery, equipment, furniture, recycling	.1725	-.2546	-.1493	-.4422
Metals & metal products	2.4188	2.7288	2.3430	2.2128
Other services	-.4896	-.4825	-1.2853	-.5910
Wholesale & retail trade	.1308	.3888	1.0047	.8362

This table provides an overview of the z-statistic of the estimated models of the intra-industry estimation sample 2004-2006 compared to their inter-industry counterpart. A 'M' indicates that the model incorporates macroeconomic factors as predictor variables. The z-statistic compares the accuracy of each model with its inter-industry counterpart and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. For example, the -.62845 indicates that the MDA model of the intra-industry sample of the construction sector performs worse than its inter-industry counterpart on accuracy.

Table 25 – Industry classifications and bankruptcies hold-out samples

Hold-out sample 2007-2009

Bankruptcy	Industry					Total
	Construction	Machinery, equipment, furniture, recycling	Metals & metal products	Other services	Wholesale & retail trade	
No	260	610	220	540	750	2,380
	(10.92)	(25.63)	(9.24)	(22.69)	(31.51)	
2008	26	61	22	54	75	238
	(10.92)	(25.63)	(9.24)	(22.69)	(31.51)	
2009	37	47	41	85	86	296
	(12.50)	(15.88)	(13.85)	(28.72)	(29.05)	
2010	39	40	20	47	53	199
	(19.60)	(20.10)	(10.05)	(23.62)	(26.63)	
Total	362	758	303	726	964	3,113
	(11.63)	(24.35)	(9.73)	(23.32)	(30.97)	

Hold-out sample 2011-2013

Bankruptcy	Industry					Total
	Construction	Machinery, equipment, furniture, recycling	Metals & metal products	Other services	Wholesale & retail trade	
No	250	200	200	220	250	900
	(27.78	(22.22	(22.22	(24.44	(27.78)	
2012	25	11	7	22	25	90
	(27.78	(12.22	(7.78	(24.44	(27.78)	
2013	35	11	13	39	40	138
	(25.36	(7.97	(9.24	(28.26	(28.99)	

2014	47	18	13	31	44	153
	(30.72)	(11.76)	(8.50)	(20.26)	(28.76)	
Total	357	240	233	312	359	1,281
	(27.87)	(18.74)	(18.19)	(24.36)	(28.03)	

Note: This table provides an overview of the industry classifications and number of bankruptcies specified by year for the hold-out samples 2007-2009 and 2011-2013. The first row of figures provides the absolute number of firms, the second row provides row percentages.

Table 26 – Model performance hold-out sample 2007-2009

Inter-industry

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8754***	.8467***	.8881***	.7798***	.8705***	.8192***	.7821***	.8183***
	(.0132)	(.0153)	(.0118)	(.0188)	(.0134)	(.0162)	(.0089)	(.0084)
Information	5.1061***	7.8845***	2.9485***	3.2793***	3.0335***	3.5383***	3.3805***	3.7292***
content	(.1868)	(.4287)	(.0896)	(.1952)	(.0929)	(.1809)	(.1229)	(.2073)
z-statistic	-.6895	-2.9267	-.0797	-4.9651	-.3294	-3.3246	-6.4290	-4.9636

Construction

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8780***	.8446***	.9193***	.6421***	.8611***	.7473***	.5539***	.8541***
	(.0242)	(.0280)	(.0174)	(.0447)	(.0356)	(.0407)	(.0283)	(.0194)
Information	4.1275***	8.0965***	2.4081***	7.9523***	4.5104***	3.9092***	2.5783***	3.7741***
content	(.4754)	(1.1830)	(.2510)	(2.7844)	(.4251)	(.7224)	(.5588)	(.5930)
z-statistic	.3596	-.7422	.0118	-4.7055	.4750	-1.9031	-8.1935	-2.2539

Machinery, equipment, furniture, recycling

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8667***	.8434***	.8667***	.8168***	.8640***	.7975***	.7653***	.7854***
	(.0291)	(.0337)	(.0290)	(.0339)	(.0315)	(.0385)	(.0199)	(.0189)
Information	6.9367***	11.0008***	4.9122***	3.7148***	5.8747***	4.2338***	5.6533***	14.1833***
content	(.5095)	(1.1608)	(.3013)	(.3513)	(.3525)	(.4152)	(.3891)	(3.0655)
z-statistic	-.3659	-.9459	-.9010	-1.7331	-.4142	-1.6026	-3.4263	-2.9392

Metals & metal products

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8377***	.8270***	.7909***	.6643***	.7784***	.6440***	.6454***	.7763***
	(.0495)	(.0532)	(.0546)	(.0626)	(.0578)	(.0524)	(.0355)	(.0351)
Information	4.7363***	5.5618***	2.2592***	2.1896***	2.3217***	1.5621***	3.6469***	2.4647***
content	(.5369)	(.7737)	(.2440)	(.3296)	(.2466)	(.4002)	(.5154)	(.3578)
z-statistic	-1.7947	-2.0589	-3.0800	-4.61061	-2.8007	-4.8185	-7.1858	-4.4753

Other services

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8228***	.7762***	.8262***	.6217***	.8407***	.7518***	.7050***	.7376***
	(.0363)	(.0386)	(.0331)	(.0397)	(.0311)	(.0355)	(.0196)	(.0157)
Information	4.6711***	6.3194***	4.0983***	3.0264***	4.8744***	3.6617***	5.5794***	4.0144***
content	(.3677)	(.6969)	(.2779)	(.4592)	(.3326)	(.3667)	(.5550)	(.5650)
z-statistic	-.7151	-1.9986	-.4041	-4.5305	-.1554	-2.0808	-3.9888	-4.2165

Wholesale & retail trade

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8799***	.8319***	.8840***	.7874***	.8796***	.8215***	.7904***	.8445***
	(.0265)	(.0318)	(.0252)	(.0394)	(.0251)	(.0340)	(.0164)	(.0168)
Information	5.5725***	7.9160***	2.8588***	3.1026***	2.9032***	3.4877***	3.6932***	3.7270***
content	(.3679)	(.8125)	(.1559)	(.3058)	(.1601)	(.3187)	(.2451)	(.2942)
z-statistic	-.9887	-2.5239	-.4553	-2.9847	-0.1299	-2.0158	-4.1666	-2.5568

Note: This table provides an overview of the performance measures of the estimated models in hold-out sample 2007-2009. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The model with an positive z-statistic outperforms the estimation model of the original sample. The significance is given at 10% (*), 5% (**), and 1% (***).

Table 27 – Model performance hold-out sample 2011-2013

Inter-industry

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.4778***	.4256***	.5910***	.3541***	.5245***	.3423***	.5450***	.3840***
	(.0273)	(.0263)	(.0232)	(.0228)	(.0241)	(.0225)	(.0144)	(.0139)
Information	-.7817***	-1.1919***	.5364**	-1.3224***	.1404	-1.5850***	.0599	-1.9067***
content	(.1529)	.1449	(.2578)	(.1529)	(.3113)	(.1926)	(.5884)	(.2776)
z-statistic	-12.3993	-16.0672	-8.6818	-18.9260	-10.2057	-18.8916	-17.0515	-28.0411

Construction

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.5431***	.4991***	.4942***	.2742***	.5213***	.3768***	.5776***	.4367***
	(.0460)	(.0475)	(.0441)	.0399	(.0446)	(.0430)	(.0298)	(.0281)
Information	.9561	.1217	.1775	-1.0145***	.7201**	-.4536	1.0912***	-.4516*
content	(.5929)	(.7265)	(.2466)	(.3274)	(.2908)	(.2860)	(.2891)	(.2589)
z-statistic	-3.8383	-5.4466	-6.1910	-12.4047	-3.6186	-7.1797	-7.7155	-12.7456

Machinery, equipment, furniture, recycling

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.6000***	.5739***	.6992***	.6372***	.6921***	.6164***	.6987***	.5935***
	(.0842)	(.0869)	(.0678)	(.0731)	(.0677)	(.0757)	(.0446)	(.0445)
Information	3.8260**	2.1460	1.7174**	.5879	1.8260***	.6436	1.9593***	1.0149
content	(1.5778)	(1.6304)	(.4207)	(.4473)	(.4256)	(.4823)	(.4573)	(.5378)
z-statistic	-3.2903	-3.7792	-2.6296	-3.3462	-2.2834	-3.2562	-3.4029	-5.3402

Metals & metal products

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.6265***	.6081***	.6708***	.6862***	.6396***	.5375***	.6733***	.5969***
	(.0872)	(.0898)	(.0788)	(.0722)	(.0891)	(.0894)	(.0552)	(.0536)
Information	3.5433**	2.5365	1.5990***	.9804**	1.3603***	.2735	1.8187***	1.2418***
content	(1.75201)	(1.8846)	(.4462)	(.4242)	(.4217)	(.4677)	(.4527)	(.4509)
z-statistic	-3.5779	-3.8851	-3.6835	-3.5613	-3.6934	-5.2297	-4.6940	-6.0667

Other services

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.6245***	.5859***	.6609***	.4935***	.6766***	.5626***	.6546***	.4921***
	(.0577)	(.0599)	(.0544)	(.0540)	(.0540)	(.0584)	(.0326)	(.0309)
Information	2.5103***	.5339	1.3264***	-.3317	1.4676***	-.0980	1.476***	-.2506
content	(.6721)	(.5439)	(.2597)	(.2837)	(.2704)	(.2948)	(.2843)	(.3279)
z-statistic	-3.1792	-4.2795	-2.4609	-5.8527	-2.2365	-4.3204	-4.4960	-9.5334

Wholesale & retail trade

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.4935***	.4144***	.6132***	.4535***	.5745***	.4709***	.6686***	.5800***
	(.0511)	(.0547)	(.0455)	(.0533)	(.0490)	(.0525)	(.0272)	(.0285)
Information	1.5017**	-.3662	1.0504***	-.1676	1.0351***	-.1536	1.1798***	.8147***
content	(.7132)	(.6252)	(.2235)	(.2425)	(.2375)	(.2664)	(.2331)	(.2547)
z-statistic	-7.0683	-9.7233	-4.4956	-8.3807	-4.5556	-7.4821	-6.5994	-9.1971

Note: This table provides an overview of the performance measures of the estimated models in hold-out sample 2011-2013. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The model with an positive z-statistic outperforms the estimation model of the original sample. The significance is given at 10% (*), 5% (**), and 1% (***).

Table 28 – Variance inflation factor statistic

2004-2006

Variable	Inter-industry	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5
ADR	1.37	1.25	1.67	1.63	1.31	1.34
INT	1.43	1.29	1.69	1.65	1.38	1.42
GDP	1.05	1.04	1.02	1.02	1.06	1.07

2007-2009

Variable	Inter-industry	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5
ADR	10.22	11.20	9.59	9.67	10.51	11.90
INT	3.01	3.43	4.04	3.34	3.50	2.47
GDP	9.40	10.30	8.61	8.81	9.56	10.79

2007-2009

Variable	Inter-industry	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5
ADR	2.18	2.31	1.93	2.02	2.15	2.35
INT	2.23	2.25	2.02	2.17	2.15	2.49
GDP	1.46	1.46	1.51	1.45	1.48	1.45

Note: This table provides an overview of the variance inflation (VIF) statistics of the three sample periods. Ind.1 to Ind. 5 indicate the five different industries.

Table 29 – Model performance robustness sample test inter-industry

Sample 2004-2006

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.8945***	.9236***	.8903***	.9196***	0.8800***	0.9120***	.8823***	.8922***
	(.0170)	(.01280)	(.0192)	(.0139)	(0.0208)	(0.0152)	(.0090)	(.0081)
Information	6.7668***	6.4398***	3.6381***	3.7347 ***	3.8967***	4.0949***	4.4698***	4.5139***
content	(.3187)	(.2885)	(.1384)	(.1398)	(.1506)	(.1506)	(.1641)	(.1615)
Mean VIF	1.53	1.48	1.53	1.66	1.43	1.37	1.48	1.54
Max. VIF	2.66	2.67	2.26	2.53	2.17	2.24	2.24	2.24

Sample 2007-2009

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	. 8807***	.9075***	.9018***	.9474***	.8751***	.9404***	.8516***	.8808***
	(.0131)	(.0108)	(.0106)	(.0064)	(.0133)	(.0067)	(.0074)	(.0079)
Information	5.4190***	5.8708***	3.5266***	1.5858***	4.0511***	1.8839***	4.4067***	4.3955***
content	(.1872)	(.2475)	(.1061)	(.1254)	(.1213)	(.1249832)	(.1278)	(.1457)
z-statistic Est.	-.5011	-.6641	.4235	1.2139	-.1707	1.1872	-2.1868	-.8144
z-statistic Hold.	.2340	2.692	.6433	7.3915	.1997	5.5166	5.0779	4.8994
Mean VIF	1.45	1.50	1.57	1.63	1.37	1.36	1.50	1.74
Max. VIF	2.23	2.26	2.26	2.27	1.95	1.95	2.24	3.05

Sample 2011-2013

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.7725***	. 8533***	. 8024***	.8708***	.7556***	.8609***	.7569***	.8061***
	(.0206)	(.0152)	(.0188)	(.0139)	(.0211)	(.0140)	(.0129)	(.0107)
Information	3.3618***	3.0107***	3.6770***	3.1529***	4.1568***	3.5241***	4.6009***	4.8318***
content	(.2467)	(.2229)	(.2415)	(.1923)	(.2934)	(.2157)	(.2914)	(.2603)
z-statistic Est.	-3.7763	-2.5190	-2.7605	-1.7719	-3.7123	-1.7921	-6.6412	-4.8231
z-statistic Hold.	8.6518	13.7215	6.2169	17.7421	6.6409	17.7487	9.7340	21.3130
Mean VIF	1.38	1.52	1.45	1.64	1.18	1.32	1.46	1.64
Max. VIF	2.13	2.14	2.40	2.70	1.34	1.77	2.53	2.57

Note: This table provides an overview of the performance measures of the estimated models of the inter-industry samples 2004-2006, 2007-2009, and 2011-2013. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The z-statistic Est. compares each model with the same model of sample 2004-2006 and therefore provides an indication of the relative performance of the re-estimated model. For example, the -.50108 indicates that the re-estimated MDA model without macroeconomic predictors underperforms relative to its 2004-2006 counterpart. The z-statistic Hold. compares each model with the equivalent hold-out counterpart. The model with an positive z-statistic outperforms the other model. For example, the .23399 indicates that the re-estimated MDA model without macroeconomic predictors performs better than the equivalent model using the coefficients generated in the estimation sample. The significance of the AUC statistic and information content is given at 10% (*), 5% (**), and 1% (***).

Table 30 – Relative performance robustness predictors

Model	MDA	Logit	Probit	Hazard
MDA		-2.7623	-2.7776	-2.6503
Logit	2.7623		-.0152	.7272
Probit	2.7776	.0152		.7472
Hazard	2.6503	-.7272	-.7472	
Model	MDA macro	Logit macro	Probit macro	Hazard macro
MDA macro		-2.9314	-3.0177	-2.2743
Logit macro	2.931		-.0873	1.3853
Probit macro	3.018	.0873		1.5068
Hazard macro	2.274	-1.3853	-1.5068	

Note: This table provides an overview of the z-statistic of the estimated models of the inter-industry estimation sample 2004-2006 using the set of predictors named at 4.4.2. The z-statistic compares each model with the other models and therefore provides an indication of the relative performance of the model. The model with an positive z-statistic outperforms the other model. For example, the -2.76233 indicates that the MDA model without macroeconomic variables underperforms relative to the logit model without macroeconomic factors on accuracy.

Table 31 – Model performance inter-industry

Sample 2004-2006

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.7811***	.8154***	.8847***	.9165***	.8852***	.9190***	.8655***	.8840***
	(.0241)	(.0219)	(.0201)	(.0143)	(.0199)	(.0140)	(.0106)	(.0088)
Information	-6.8934***	.00124***	3.5625***	3.7368 ***	3.8319***	4.0511***	4.1817***	4.3093***
content	(.3215)	(.0004)	(.1383)	(.1391)	(.1482)	(.1485)	(.1629)	(.1601)
z-statistic M.	-.84795	.8480	-1.0264	1.0264	-1.0983	1.0983	-1.0908	1.0908
z-statistic Or.	-3.0657	-3.1790	-.1714	-.1085	.15640	.2417	-.9878	-.5058

Sample 2007-2009

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.1507***	.1868	.8738***	.8215***	.8747***	.8217***	.8180***	.7866***
	(.0148)	(.0175)	(.0132)	(.0165)	(.0131)	(.0162)	(.0088)	(.0083)
Information	-4.6408***	-6.6756	2.7871***	3.3461***	2.9660***	3.5555***	3.0982***	4.4059***
content	(.1818)	(.4031)	(.0871)	(.1839)	(.0919)	(.1862)	(.0957)	(.3313)
z-statistic M.	-2.2478	2.2478	2.1255	-2.1255	2.1570	-2.1570	2.2263	-2.2263
z-statistic Or.	-37.6721	-30.9258	-.6377	1.5402	.1822	.0954	2.5369	-2.2482
z-statistic Est.	-20.2321	-20.6867	-.38335	-3.4532	-.37006	-3.5631	-3.0247	-6.2875

Sample 2011-2013

Measure	MDA	MDA M	Logit	Logit M	Probit	Probit M	Hazard	Hazard M
AUC	.4926***	.6391***	.5599***	.3563***	.5650***	.3711***	.5486***	.3770***
	(.0249)	(.0238)	(.0238)	(.0224)	(.0237)	(.0225)	(.0155)	(.0136)
Information	-.2848	2.3857***	.1614	-1.4500***	.2245	-1.4508***	-.0877	-1.8374***
content	(.2897)	(.2890)	(.2760)	(.1752)	(.2900)	(.1838)	(.4099)	(.2367)

z-statistic M.	-4.0796	4.0796	5.9869	-5.9869	5.6521	-5.6521	9.1286	-9.1286
z-statistic Or.	.4176	6.0801	-.8535	.0701	1.1173	.9160	.1595	-.3507
z-statistic Est.	-7.4614	-4.6609	-9.3485	-18.5784	-9.2197	-18.0858	-15.7058	-27.7882

Note: This table provides an overview of the performance measures of hold-out models using the same predictors in the inter-industry samples 2004-2006, 2007-2009, and 2011-2013. The area under the curve (AUC) measures the accuracy of the model and the information content is measured using Cox regression. For the information content the coefficient and standard error is provided. The hazard ratio and related standard error deviate from these estimations but result in the same t-value (Wald statistic for logit, probit, and hazard). The z-statistic M. shows the performance on accuracy of these models related to their counterpart that does include macroeconomic factors as predictors. For example, the -.84795 indicates that that the MDA model without macroeconomic factors as predictors in the 2004-2006 sample underperforms relative to the model that does incorporate those factors. The z-statistic Or. Shows the performance relative to the original models. For example, the -3.06569 indicates that the MDA model without macroeconomic predictors in the 2004-2006 sample underperforms relative to the MDA model using the original set of predictors in the 2004-2006 estimation sample. The z-statistic Est. shows the performance relative compared to the estimation model of the 2004-2006 which used the alternative set of predictors. For example, the -20.23208 indicates that the MDA model using the alternative set of predictors performs worse on accuracy in the 2007-2009 sample than in the 2004-2006 sample. The significance of the AUC statistic and information content is given at 10% (*), 5% (**), and 1% (***).