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The divergence between corporate success and crisis: The separability of recovered and healthy companies

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Abstract

The variable NITA (net income to total assets), adjusted for yearly inflation rate, was used in this paper to assign companies into three states of corporate health. These states comprised healthy, successfully and unsuccessfully recovered companies. This was done in order to determine how unsuccessfully recovered companies differ from the two other types of firms by analyzing selected accounting ratios, industry-related accounting ratios as well as variable GDPgrowth, which was used as a proxy for the insolvency rate of an industry. The results provide evidence that unsuccessfully recovered companies show significantly inferior performance when compared to the other two types of firms, whereas successfully recovered and healthy firms show almost no statistically significant differences. However, the inclusion of industry-related accounting variables was helpful in increasing the prediction accuracy of the models and provides evidence that unsuccessfully recovered firms exhibited weak profitability in comparison to industry medians. For interim managers, this means that they must exceed the industry median in terms of profitability ratios in order to be sure that their turnaround activities can assist the successful recovery of the firm.

Keywords: Accounting variables, discriminant analysis, distress, industry, inflation, insolvency, recovery

1 Introduction

The early detection of corporate crises and insolvencies remains a prominent topic in science and practice, despite several decades of research. Even if sophisticated methods are sometimes applied to determine the probability of a company's default, the evolution of corporate crises and the occurrence of different stages of corporate health have not been measurable, nor have they been understood. The first approaches towards gaining some understanding of the differences between bankrupt and non-bankrupt companies were conducted by Beaver (1966), Altman (1968), Beaver (1968) or Edmister (1972), who used financial statement data (Edmister (1972) also included industry variables). Their ideas have been re-developed by further studies and several important implications are currently known which are beneficial for progressing knowledge in this area. These studies also provide insights into the hurdles which research and practice must overcome, such as, by way of example, the non-stationarity of prediction models over time (Betts & Belhoul, 1987; Grice & Dugan, 2001; Haber, 2005; Pindado, Rodrigues & de la Torre, 2008), the lack of common definitions for the stages of bankruptcy, insolvency or distress (Kaiser, 1996; Keasey & Watson, 1991; Pretorius, 2009) or the missing theoretical link between crisis indicators and the different stages of corporate health (Butera & Faff, 2006; Pretorius, 2008).

A main implication is that the economic and financial stages of the firm cannot be captured by dichotomous thinking and the division of firms into either bankrupt or non-bankrupt. This problem was addressed relatively early by Altman (1968), who introduced a grey-area in his model, where it is not possible to determine the situation of the firm based solely on accounting ratios. He also argued that other non-financial indicators must be evaluated, before the correct stage can be assigned. The same approach was also found to be the case in the study of Edmister (1972). These were the indications that the two stages are an oversimplification and thus unsuitable for scientific and practical implications, as stated by Dietrich (1984). The degree of corporate health can instead be explained by a continuum between the extremes of bankrupt and healthy, where a company moves steadily in-between both states (Cestari, Risaliti & Pierotti, 2013; Haber, 2005; Keasey & Watson, 1991; Ward, 1999).

The motivation for this study was driven by two aspects. Firstly, the early detection of corporate crisis and the detection of companies which have undergone an unsuccessful recovery is an important aspect from a macroeconomic viewpoint. The potential of a company to go into bankruptcy can be seen as a kind of market imperfection, affecting valuation properties in both a theoretical and an empirical sense (Altman, 1969, p. 888). The insolvency rate of a state therefore reflects the development and robustness of the economy (McKee, 2000, p. 159).

In order to avoid market imperfection, it is therefore valuable to be able to recognize potential bankruptcies in order to avoid several associated problems, such as losses for creditors or job losses for employees (Exler & Situm, 2013, p. 161). From a theoretical viewpoint, it is far more preferable to eliminate a company from the market before it reaches the stage of bankruptcy, as during the stages between distress and the final outcome of insolvency, a company requires additional resources and liquidity (McKee, 2003, p. 573 – 576; McKee, 1995, p. 30). If the potential of bankruptcy could be predicted in advance, then the firm could be closed much earlier and the resources could then be used by other companies which have better chances of survival. This process would therefore improve the efficient use of resources in an economy.

Secondly, one could consider investors and debt holders, who provide liquidity to companies in order to run their businesses accordingly. More specifically, one could consider investors who invest in distressed companies in order to achieve future returns (Altman & Hotchkiss, 2006, p. 46; Moyer, 2005, p. 8). This is a very risky type of investment, as it is difficult to predict in advance whether a distressed company will successfully recover or not. However, such investment is useful in many situations to help a distressed firm to restructure, as the reasons for a firm's state of distress can be manifold and must not only be internally driven. For such companies, an external injection of liquidity can make its very survival and indeed further growth opportunities possible.

The outline of the paper is structured as follows: Firstly, a literature review is provided, including the topics of methods used in bankruptcy prediction and empirical findings concerning the different stages of corporate health. Some comments are also highlighted concerning the application of inflation and industry benchmarking to bankruptcy prediction. Secondly, definitions were provided for the identification of financial distress and recovery, based on empirical findings from prior research. However, these results were extended by using a more theoretically sound distress indicator, which was adjusted for yearly inflation, to measure real values instead of nominal values. Companies were assigned into three states: healthy companies, successfully recovered companies and unsuccessfully recovered companies.

Thirdly, the research design is presented, including a description of the database (which consisted of Austrian companies taken from selected industries for the time period 2007 to 2010), the applied methodology, research hypotheses and questions as well as a presentation of the applied variables. Fourthly, the empirical results are presented and compared to the findings of prior literature. Within this section, several prediction models (based on linear discriminant analysis) are presented in order to divide between the three defined stages of corporate health including the selected variables. Finally, the paper concludes with a summary of the main findings, a discussion including the test of research hypotheses and answers to the research questions, important limitations of the study and some recommendations for future research.

2 Methods for the development of bankruptcy prediction models

On first viewing, there is a need get an overview of the applied methods of bankruptcy prediction. Different methods have been used by researchers in order to predict the different outcomes of corporate health (e. g. bankrupt vs. non-bankrupt; distressed vs. non-distressed; failed vs. non-failed etc.). These outcomes illustrate the problems associated with drawing comparisons across studies, as researchers very often select data based on different definitions. However, this is a pre-existing problem in research and not the purpose of this study. After a review of 320 papers related to bankruptcy prediction, a systematic overview is provided within *table 1*. The aim of this review was to provide an overview of past and future, and the table was set up under the following conditions:

- In the first column, the method is mentioned corresponding to the first time it appeared chronologically in the reviewed papers.
- In the second column, the different applied definitions for failure (bankruptcy, failure and insolvency) actually describe the same phenomenon, namely that companies disappeared from the market due to the legal definitions of insolvency/bankruptcy (ordered alphabetically).
- In the last column, the references are ordered according to the year of the publication, ranging from past to present.

The summary reveals that the most prominent methods of bankruptcy prediction are linear discriminant analysis, logistic regression and neural networks, which is in congruence with the findings of Du Jardin (2009, p. 44). Other methods were also applied (such as quadratic discriminant analysis, non-parametric discriminant analysis or rough set theory), but they were not able to construct superior prediction models when compared to the three previously mentioned methods, meaning that their usage as a prediction tool was either reduced or indeed stopped entirely over time.

Table 1:

Overview of methods applied to predict bankruptcies, failures and insolvencies

The table provides an approximate overview of the applied methods for the prediction of bankruptcies and insolvencies. Empirical papers, which analyzed other economic situations such as distress, defaults etc. were not included within this summary. A description of related studies for this task follows in the next chapter. The definitions of bankruptcy, failure and insolvency were equally set within the studies and include the situations where firms were closed due to the legal definitions of bankruptcy/insolvency.

Method	Prediction purpose	Reference
Dichotomous classification test	failed vs. non-failed	Beaver (1966), Beaver (1968)
Linear discriminant analysis	bankrupt vs. non-bankrupt	Altman (1968), Altman, Haldeman & Narayanan (1977), Norton & Smith (1979), Casey & Bartczak (1985); Frydman, Altman & Kao (1985), Aziz, Emanuel & Lawson (1988), Howpood, McKeown & Mutchler (1988), Aziz & Lawson (1989), Barniv & Raveh (1989), Chatterjee & Srinivasan (1992), Baetge, Beuter & Feidicker (1992), Platt, Platt & Pedersen (1994), Boritz, Kennedy & de Miranda e Albuquerque (1995), Begley, Ming & Watts (1996), Agarwal (1999), Sung, Chang & Lee (1999), Nanda & Pendharkar (2001), Shumway (2001), Ogawa (2002), Hillegeist et al. (2004), Dietrich Arcelus & Srinivasan (2005), Min & Lee (2005), Mohamad (2005), Pompe & Bilderbeek (2005), Neves & Vieira (2006), Kim & Gu (2006), Hwang, Cheng & Lee (2007), McKee (2007), Min & Lee (2008), Hayes, Hodge & Hughes (2010)
	distressed vs. non-distressed	Doumpos & Zopounidis (1998)
	failed vs. non-failed	Edmister (1972), Blum (1974), Dambolena & Khoury (1980), Mensah (1984), Whittred & Zimmer (1984), Gentry, Newbold & Whitford (1985), Chalos (1985), Gombola et al. (1987), Houghton & Woodliff (1987), Pacey & Pham (1990), Abidali & Harris (1995), Dimitras et al. (1999), Lennox (1999b), Ahn, Cho & Kim (2000), Brabazon & Keenan (2004), Boritz, Kennedy & Sun (2007)
	insolvent vs. solvent	Stanisic, Mizdrakovic & Knezevic (2013), Pang & Kogel (2013)
Quadratic discriminant analysis	bankrupt vs. non-bankrupt	Altman, Haldeman & Narayanan (1977), Boritz, Kennedy & de Miranda e Albuquerque (1995)
	failed vs. non-failed	Gombola et al. (1987), Pacey & Pham (1990)
Logistic regression	bankrupt vs. non-bankrupt	Ohlson (1980), Casey & Bartczak (1985), Aziz, Emanuel & Lawson (1988), Aziz & Lawson (1989), Hopwood, McKeown & Mutchler (1988), Barniv & Raveh (1989), Gilbert, Menon & Schwartz (1990), Boritz, Kennedy & de Miranda e Albuquerque (1995), Begley, Ming & Watts (1996), Foster, Ward & Woodroof (1998), Mossman et al. (1998), Zhang, Hu & Patuwo (1999). Nam & Jinn (2000), Shumway (2001), Hillegeist et al. (2004), Min & Lee (2005), Chi & Tang (2006), Kim & Gu (2006), Min, Lee & Han (2006), Hol (2007), Hwang, Cheng & Lee (2007), Youn & Gu (2010), Hauser & Booth (2011), Chaudhuri (2013), Hossein, Seyed & Rasoul (2013); Trabelsi et al (2015)
	distressed vs. non-distressed	Doumpos & Zopounidis (1998)
	failed vs. non-failed	Mensah (1984), Gentry, Newbold & Whitford (1985), Fanning & Cogger (1994), Kane, Richardson & Meade (1998), Laitinen & Laitinen (1998), Dimitras et al. (1999), Lennox (1999b), Laitinen & Laitinenen (2000), Charitou, Neophytou & Charalambous (2004), Boritz, Kennedy & Sun (2007)
	insolvent vs. solvent	Bartual et al. (2012), Stanisic, Mizdrakovic & Knezevic (2013)
Generalized squared distance classification model	bankrupt vs. non-bankrupt	Casey (1980)
Probit regression	bankrupt vs. non-bankrupt	Zmijewski (1984), Hopwood, McKeown & Mutchler (1988), Barniv & Raveh (1989), Boritz, Kennedy & de Miranda e Albuquerque (1995), Bryant (1997),
	failed vs. non-failed	Gentry, Newbold & Whitford (1985), Gombola et al. (1985), Pacey & Pham (1990), Lennox (1999a and 1999b)
Recursive partitioning	bankrupt vs. non-bankrupt	Frydman, Altman & Kao (1985), McKee (2000)
Non-parametric discriminant analysis	bankrupt vs. non-bankrupt	Barniv & Raveh (1989), Boritz, Kennedy & de Miranda e Albuquerque (1995)
Classification tree/Decision trees	bankrupt vs. non-bankrupt	Chatterjee & Srinivasan (1992), Sung, Chang & Lee (1999), Santos et al. (2006), Hossein, Seyed & Rasoul (2013)
	insolvent vs. solvent	Stanisic, Mizdrakovic & Knezevic (2013)
Neural networks	bankrupt vs. non-bankrupt	Boritz, Kennedy & de Miranda e Albuquerque (1995), Agarwal (1999), Zhang, Hu & Patuwo (1999), Charalambous, Charitou & Kaourou (2000); Shah & Murtaza (2000), Vlachos & Tolias (2003), Min & Lee (2005), Pompe & Bilderbeek (2005), Shin, Lee & Kim (2005), Min, Lee & Han (2006), Neves & Vieira (2006), Santos et al. (2006), Tsakonas et al. (2006), Youn & Gu (2010)
	failed vs. non-failed	Fanning & Cogger (1994), Ahn, Cho & Kim (2000), Charitou, Neophytou & Charalambous (2004), Brabazon & Keenan (2004)
	insolvent vs. solvent	Stanisic, Mizdrakovic & Knezevic (2013), Callejon et al. (2013)

Gambler´s ruin	failed vs. non-failed	Fanning & Cogger (1994)
Induction	failed vs. non-failed	McKee (1995)
Case based reasoning	bankrupt vs. non-bankrupt	Bryant (1997)
Non-parametric multi-group hierarchical discrimination	distressed vs. non-distressed	Doumpos & Zopounidis (1998)
Rough set theory	bankrupt vs. non-bankrupt	McKee (2000), McKee & Lensberg (2002), McKee (2003)
	failed vs. non-failed	Dimitras et al. (1999), Ahn, Cho & Kim (2000)
Fuzzy set theory/Fuzzy logic	bankrupt vs. non-bankrupt	Baetge & Heitmann (2000), Vlachos & Tolias (2003), Korol & Korodi (2011)
Genetic algorithm/programming	bankrupt vs. non-bankrupt	Nanda & Penharkar (2001), McKee & Lensberg (2002), Min, Lee & Han (2006), Tsakonas et al. (2006), McKee (2007), Bahiraie, bt Ibrahim & Azhar (2009)
	failed vs. non-failed	Brabazon & Keenan (2004)
Hazard model	bankrupt vs. non-bankrupt	Shumway (2001), Chava & Jarrow (2004), Sun (2007), Chaudhuri (2013); Trabelsi et al (2015)
Option pricing model	bankrupt vs. non-bankrupt	Hillegeist et al. (2004)
Data envelopment analysis	bankrupt vs. non-bankrupt	Paradi, Asmild & Simak (2004), Min & Lee (2008)
Support vector machines	bankrupt vs. non-bankrupt	Min & Lee (2005), Shin, Lee & Kim (2005), Min, Lee & Han (2006)
Generalized Linear Models	bankrupt vs. non-bankrupt	Dakovic, Czado & Berg (2010)
Bayesian analysis/model	bankrupt vs. non-bankrupt	Chaudhuri (2013); Trabelsi et al (2015)

In the next chapter, the researched literature was reviewed in order to detect analysis related to the economic stages between the two dichotomous states. It was found that the number analyzed was relatively low when compared to the number of studies conducted in general. This aspect further emphasizes the need for additional research and may also explain why, from a current viewpoint, sufficient knowledge does not exist to explain the corporate evolution process over time, including the movement from healthy to crisis situations, the potential for recovery and arguably also the final outcome of insolvency.

3 Empirical findings about the different stages of corporate health

To complete a review of the relevant literature, the following table summarizes some of the papers reviewed which did not analyze the dichotomous outcomes of bankrupt and non-bankrupt. Instead, they attempted to investigate the behavior in-between these two points, meaning that different degrees of corporate health were therefore observed and investigated.

Table 2:

Overview of studies investigating the different stages of corporate health

In contrast to *table 1*, this overview provides a summary of studies which analyzed the different stages of corporate health beyond the dichotomous states of bankrupt and non-bankrupt. The table outlines the stages which were analyzed, including their definitions (where needed), the main results and the authors of the papers.

Definitions concerning corporate stages	**Main results**	**Reference**
Introduction of five states [financially stable firms = stage 0; firms omitting or reducing dividend payment = state 1; firms in technical default and in default on loan payments = state 2; protection under Chapter X or XI = state 3; and bankrupt or liquidated firms = state 4]	Certain states can be predicted well, whereas others are quite difficult to predict	Lau (1987)
Comparison of bankrupt and non-bankrupt as well as bankrupt and distressed firms; distress was defined as the occurrence of negative cumulative earnings over any consecutive three year period between 1972	Different indicators were relevant to distinguish between the different types of firms; a separation between bankrupt and distressed is more difficult than a segregation between bankrupt and non-	Gilbert, Menon & Schwartz (1990)

and 1983	bankrupt companies	
Merged and acquired firms, as well as Chapter 11 and Chapter 7 filings	The different types of companies experience some common characteristics such as operating losses negatively affecting working capital, leading to cash flow problems and credit squeeze; some factors were found only to be relevant for one of the three groups	Anyane-Ntow (1991)
Firms completing a bankruptcy process and tracking four outcomes after reorganization: successful reorganization, partially successful organization, mergers or acquisitions and liquidations	Size and the rate of decline (number of years in which the firm had a negative net income during the six years prior to bankruptcy) were statistically significant discriminators; a distinction between the different stages was reported to be difficult	Moulton & Thomas (1993)
Distressed and non-distressed firms; distress was defined, when a firm received a going-concern opinion and passed a screening process	The model provided a good distinction, but the clear explanation about the reasons was not given as neural networks do not provide a classification function	Coats & Fant (1993)
Introduction of four states [healthy = stage 0; reduction in cash dividends or more than 40 per cent per share after a history of successive cash dividends per share = stage 1; loan principal/interest default or loan accommodation = stage 2; filing for Chapter XI protection = stage 3]	Using a multi-state model, is was possible to achieve strong predictive power and a good segregation between the different types of companies	Ward (1994)
Bankrupt firms, firms in distress and firms in turnaround; several versions of Z-scores were applied to define failing firms as turnarounds	No satisfactory results were obtained and the authors state doubt about the use of financial ratios as explanatory variables for the segregation of the different types of firms	Poston, Harmon & Gramlich (1994)
Non-failed firms, failed and distressed-acquired firms	Their model provided an accuracy of 98.2 percent for the three states; the differentiation between failed and distressed acquired was very difficult and indicates that both types of firms have common characteristics	Wilson, Chong & Peel (19995)
Non-acquired distressed, acquired distressed and non-distressed companies; distress was defined as the situation where a firm exhibited at least one of the following characteristics: debt default, debt renegotiation attempts and/or an inability to meet fixed payment obligations on debt	Different predictors were relevant to divide between the different types of firms; the distinction between distressed acquired and distressed non-acquired remained difficult	Theodossiou et al. (1996)
Chapter XI filings, prepacks and private and public workout firms	There are significant differences in size and level of debt among the four restructuring methods; the other types of companies are less economically distressed than Chapter XI firms	Chatterjee, Dhillon & Ramirez (1996)
Chapter VII and XI companies	The tendency to file for Chapter XI increases with the value of intangible assets and with favourable business conditions in the industry and decreases with the associated costs of this procedure	Tucker & Moore (1999)
Distressed and recovered firms; financial distress was seen to be pre-existing, when the cash flow was less than the current maturity of long-term debt; recovery was defined as the situation where a firm´s cash flow is greater than the current maturity of long term debt	Management actions are a significant factor for an improvement in industry-adjusted market value; management actions are not relevant, when distress is caused by a general decline of economic conditions in the industry	Whitaker (1999)
Distressed and non-distressed firms; distressed is the situation, where a firm exhibited negative cash flow from operations, reduced or omitted dividend payments, showed debt default or was engaged in troubled debt restructuring	Good model accuracies were found (similar to Coats & Fant (1993)); due to the application of a neural network an explanation was also not provided, explaining why the results were obtained	Anandarajan, Lee & Anandarajan (2001)
Investigation of failure process, using the change of operational cash flow from positive to negative	Higher financial leverage is positively associated with default; default has a significant association with business failure; certain states are closely associated to each other	Turetsky & McEwen (2001)
Application of Taffler´s Z-score (1983, 1984) to	Both types of firms can be relatively well	Sudarsanam & Lai

assign firms as recovered and non-recovered; recovery was defined as the situation where a firm exhibited two consecutive years of positive Z-scores	distinguished by using profitability ratios; recovered firms showed significantly better values in these ratios when compared to non-recovered firms	(2001)
Filing firms, acquired firms, merged and liquidated firms	Good classification results were obtained by detecting merged and liquidated firms, but low results were obtained for acquired firms; the detection of distressed-acquired is difficult, similar to the findings of Theodossiou et al. (1996) and Wilson, Chong & Peel (1995)	Barniv, Agarwal & Leach (2002)
Firms went into bankruptcy for strategic reasons and firms went to bankruptcy for financial reasons	Firms filing for strategic reasons exhibited significantly less negative abnormal returns compared to firms filing bankruptcy for financial reasons; the distinction between the two types of firms however remains difficult	Rose-Green & Dawkins (2002)
Non-failed firms, firms with solvency problems and failed firms	Some ratios related to the cash position of the firm indicated a strong statistical impact on the probability of being assigned into one of the three states; the signs of the predictors did not always lead to consistent results	Jones & Hensher (2004)
Targets and non-targets for corporate mergers and bankrupt and non-bankrupt firms	A differentiation between bankrupt and non-bankrupt functioned quite well; the distinction between the two types of mergers only allowed for less accurate results	Sen, Ghandforoush & Stivason (2004)
Firms classified as having special treatment (ST) and firms without ST; ST was assumed to be pre-existing, when a firm experienced losses in two consecutive years	The authors achieved mixed results when using different statistical methods and concluded accordingly that it is difficult to assign firm into the correct group	Chen et al. (2006)
The same definitions as used by Lau (1987)	These definitions showed a high overall level of accuracy and low type I and type II errors.	Cheng, Su & Li (2006)
Introduction of four states [non-failed firms = stage 0; insolvent firms = stage 1; financially distressed firms = state 2; firms filed for bankruptcy = state 3]	These results provided quite accurate overall results; however, the assignment of distressed and bankrupt firms was more difficult to achieve	Hensher et al. (2007)
Active companies, distressed external administration companies and distressed takeovers, mergers or acquisitions	Based on survival analysis, the authors concluded that active and distressed takeovers are very similar in nature, so that making a distinction between them is difficult	Chancharat et al. (2010)
Slightly distressed firms, firms in reorganization or bankruptcy and non-distressed firms	The application of financial ratios was statistically insignificant for slightly distressed firms, providing less warning signals compared to firms in reorganization and bankruptcy	Tsai (2013)

This summary shows that it is, in general, difficult to distinguish reliably between the different types of corporate health. It is also visible that different definitions have been applied by researchers relating to the assignment of firms into the different stages, meaning that results can be difficult to compare across studies. This emphasizes the need for additional research in order to better understand the crisis evolution process. In terms of current data, there is lack of knowledge as to how the different stages of corporate health can be reliably defined and economically explained (Pretorius, 2009).

4 Definitions for distress and recovery

Based on the results of the literature review, it can be observed that there is no single, accepted definition in research and practice of the stages of (financial) distress and recovery (Platt & Platt, 2008, p. 132; Pretorius, 2009). A potential definition attempting to recognize distress is the event of decline, as proposed by Krueger & Willard (1991). This means that a specific distress indicator deteriorates over a minimum of two consecutive years. This proposition seems appealing and indeed it was followed by several prior studies (for example in Hoshi, Kashyap & Scharfstein, 1990; Platt & Platt, 2008; Sudarsanam & Lai, 2001). A further improvement of the distress indicator can be associated with recovery. This time period should be between two and four years in duration (Krueger & Willard, 1991, p. 28 – 29).

Within this paper the following definitions for distress and recovery were used:

1. Distress was assumed to be the case, when the indicator NITA (= net income to total assets), adjusted by yearly inflation based on *equation 1*, shows negative values for two consecutive years. The consideration of inflation seems appealing, as non-adjusted figures provide distorted information (Bulow & Shoven, 1982, p. 234; Dearden, 1981, p. 8). The effect of distortion seems to be higher for countries where the inflation rates are relatively high (Koller, Goedhard & Wessels, 2010, p. 611). The adjustment for inflation is also a useful measurement of the performance of restructured companies (Bartley & Boardman, 1990, p. 68), with the result that its application for the purposes of this study appears to be justified.
2. Recovery was assumed, if a firm exhibited two consecutive years of positive NITA, adjusted for yearly inflation. This approach follows the minimum requirement necessary in order to detect this situation based on Krueger & Willard (1991). A similar concept was applied by Jostarndt & Sautner (2008), but their distress and recovery indicator was interest coverage based on EBIT.

The adjustment for inflation was calculated based on *equation 1* (Coulthurst, 1986, p. 33; Solnik & McLeavey, 2009, p. 43).

$$(1 + i_{real}) \times (1 + \text{inflation rate}) = (1 + i_{nominal}) \quad (1)$$

$$i_{real} = \frac{(1 + i_{nominal})}{(1 + \text{inflation rate})} - 1 \quad (2)$$

NITA computed on a nominal base is inserted instead of "$i_{nominal}$" in order to obtain a variable nominated in real values. The inflation rates were retrieved from Statistik Austria, which is a Federal Institution under Public Law in Austria which compiles different statistics, including statistical analysis, forecasts and statistical models in the public interest. The applied inflation rates for the different observation periods are show in *table 3*

5 Research design

5.1 Sample description

The sample consists of Austrian companies from different industries[1], whose financial statement data was available for the years 2007 to 2010. This time period was necessary in order to assign companies into three stages of corporate health based on the previously described definitions of distress and recovery. The composition of the sample is shown in *table 3*. Three stages of corporate health were analyzed. The single stages were categorized as follows:

- Firms exhibiting two consecutive years of negative NITA, when adjusted for yearly inflation, were assigned as being distressed, based on the previously outlined definitions.
- Next, the development of the distress indicator was observed over a two year period. If the indicator remained positive for two consecutive years, then a successful recovery (group 1) was assumed (Jostarndt & Sautner, 2008). If the distress indicator was positive in the first year, but then became negative in the second year, then the firm was assigned as being unsuccessful recovered (group 0) (based on Krueger & Willard, 1991, p. 28 – 29, as recovery was assumed to be the case when a minimum of two positive years after distress is displayed).
- Firms exhibiting four consecutive years of positive NITA, adjusted for yearly inflation, were assigned as being healthy (group 2).

Table 3

Composition of samples for the development group

This table provides an overview of how many companies were assigned into the three different degrees of corporate health. A minus indicates that the distress indicator adjusted for inflation was negative in the respective year and a plus indicates that it was positive. Based on the values, companies could then be assigned into groups according to the definitions provided. The data for yearly inflation rates was taken from Statistik Austria.[2]

	Development of distress indicator $NITA_{infl.}$				**Number of identified companies**
	2007	**2008**	**2009**	**2010**	
Unsuccessful recovered (Group = 0)	-	-	+	-	47
Successful recovered (Group = 1)	-	-	+	+	64
Healthy (Group = 2)	+	+	+	+	39
Yearly inflation rate	2.2 %	3.2 %	0.5 %	1.9 %	

[1] The industry classes were based on the Austrian ÖNACE 2008 code and contain: B = Mining and quarrying, C = Manufacturing, D = Electricity, gas, steam and air condition supply, E = water supply, sewerage, waste management and remediation activities, F = Construction, G = Wholesale and retail trade and repair of motor vehicles and motorcycles , H = Transporting and storage, I = Accommodation and food service activities , J = Information and communication, L = Real estate activities, M = Professional, scientific and technical activities, and N = Administrative and support service activities.

[2] Data was taken from http://www.statistik.at/web_de/statistiken/wirtschaft/preise/verbraucherpreisindex_vpi_hvpi/023344.html, retrieved 4th February 2016

The sample selection process appears to be the most crucial element of empirical research. The higher the number of selected firms, the better the different patterns of behavior between companies can be described and hence the better the model quality (Anderson, 2007, p. 350; Thomas, Edelman & Crook, 2002, p. 122). The sample size within this study is relatively low due to restricted data access and the fact that with the detection process, only those companies were integrated which fulfilled the defined pre-conditions concerning distress and recovery. These samples were therefore selected randomly, so that no stratification bias can be assumed (Ward, 1999, p. 170). The sample of this study is comparable in size to other studies, where different stages of corporate health were also analyzed (Sen, Ghandforoush & Stivason, 2004; Wilson, Chong & Peel, 1995). However, it must be noted that model quality may be affected by the relatively lower number of companies used within the development sample.

5.2 Methodology

The companies from the development sample were used for the purpose of model building. The following procedures must be applied before this can be done:

1. Selection of potential discriminating variables:

   Several accounting ratios which had been useful in prior studies were used for this section. A description of these variables is provided in *appendix 1* of this paper. The age of the firm was included beside the accounting ratios, due to the theoretical assumption that older firms have a lower probability of bankruptcy (Bates, 1990; Jovanovic & McDonald, 1984; Jovanovic, 1982). Additionally, a comparison of selected accounting ratios to the industry-mean[3] was conducted using *equation 2*. A similar approach was used by Edmister (1972) and Lau (1987).

$$Ratio_{ind.} = \frac{Accounting\ ratio\ for\ the\ firm}{Median\ of\ the\ accounting\ ratio\ for\ industry} \quad (3)$$

   The study of Edmister (1972) indicated that the inclusion of such variables can increase the classification accuracy of a model, a fact which was also confirmed by Chava & Jarrow (2004). Therefore it can be expected that this occurrence should also be assumed within this study. The accounting ratios associated with profitability were adjusted for inflation based on *equation 1*. The reason for the adjustment for inflation is that some studies showed that by considering inflation, classification accuracy can be increased (for example in Bartley & Boardman, 1990; Butera & Faff, 2006; Gudmundsson, 2002; Liou & Smith, 2007; Tirapat & Nittayagasetwat, 1999). Therefore, it is expected that the inclusion of such ratios will provide a higher degree of classification accuracy. Finally, the GDP_{growth} variable was used, being defined as 1 when the industry the firm operates in provided a positive contribution to GDP growth and being defined otherwise as 0.[4] This attempt can be seen as the equivalent to considering the inflation rate of the industry

[3] The data of industry-medians was obtained from the homepage of Oesterreichische Nationalbank; see https://www.oenb.at/jahresabschluss/ratioaut, retrieved 4th February 2016.
[4] The contribution of each industry to gross value added to economy was taken from the homepage of Statistik Austria; see http://www.statistik.at/web_de/statistiken/wirtschaft/volkswirtschaftliche_gesamtrechnungen/bruttoinlandsprodukt_und_hauptaggregate/jahresdaten/019504.html, retrieved 4th February 2016.

within model building (Altman et al., 2008, p. 229). All of the defined variables were computed for the years 2009 and 2010.

2. Winzorisation of data:

   All variables were winsorized on the two percent level during the next step in order to eliminate outliers which could potentially affect further model building. This approach is proposed by Löffler & Posch (2006, p. 15 – 19) in order to increase model quality. The technique will not guarantee normally distributed data, but it can help to eliminate extreme deviations from normality, so that linear discriminant analysis can be applied accordingly. Even if the normality of data is a theoretical pre-condition for the correct application of linear discriminant analysis (Afifi, May & Clark, 2003, p. 274), slight deviations from normality do not appear to be problematic (Feldesman, 2002, p. 268; Kim & Gu, 2006; Neophytou & MarMolinero, 2004).

3. Descriptive statistics and test for differences:

   The next step involves the computation of descriptive statistics (using mean, median and standard deviations). This is complemented using a test for differences, as it is important to identify the most relevant risk drivers (Porath, 2011, p. 32). For this purpose, t-test and ANOVA (as parametric approaches) and U-test and H-test (as non-parametric alternatives) were applied. These analyses will show how well the different stages of corporate health can be discriminated between on a univariate basis.

4. Principal component analysis (PCA):

   This analysis seems necessary in order to check for redundancy in data. The discriminators in a discriminant function may not be a linear combination of another discriminating variable (Afifi, May & Clark, 2003, p. 274; Chan, 2006, p. 56; Klecka, 1980, p. 11). If this is the case, then the classification accuracy of the model may be decreased (Etheridge & Sriram, 1997; Doumpos & Zopounidis, 1998; Low, Nor & Yatim, 2001; Mensah, 1984).

5. Computation of discriminant functions:

   Discriminant functions were computed, based on the results obtained, in order to differentiate between the different types of firms (successful recovered vs. unsuccessful recovered, and unsuccessful recovered vs. healthy). This makes it therefore possible to determine the contribution of each variable for early detection.

6. Model evaluation:

   The final step is to evaluate the models with regards to their classification accuracy as proposed by Fawcett (2006) and Metz (1978) (using the ratio accuracy, type I as well as type II errors) and performance measures as proposed by Agarwal & Taffler (2007) and Grzybowski & Younger (1997) (Gini-coefficients).

5.3 Development of hypothesis and research questions

According to the previous literature review, the following research hypotheses shall be tested:

Hypothesis 1: Inflation-adjusted accounting ratios can improve the accuracy and performance of prediction models.

Hypothesis 2: Industry-related accounting ratios can improve the accuracy and performance of prediction models.

Additionally, the following research questions shall be answered:

Which variables are most suitable to explain the differences between the three types of companies?

How relevant are industry-related accounting variables in the prediction of the two types of recovery?

Can the implicit consideration of the industry insolvency rate (here replicated by the variable GDP_{growth}) help to increase the prediction accuracy and performance of models?

6 Results

6.1 Statistical pre-analysis

The results of the statistical pre-analysis are provided in the appendix of this work in the tables *2A* and 3*A* and include descriptive statistics for the time period two years after distress, testing for normality of data and testing for differences. The results one year after recognition of distress (not reported here in detail) provide unexpected results, as almost insignificant statistical differences can be found across the variables. The expectation was that the ratios would be significantly lower for successful and unsuccessful recovered firms when compared to healthy companies. This is not however the case for the companies of the development sample. Both types of recovered firms improved quickly in performance after distress and exhibited partially better/higher ratios when compared to healthy firms (this is visible for example in the ratios measured by median: SIZE, EBITTA & $EBITTA_{infl.}$ & $EBITTA_{ind.}$, EBITS & $EBITS_{infl.}$ & $EBITS_{ind.}$, EBITTD & $EBITTD_{infl.}$ or STA).

These results indicate that healthy firms are in a better position to manage their gross profits in relation to sales, which is not the case for both types of recovered firms. A higher gross profit value can be associated with the increased health of a firm (Doumpos & Zopounidis, 1998, p. 84) and would therefore support the obtained results. The value for GPS is higher for successful recovered firms compared to unsuccessful recovered firms and would support the result that professional gross profit management increases the probability of a successful recovery (Situm, 2015a). This aspect is also true for the period two years after distress, as successfully recovered companies tend on average to exhibit higher values when compared to unsuccessful recovered companies. Despite these observations, the influence of GPS remains insignificant when dealing with the assignment of a firm into one of the three stages.

The view changes dramatically, however, upon observation and analysis of the time period two years after distress. In the second year after recovery, it is then interesting to note that unsuccessful recovered firms display statistically significant differences to both successfully recovered and healthy firms. This implies that after the deterioration in performance based on inflation-adjusted NITA, after the first year of recovery a great step is made, which sufficiently differentiates the unsuccessfully recovered from the two other types of companies. However, the differences in the ratios between successfully recovered and healthy firms are not seen to be statistically significant at all. This means that a two year period of positive inflation-adjusted NITA seems to capture the circumstances of a successful recovery quite well, which was proposed by Krueger & Willard (1991, p. 28 – 29) as the minimum time frame. This also means that making a distinction between these two types of firms remains difficult. A similar observation was made by Gray, Mirkovic & Ragunathan (2006), who analyzed the differences between firms who were rated AAA/AA, A and BBB. They found that the higher rating grades are very difficult to differentiate between, as companies in such rating categories appear to have similar relations to financial ratios and industry variables of their model.

The firm's size does not appear to play a significant role in restructuring, which is a contrasting finding to that of Datta & Iskandar-Datta (1995). The differences in results may be attributable to the different research design of this study. They used non-financial firms which had filed for bankruptcy under Chapter 11, which was not the case in this study. Here, it appears that the type of "distress" plays a significant role in determining whether or not size is an important variable of recovery. For most of the variables, the ratios exhibit a predictable ranking order between the three types of firms, meaning the highest/lowest values are attributed to healthy firms, followed by values for successfully recovered and finally unsuccessfully recovered firms (for example the ratios NIS & $NIS_{infl.}$, EBITDAS & $EBITDAS_{infl.}$, STAFFS, RETA, STA, EBITINT, EBITDAINT, $EBITTA_{ind.}$, $GPS_{ind.}$ or $STA_{ind.}$). These results support the assumption that healthy firms should display higher levels of performance when compared to recovered firms. It is also interesting to note that in this period the firm's industry was found to be significant, which was not the case in the first year after distress.

6.2 Model building results

As previously alluded to in this study, the results of model building using linear discriminant analysis are presented. The detailed results can be found in the appendix of this apper within *tables 4A and 5A* respectively. Generally, it must be emphasized that Box´s M-test was found to be significant for all models, meaning that the variance (covariance) matrices of the groups were not equal, which is another theoretical pre-condition for the correct application of linear discriminant analysis (Afifi, May & Clark, 2003, p. 274; Atkinson, Riani & Cerioli, 2004, p. 300). However, this problem appears to be of minor relevance if both the amount of discriminators and the differences in group sizes are low (Klecka, 1980, p. 61), which is the case for this study. This is also visible in the relatively high explanatory variance of the models, which were all above 38 %. Nevertheless, it must be considered that this violation could be the reason for lower discrimination between the groups (Subhash, 1996, p. 264).

It is difficult to determine the most important explanatory variables due to the high number of statistically significant variables. A potential solution when using discriminant analysis is to use a step-wise method, which is able to reduce the number of variables to the most important ones. A further method was used within this study, in order to avoid multicollinearity of data when using linear discriminant analysis (Raykov & Marcoulides, 2008, p. 365). For the purposes of reduction, it is suitable to use principal component analysis (Raykov & Marcoulides, 2008, p. 211) in order to detect inherent problems concerning an overly high correlation between variables. The results of PCA are not reported in detail here, but the respective variables selected for the development of discriminant functions can be found in *tables 4A* and *5A* in the appendix of this paper.

In *table 4A*, it can be seen that the application of inflation-adjusted accounting ratios did not provide higher accuracy or model performance. The effect of inflation, when used to adjusted accounting ratios for yearly inflation, cannot therefore be assumed. This may be explained by the fact that the yearly inflation rates are quite low, with the result that the statistical estimation procedures were not significantly affected when compared to those used for unadjusted accounting ratios. Based on this result, the first research hypothesis of this work must be rejected, which is in congruence to the findings of Norton & Smith (1979). This is also true where the functions are applied to the data for the period one year after distress, as the Gini-coefficients do not differ. The only thing that changes in this period are type I and II.

The inclusion of industry-related variables increased the explained variances of all models, which was beneficial in leading to higher prediction accuracies. These ratios helped to reduce type I errors in differentiation between unsuccessfully recovered and healthy firms and reduced type II error in distinguishing between unsuccessfully and successfully recovered firms. According to these results, the second research hypothesis cannot be disproved. This finding is similar to other studies which found that the benchmarking of a company to its respective industry provides useful information to explain corporate crises and insolvencies (Butera & Faff, 2006; Chava & Jarrow, 2004; Thornhill & Amit, 2003).

Here, it must also be emphasized that the combination of inflation-adjusted accounting ratios and industry-related ratios provided better performance based Gini-coefficients than the combination of unadjusted accounting ratios and industry-related ratios for the period one year after distress. It seems that a combination of both inflation and industry is helpful to increase prediction ability of models. However, the Gini-coefficients for two years after distress are all statistically significant at the one percent level, thereby indicating that the models can assign the companies a-posteriori more reliably than a random assignment. This is not the case for the period one year after distress, where all Gini-coefficients were seen to be statistically insignificant. Therefore, the combination of inflation and industry was not helpful in providing statistically significant results, meaning that their superiority for the year after distress is of minor relevance in the absence of a reliable general conclusion.

7 Main results, discussion and limitations of the study

The test of research hypotheses is summarized in *table 4* and shows that inflation-adjusted accounting ratios are do not contribute to a better segregation between the different types of firms and it follows that the first hypothesis must therefore be rejected. The inclusion of industry-related variables helped to increase the explanatory power and the prediction accuracy of the models, meaning that the second research hypothesis cannot be disproved.

Table 4

Results from hypothesis testing

The table shows a summary of the results concerning testing of research hypothesis. Firstly, the definition of the research hypothesis is provided, followed by the result and finally the respective test procedure which was the basis for the final result, is explained.

No.	Hypothesis	Test result	Test procedure
H1	The consideration of inflation-adjusted accounting ratios can improve the accuracy and performance of prediction models.	Rejected	Comparison of explained variances for the different models as well as the accuracies, type I and type II errors; additionally the Gini-coefficients were compared showing the same values for the period two years and one year after distress (when no industry-related variables are assumed), but dissimilar Gini-coefficients for the period one year after distress; due to statistical insignificance of the AUC the superiority of inflation-adjusted models cannot be concluded
H2	The consideration of industry-related accounting ratios can improve the accuracy and performance of prediction models.	Not falsified	Comparison of explained variances for models with and without industry-related variables; the inclusion of such variables led to reduction of type I errors (an unsuccessfully recovered firm is assigned as successfully recovered or healthy) and to higher explanatory power of the models; generally the accuracies of the models increased

The most important predictors are NIS and EBITTA (profitability ratios). Their signs are in congruence both with expectations and results from prior research. Companies which display higher profitability have a higher probability of achieving a successful recovery from distress (Begley, Ming & Watts, 1996; Doumpos & Zopounidis, 1998; Situm, 2015a; Sudarsanam & Lai, 2001). Additionally, TETA was seen to be statistically significant, indicating that companies exhibiting a higher equity-ratio (lower debt-ratio) are more likely to successfully recover (Bartual et al., 2012; Grunert, Norden & Weber, 2005; Pompe & Bilderbeek, 2005).

The relevance of industry-related ratios was assumed within this study, as the inclusion of such variables was beneficial for the purposes of higher model quality and prediction accuracy. This means that a benchmarking of the ratios of a company to the median values of its respective industry is significant and provides additional useful information towards making more accurate predictions. The importance of the firm's industry for prediction purposes was also referred to in the studies of Edmister (1972), Chava & Jarrow (2004), Hoshi, Kashyap & Scharfstein (1990) or Thornhill & Amit (2003). This is in contrast with other studies which did not find empirical evidence that prediction models were sensitive to industry (Hodgin & Marchesini, 2011; Sheppard, 1994). The differences may be attributable to the different research designs, with the result that the importance of industry depends on the severity of corporate distress and recovery.

The variable GDP_{growth} was not seen to be statistically significant at all, meaning that its application as a prediction variable could not be assumed. This is surprising, as it was used as a replication of the insolvency rate of the industry as proposed by Altman et al. (2008, p. 229). The missing contribution may be attributable to the low number of companies analyzed within this study, which was due to restricted access to data. Additionally, it must be stated that the non-normality of data and the unequal variance (covariance) matrices had an influence on the estimation procedure. Despite this, the explained variances are quite high, with the result that model performances for the period two years after distress were quite high and satisfactory. However, a more detailed analysis would be appropriate with an enlarged database, in order to gain further insights.

Nevertheless, it is clearly shown that a distinction between unsuccessfully recovered and successfully recovered as well healthy firms two years after distress is possible to achieve. This provides evidence that a deterioration in performance after recognition of distress leads to statistically significant differences between the different types of firms. The definition of unsuccessful recovered seems therefore to be suitable for scientific and practical purposes. A distinction between successful and healthy firms is almost as difficult to make because statistically significant differences were not detected. This leads to the conclusion that both types of firms are quite similar and that a time frame of two years can be sufficient to return a distressed firm back to a healthy state.

Reference list

Abidali, A. F., & Harris, F. (1995). A methodology for predicting company failure in the construction industry. *Construction Management and Economics, 13(3)*, 189–196.

Afifi, A., May, S., & Clark. V. A. (2003). *Computer-aided multivariate analysis* (4th edition). Boca Raton, FL: Chapman & Hall.

Agarwal, A. (1999). Abductive networks for two-group classification: A comparison with neural networks. *The Journal of Applied Business Research, 15(2)*, 1–12.

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

Ahn, B. S., Cho, S. S., & Kim, C. Y. (2000). The integrated methodology of rough set theory and artificial neural network for business failure prediction. *Expert Systems with Applications, 18(2)*, 65–74.

Aktan, S. (2011). Application of machine learning algorithms for business failure prediction. *Investment Management and Financial Innovations, 8(2)*, 52–65.

Altman, E. I., Sabato, G., & Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. *The Journal of Credit Risk, 6(2)*, 1–33.

Altman, E. I., Brady, B., Resti, A., & Sironi, A. (2008). The link between default and recovery rates: Theory, empirical evidence, and implications. In N. Wagner (Ed.), *Credit risk: Models, derivatives, and management* (pp. 211-234). Boca Raton, FL: Taylor & Francis.

Altman, E. I., & Hotchkiss, E. (2006). *Corporate financial distress and bankruptcy: Predict and avoid bankruptcy, analyze and invest in distressed debt*. Hoboken, NJ: John Wiley.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977), ZETA^{TM} analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance, 1(1)*, 29–54.

Altman, E. I. (1969). Corporate bankruptcy potential, stockholder returns and share valuation. *The Journal of Finance, 24(5)*, 887-900.

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

Anandarajan, M., Lee, P., & Anandarajan, A. (2001). Bankruptcy prediction of financially stressed firms: An examination of the predictive accuracy of artificial neural networks. *International Journal of Intelligent Systems in Accounting, Finance & Management, 10(2)*, 69–81.

Anderson, R. (2007). *The credit scoring toolkit: Theory and practice for retail credit risk management and decision automation*. Oxford, England: Oxford University Press UK.

Anyane-Ntow, K. (1991). Accounting information and its relationship to corporate financial distress process. *The Journal of Applied Business Research, 7(3)*, 29–35.

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

Atkinson, A. C., Riani, M., & Cerioli, A. (2004). *Exploring multivariate data with the forward search.* New York, NY: Springer.

Aziz, A., Emanuel, D. C., & Lawson, G. H. (1988). Bankruptcy prediction – An investigation of cash flow based models. *Journal of Management Studies, 23(5)*, 419-437.

Aziz, A., & Lawson, G. H. (1989). Cash flow reporting and financial distress models: Testing of hypotheses. *Financial Management, 18(1)*, 55–63.

Baetge, J., & Heitmann, C. (2000). Creating a fuzzy rule-based indicator for the review of credit standing. *Schmalenbach Business Review, 52*, 318–343.

Baetge, J., Beuter, H., & Feidicker, M. (1992). Kreditwürdigkeitsprüfung mit Diskriminanzanalyse. *Die Wirtschaftsprüfung, 24*, 749–761.

Bahiraie, A., bt Ibrahim, N. A., & Azhar, A. K. M. (2009). On the predictability of risk box approach by genetic programming method for bankruptcy prediction. *American Journal of Applied Sciences, 6(9)*, 1748–1757.

Barniv, R., Agarwal, A., & Leach, R. (2002). Predicting bankruptcy resolution. *Journal of Business Finance & Accounting, 29(3-4)*, 497–520.

Barniv, R., & Raveh, A. (1989). Identifying financial distress: A new nonparametric approach. *Journal of Business Finance & Accounting, 16(3)*, 361–383.

Bartley, J. W., & Boardman, C. M. (1990). The relevance of inflation adjusted accounting data to the prediction of corporate takeovers. *Journal of Business Finance & Accounting, 17(1)*, 53- 72.

Bartual, C., Garcia, F., Gimenez, V., & Romero-Civera, A. (2012). Credit risk analysis: Reflection on the use of the logit model. *Journal of Applied Finance & Banking, 2(6)*, 1–13.

Bates, T. (1990). Entrepreneur human capital inputs and small Business longevity. *The Review of Economics and Statistics, 72(4)*, 551–559.

Beaver, W. H. (1968). Alternative accounting measures as predictors of failure. *The Accounting Review, 43(1)*, 113–122.

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

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

Betts, J., & Belhoul, D. (1987). The effectiveness of incorporating stability measures in company failure models. *Journal of Business Finance & Accounting, 14(3)*, 323–334.

Blum, M. (1974). Failing company discriminant analysis. *Journal of Accounting Research, 12(1)*, 1–25.

Boritz, J. E., Kennedy, D. B., & Sun, J. Y. (2007). Predicting business failure in Canada. *Accounting Perspectives, 6(2)*, 141–165.

Boritz, J. E., Kennedy, D. B., & de Miranda e Albuquerque, A. (1995). Predicting corporate failure using a neural network approach. *Intelligent Systems in Accounting, Finance and Management, 4(2)*, 95–111.

Brabazon, A., & Keenan, P. B. (2004). A hybrid genetic model for the prediction of corporate failure. *Computational Management Science, 1(3-4)*, 293 – 310.

Bruse, H. (1978). Die Prognosefähigkeit von Kennzahlen bei verschiedenen Maßen für das Unternehmenswachstum. *Zeitschrift für Betriebswirtschaft, 48*, 138–152.

Bryant, S. M. (1997). A case-based reasoning approach to bankruptcy prediction modeling. *Intelligent Systems in Accounting, Finance and Management, 6(3)*, 195–214.

Bulow, J. I., & Shoven, J. B. (1982). Inflation, corporate profits, and the rate of return to capital. In R. E. Hall (Ed.), *Inflation: Causes and effects* (pp. 233-260). Chicago: University of Chicago Press.

Burns, R., & Burns, R. (2008). *Business research methods and statistics using SPSS*. London, England: Sage UK.

Butera, G., & Faff, R. (2006). An integrated multi-model credit rating system for private firms. *Review of Quantitative Finance & Accounting, 27(3)*, 311–340.

Callejon, A. M., Casado, A. M., Fernández, M. A., & Peláez, J. I. (2013). A system of insolvency prediction for industrial companies using a financial alternative model with neural networks. *International Journal of Computational Intelligence Systems, 6(1)*, 29–37.

Casey, C., & Bartczak, N. (1985). Using operating cash flow data to predict financial distress: Some extensions. *Journal of Accounting Research, 23(1)*, 384–401.

Casey, C. J. (1980). Variation in accounting information load: The effect on loan officers´ predictions of bankruptcy. *The Accounting Review, 55(1)*, 36–49.

Cestari, G., Risaliti, G., & Pierotti, M. (2013). Bankruptcy prediction models: Preliminary thoughts on the determination of parameters for the evaluation of effectiveness and efficiency. *European Scientific Journal, 9(16)*, 265–290.

Chalos, P. (1985). Financial distress: A comparative study of individual, model, and committee assessments. *Journal of Accounting Research, 23(2)*, 527–543.

Chan, Y. H. (2005). Biostatistics 303. Discriminant analysis. *Singapore Medical Journal, 46(2)*, 54–62.

Chancharat, N., Tian, G., Davy, P., McCrae, M. & Lodh, S. (2010). Multiple states of financially distressed companies: Tests using a competing risk-model. *Australasian Accounting Business and Finance Journal, 4(4)*, 27–44.

Charalambous, C., Charitou, A., & Kaourou, F. (2000). Comparative analysis of artificial neural network models: Application in bankruptcy prediction. *Annals of Operations Research, 99(1)*, 403-425.

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

Chatterjee, S., Dhillon, U. S., & Ramirez, G. G. (1996). Resolution of financial distress: Debt restructurings via chapter 11, prepackaged bankruptcies, and workouts. *Financial Management, 25(1)*, 5–18.

Chatterjee, S., & Srinivasan, V. (1992). Graphical analysis and financial classification: A case study. *Managerial and Decision Economics, 13(6)*, 527–537.

Chaudhuri, A. (2013). Bankruptcy prediction using Bayesian, hazard, mixed logit and rough Bayesian models: A comparative analysis. *Computer and Information Science, 6(2)*, 103–125.

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

Chen, J., Marshall, B. R., Zhang, J., & Ganesh, S. (2006). Financial distress prediction in China. *Review of Pacific Basin Financial Markets and Policies, 9(2)*, 317–336.

Chen, K.H., & Shimerda, T. A. (1981). An empirical analysis of useful financial ratios. *Financial Management, 10(1)*, 51 – 60.

Chen, W.-S., & Du, Y.-K. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert Systems with Applications, 36(2)*, 4075–4086.

Cheng, W.-Y., Su, E., & Li, S.-J. (2006). A financial distress pre-warning study by fuzzy regression model of TSE-listed companies. *Asian Academy of Management Journal of Accounting and Finance, 2(2)*, 75–93.

Chi, L.-C., & Tang, T.-C. (2006). Bankruptcy prediction: Application of logit analysis in export credit risks. *Australian Journal of Management, 31(1)*, 17–27.

Coats, P. K., & Fant, F. L. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management, 22(3)*, 142–155.

Coulthurst, N. J. (1986). Accounting for inflation in capital investment: The state of the art and science. *Accounting and Business Research, 17(65)*, 33-42.

Dakovic, R., Czado, C., & Berg, D. (2010). Bankruptcy prediction in Norway: A comparison study. *Applied Economic Letters, 17(17)*, 1739–1746.

Dambolena, I. G., & Khoury, S. J. (1980). Ratio stability and corporate failure. *The Journal of Finance, 35(4)*, 1017–1026.

Datta, S., & Iskandar-Datta, M. E. (1995). Reorganization and financial distress: An empirical investigation. *The Journal of Financial Research, 18(1)*, 15-32.

Dearden, J. (1981). Facing facts with inflation accounting. *Harvard Business Review, July-August*, 8-16.

Dietrich, J., Arcelus, F. J., & Srinivasan, G. (2005). Predicting financial failure: Some evidence from new Brunswick agricultural co-ops. *Annals of Public and Cooperative Economics, 76(2)*, 179–194.

Dietrich, R. J. (1984). Discussion of methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research, 22*, 83–86.

Dimitras, A. I., Slowinski, R., Susmaga, R., & Zopounidis, C. (1999). Business failure prediction using rough sets. *European Journal of Operational Research, 114(2)*, 263–280.

Doumpos, M., & Zopounidis, C. (1998). A multicriteria discrimination method for the prediction of financial distress: The case of Greece. *Multinational Finance Journal, 3(2)*, 71–101.

Du Jardin, P. (2009). Bankruptcy prediction models: How to choose the most relevant variables?. *Bankers, Markets and Investors, 98, January – February*, 39–46.

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small failure prediction. *Journal of Financial and Quantitative Analysis, 7(2)*, 1477–1493.
Etheridge, H. L., & Sriram, R. S. (1997). A comparison of the relative costs of financial distress models: Artificial neural networks, logit and multivariate discriminant analysis. *Intelligent Systems in Accounting, Finance and Management, 6(3)*, 235–248.
Exler, M. & Situm, M. (2013). Früherkennung von Unternehmenskrisen: Systematische Zuordnung von Krisenfrüherkennungsindikatoren zu den unterschiedlichsten Krisenphasen eines Unternehmens. *Krisen-, Sanierungs- und Insolvenzberatung, 9(4)*, 161-166.
Fanning, K. M., & Cogger, K. O. (1994). A comparative analysis of artificial neural networks using financial distress prediction. *Intelligent Systems in Accounting, Finance and Management, 3(4)*, 241–252.
Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters, 27(8)*, 861–874.
Feldesman, M. R. (2002). Classification trees as an alternative to linear discriminant analysis. *American Journal of Physical Anthropology, 119(3)*, 257–275.
Foster, B. P., Ward, T. J., & Woodroof, J. (1998). An analysis of the usefulness of debt defaults and going concern opinions in bankruptcy risk assessment. *Journal of Accounting, Auditing & Finance, 13(3)*, 351–371.
Freund, J. E., & Perles, B. M. (2014). *Modern elementary statistics*. 12th ed., Essex, UK: Pearson.
Frydman, H., Altman, E. I., & Kao, D.-L. (1985). Introducing recursive partitioning for financial classification: The case of financial distress. *The Journal of Finance, 40(1)*, 269–291.
Gebhardt, G. (1980). *Insolvenzfrüherkennung aus aktienrechtlichen Jahresabschlüssen*. Wiesbaden: Gabler.
Gentry, J. A., Newbold, P., & Whitford, D. T. (1985). Classifying bankrupt firms with funds flow components. *Journal of Accounting Research, 23(1)*, 146–160.
Gilbert, L. R., Menon, K., & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business Finance & Accounting, 17(1)*, 161–171.
Gombola, M. J., Haskins, M. E., Ketz, E. J., & Williams, D. D. (1987). Cash flow in bankruptcy prediction. *Financial Management, 16(4)*, 55–65.
Gray, S., Mirkovic, A., & Ragunathan, V. (2006). The determinants of credit ratings: Australian evidence. *Australian Journal of Management, 31(2)*, 333 – 354.
Grice, J. S., & Dugan, M. T. (2001). The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting, 17(2)*, 151-166.
Grunert, J., Norden, L., & Weber, M. (2005). The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance, 29(2)*, 509–531.
Grzybowski, M., & Younger, J. G. (1997). Statistical methodology: III. Receiver operating characteristic (ROC) curves. *Academic Emergency Medicine, 4(8)*, 818-826.
Gudmundsson, S. V. (2002). Airline distress prediction using non-financial indicators. *Journal of Air Transportation, 7(2)*, 3–24.
Haber, J. R. (2005). Assessing how bankruptcy prediction models are evaluated. *Journal of Business & Economics Research, 3(1)*, 87–92.
Hauser, R. P., & Booth, D. (2011). Predicting bankruptcy with robust logistic regression. *Journal of Data Science, 9(4)*, 565–584.
Hayes, S. K., Hodge, K. A., & Hughes, L. W. (2010). A study of the efficacy of Altman´s Z to predict bankruptcy of speciality retail firms doing business in contemporary times. *Economics & Business Journal: Inquiries & Perspective, 3(1)*, 122–134.
Hensher, D. A., Jones, S., & Greene, W. H. (2007). An error component logit analysis of corporate bankruptcy and insolvency risk in Australia. *The Economic Record, 83 (260)*, 86–103.
Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies, 9(1)*, 5–34.
Ho, R. (2006). *Handbook of univariate and multivariate data analysis and interpretation with SPSS*. Boca Raton, FL: Chapman & Hall.

Hodgin, R. F., & Marchesini, R. (2011). Financial distress models: How pertinent are sampling bias criticism?. *Journal of Applied Business and Economics, 12(4)*, 29–35.
Hol, S. (2007). The influence of the business cycle on bankruptcy probability. *International Transactions in Operational Research, 14(1)*, 75–90.
Hopwood, W., McKeown, J., & Mutchler, J. (1988). The sensitivity of financial distress prediction models to departures from normality. *Contemporary Accounting Research, 5(1)*, 284–298.
Hoshi, T., Kashyap, A., & Scharfstein, D. (1990). The role of banks in reducing the costs of financial distress in Japan. *Journal of Financial Economics, 27(1)*, 67–88.
Hossein, R. D., Seyed, M. H., & Rasoul, T. (2013). Using decision tree model and logistic regression to predict companies financial bankruptcy in Tehran stock exchanges. *International Journal of Emerging Research in Management & Technology, 2(9)*, 7–16.
Houghton, K. A., & Woodliff, D. R. (1987). Financial ratios: The prediction of corporate ´success´ and failure. *Journal of Business Finance & Accounting, 14(4)*, 537–554.
Hwang, R.-C., Cheng, K. F., & Lee, J. C. (2007). A semiparametric method for predicting bankruptcy. *Journal of Forecasting, 26(5)*, 317–342.
Iazzolino, G., Migliano, G., & Gregorace, E. (2013). Evaluating intellectual capital for supporting credit risk assessment: An empirical study. *Investment Management and Financial Innovations, 10(2)*, 44–54.
Jones, S., & Hensher, D. A. (2004). Predicting firm financial distress: A mixed logit model. *The Accounting Review, 79(4)*, 1011–1038.
Jostarndt, P., & Sautner, Z. (2008). Financial distress, corporate control, and management turnover. *Journal of Banking & Finance, 32(10)*, 2188–2204.
Jovanovic, B., & MacDonald, G. M. (1994). The life cycle of a competitive industry. *Journal of Political Economy, 102(2)*, 322–347.
Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica, 50(3)*, 649–670.
Kaiser, K. M. J. (1996). European bankruptcy laws: Implications for corporations facing financial distress. *Financial Management, 25(3)*, 67–85.
Kane, G. D., Richardson, F. M., & Meade, N. L (1998). Rank transformation and the prediction of corporate failure. *Contemporary Accounting Research, 15(2)*, 145-166.
Keasey, K., & Watson, R. (1991). Financial distress prediction models: A review of their usefulness. *British Journal of Management, 2(2)*, 89–102.
Kim, H., & Gu, Z. (2006). Predicting restaurant bankruptcy: A logit model in comparison with a discriminant model. *Journal of Hospitality & Tourism Research, 30(4)*, 474–493.
Kim, M. H., & Partington, G. (2015). Dynamic forecasts of financial distress of Australian firms. *Australian Journal of Management, 40 (1)*, 135–160.
Klecka, W. R. (1980). *Discriminant analysis*. SAGE University Papers, Series: Quantitative Applications in the Social Sciences, Newbury Park, CA: Sage.
Ko, L.-J., Blocher, E. J., & Lin, P. P. (2001). Prediction of corporate financial distress: An application of the composite rule induction system. *The International Journal of Digital Accounting Research, 1(1)*, 69–85.
Koller, T., Goedhart, M., & Wessels, D. (2010). *Valuation: Measuring and managing the value of companies*. Hoboken, NJ: John Wiley.
Korol, T., & Korodi, A. (2011). An evaluation of effectiveness of fuzzy logic model in predicting the business bankruptcy. *Romanian Journal of Economic Forecasting, 14(3)*, 92–107.
Krueger, D. A., & Willard, G. E. (1991). Turnarounds: A process, not an event. *Academy of Management Best Papers Proceedings*, 26-30.
Laitinen, E. K., & Laitinen, T. (2000). Bankruptcy prediction: Application of the Taylor´s expansion in logistic regression. *International Review of Financial Analysis, 9(4)*, 327–349.
Laitinen, E. K., & Laitinen, T. (1998). Cash management behavior and failure prediction. *Journal of Business Finance & Accounting, 25(7-8)*, 893–919.
Lau, A. H.-L. (1987). A five-state financial distress prediction model. *Journal of Accounting Research, 25(1)*, 127–138.

Laurent, C. R. (1979). Improving the efficiency and effectiveness of financial ratio analysis. *Journal of Business Finance & Accounting, 6(3)*, 401–413.

Lennox, C. S. (1999b). The accuracy and incremental information content of audit reports in predicting bankruptcy. *Journal of Business Finance & Accounting, 26(5-6)*, 757–778.

Lennox, C. (1999a). Identifying failing companies: A re-evaluation of the logit, probit and DA approaches. *Journal of Economics and Business, 51(4)*, 347–364.

Li, H., & Sun, J. (2011). Predicting business failure using forward ranking-order case-based reasoning. *Expert Systems with Applications, 38(4)*, 3075–3084.

Libby, R. (1975). Accounting ratios and the prediction of failure: Some behavioural evidence. *Journal of Accounting Research, 13(1)*, 150–161.

Liou, D.-K., & Smith, M. (2007). Macroeconomic variables and financial distress. *Journal of Accounting, Business & Management, 14(1)*, 17–31.

Low, S.-W., Nor, F. M., & Yatim, P. (2011). Predicting corporate financial distress using the logit model: The case of Malaysia. *Asian Academy of Management Journal, 6(1)*, 49–61.

Löffler, G., & Posch, P. N. (2007). *Credit risk modeling using Excel and VBA*. West Sussex, England: Wiley UK.

Marchesini, R., Perdue, G., & Bryan V. (2004). Applying bankruptcy prediction models to distressed high yield bond issues. *The Journal of Fixed Income, 13(4)*, 50–56.

McKee, T. E. (2007). Altman's 1968 bankruptcy prediction model revisited via genetic programming: New wine from an old bottle or a better fermentation process? *Journal of Emerging Technologies in Accounting, 4(1)*, 87–101.

McKee, T. (2003). Rough sets bankruptcy prediction models versus auditor signaling rates. *Journal of Forecasting, 22(8)*, 569–586.

McKee, T., & Lensberg, T. (2002). Genetic programming and rough sets: A hybrid approach to bankruptcy prediction. *European Journal of Operational Research, 138(2)*, 436–451.

McKee, T. E. (2000). Developing a bankruptcy prediction model via rough sets theory. *International Journal of Intelligent Systems in Accounting, Finance & Management, 9(3)*, 159–173.

McKee, T. E. (1995). Predicting bankruptcy via induction. *Journal of Information Technology, 10(1)*, 26–36.

Mensah, Y. M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: A methodological study. *Journal of Accounting Research, 22(1)*, 380–395.

Metz, C. E. (1978). Basic principles of ROC analysis. *Seminars in Nuclear Medicine, 8(4)*, 283–298.

Min, J. H., & Lee, Y.-C. (2008). A practical approach to credit scoring. *Expert Systems with Applications, 35(4)*, 1762 – 1770.

Min, J. H., & Lee, Y.-C. (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameter. Expert Systems with Applications, 28(4), 603–614.

Min, S.-H., Lee, J., & Han, I. (2006). Hybrid genetic algorithms and support vector machines for bankruptcy prediction. *Expert Systems with Applications, 31(3)*, 652–660.

Mohamad, I. (2005). Bankruptcy prediction model with ZETAC optimal cut-off score to correct type I errors. *Gadjah Mada International Journal of Business, 7(1)*, 41–68.

Mossman, C. E., Bell, G. B., Swartz, M. L., & Turtle, H. (1998). An empirical comparison of bankruptcy models. *The Financial Review, 33(2)*, 35–54.

Moulton, W. N., & Thomas, H. (1993). Bankruptcy as a deliberate strategy: Theoretical considerations and empirical evidence. *Strategic Management Journal, 14(2)*, 125–135.

Moyer, S. G. (2005). *Distressed debt analysis: Strategies for speculative investors*. Boca Raton, FL: Ross Publishing.

Nam, J.-H., Jinn, T. (2000). Bankruptcy prediction: Evidence from Korean listed companies during the IMF crisis. *Journal of International Financial Management and Accounting, 11(3)*, 178–197.

Nanda, S., & Pendharkar, P. (2001). Linear models for minimizing misclassification costs in bankruptcy prediction. *International Journal of Intelligent Systems in Accounting, Finance & Management, 10(3)*, 155–168.

Neophytou, E., & Mar Molinero, C. (2004). Predicting corporate failure in the UK: A multidimensional scaling approach. Journal of Business Finance & Accounting, 31(5-6), 677–710.

Neves, J. C., & Vieira, A. (2006). Improving bankruptcy prediction with hidden layer learning vector quantization. *European Accounting Review, 15(2)*, 253–271.

Norton, C. L., & Smith, R. E. (1979). A comparison of general price level and historical cost financial statements in the prediction of bankruptcy. *The Accounting Review, 54(1)*, 72–87.

Ogawa, S. (2002). Trust evaluation model for changing Japanese bankruptcy chances. *Journal of Contingencies and Crisis Management, 10(2)*, 63–72.

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

Pacey, J. W., & Pham, T. M. (1990). The predictiveness of bankruptcy models: Methodological problems and evidence. *Australian Journal of Management, 15(2)*, 315–337.

Pang, J., & Kogel, M. (2013). Retail bankruptcy prediction. *American Journal of Economics and Business Administration, 5(1)*, 29–46.

Paradi, J. C., Asmild, M., & Simak, P. C. (2004). Using DEA and worst practice DEA in credit risk evaluation. *Journal of Productivity Analysis, 21(2)*, 153–165.

Pervan, I., Pervan, M., & Vukoja, B. (2011). Prediction of company bankruptcy using statistical techniques – Case of Croatia. *Croatian Operational Research Review, 2(1)*, 158–167.

Pindado, J., Rodrigues, L., & de la Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research, 61(9)*, 995–1003.

Platt, H. D., & Platt, M. B. (2008). Financial distress comparison across three global regions. *Journal of Risk and Financial Management, 1(1)*, 129–162.

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

Platt, H. D., Platt, M. B., & Pedersen. J. G. (1994). Bankruptcy discrimination with real variables. *Journal of Business Finance & Accounting, 21(4)*, 491–510.

Pohlman, R. A., & Hollinger, R. D. (1981). Information redundancy in sets of financial ratios. *Journal of Business Finance & Accounting, 8(4)*, 511–528.

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

Porath, D. (2011). Scoring models for retail exposures. In B. Engelmann, & R. Rauhmeier (Eds.), *The Basel II risk parameters: Estimation, validation, stress testing – with applications to loan risk management* (pp. 25-36). Berlin-Heidelberg: Springer.

Poston, K. M., Harmon, K. W., & Gramlich, J. D. (1994). A test of financial ratios as predictors of turnaround versus failure among financially distressed firms. *Journal of Applied Business Research, 10(1)*, 41–56.

Pretorius, M. (2009). Defining business decline, failure and turnaround: A content analysis. *South African Journal of Entrepreneurship and Small Business Management, 2(1)*, 1 – 16.

Pretorius, M. (2008). Critical variables of business failure: A review and classification framework. *South African Journal of Economic and Management Sciences, 11(4)*, 408-430.

Raykov, T., & Marcoulides, G. A. (2008). *An introduction to applied multivariate analysis*. New York, NY: Taylor & Francis.

Rose-Green, E., & Dawkins, M. (2002). Strategic bankruptcies and price reactions to bankruptcy filings. *Journal of Business Finance & Accounting, 29(9-10)*, 1319–1335.

Santos, M. F., Cortez, P., Pereira, J., & Quintela, H. (2006). Corporate bankruptcy prediction using data mining techniques. *WIT Transactions of Information and Communication Technologies, 37*, 349–357.

Sen, T. K., Ghandforoush, P., & Stivason, C. T. (2004). Improving prediction of neural networks: A study of two financial prediction tasks. *Journal of Applied Mathematics and Decision Sciences, 8(4)*, 219–233.

Shah, J. R., & Murtaza, M. B. (2000). A neural network based clustering procedure for bankruptcy prediction. *American Business Review, 18(2)*, 80–86.

Sheppard, J. P. (1994). Strategy and bankruptcy: An exploration into organizational death. *Journal of Management, 20(4)*, 795–833.
Shin, K-S., Lee, T. S., & Kim, H.-j. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications, 28(1)*, 127–135.
Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74(1)*, 101–124.
Situm, M. (2015b). The relevance of employee-related ratios for early detection of corporate crises. *Economic and Business Review, 16(3)*, 279-314.
Situm, M. (2015a). Recovery from distress and insolvent: A comparative analysis using accounting ratios. *Proceedings of the 6th Global Conference on Managing in Recovering Markets, GCMRM 2015*, 589-606.
Solnik, B., & McLeavey, D. (2009). *Global investments*. Boston, MA: Pearson Education Inc.
Stanišić, N., Mizdraković, V., & Knežević, G. (2013). Corporate bankruptcy prediction in the Republic of Serbia. *Industrija, 41(4)*, 145–159.
Subhash, S. (1996). *Applied multivariate techniques*. New York, NY: Wiley.
Sudarsanam, S., & Lai, J. (2001). Corporate financial distress and turnaround strategies: An empirical analysis. *British Journal of Management, 12(3)*, 183–199.
Sun, L. (2007). A re-evaluation of auditor´s opinios versus statistical model in bankruptcy prediction. *Review of Quantitative Finance and Accounting, 28(1)*, 55–78.
Sung, T. K., Chang, N., & Lee, G. (1999). Dynamics of modeling in data mining: Interpretive approach to bankruptcy prediction. *Journal of Management Information Systems, 16(1)*, 63–85.
Taffler, R. J. (1984). Empirical models for the monitoring of UK corporations. *Journal of Banking and Finance, 8(2)*, 199-227.
Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model. *Accounting and Business Research, 13(52)*, 295-308.
Theodossiou, P., Kahya, E., Saidi, R., & Philippatos, G. (1996). Financial distress and corporate acquisitions: Further empirical evidence. *Journal of Business Finance & Accounting, 23(5)*, 699–719.
Thomas, L. C., Edelman, D. B., & Crook, J. N. (2002). *Credit scoring and its applications*. Philadelphia: SIAM.
Thornhill, S., & Amit, R. (2003). Learning about failure: Bankruptcy, firm age, and the resource-based view. *Organization Science, 14(5)*, 497–509.
Tirapat, S., & Nittayagasetwat, A. (1999). An investigation of Thai listed firms´ financial distress using macro and micro variables. *Multinational Finance Journal, 3(2)*, 103–125.
Trabelsi, S., He, R., He, L., & Kusy, M. (2015). A comparison of Bayesian, hazard and mixed logit model of bankruptcy prediction. *Computational Management Science, 12(1)*, 81-97.
Tsai, B.-H. (2013). An early warning system of financial distress using multinomial logit models and a bootstrapping approach. *Emerging Markets Finance & Trade, 49(2)*, 43–69.
Tsakonas, A., Dounias, G., Doumpos, M., & Zopounidis, C. (2006). Bankruptcy prediction with neural logic networks by means of grammar-guided genetic programming. *Expert Systems with Applications, 30(3)*, 449–461.
Tucker, J. W., & Moore. W. T. (1999). Reorganization versus liquidation decisions for small firms. *Financial Practice and Education, 9(2)*, 70–76.
Turetsky, H. F., & McEwen, R. A. (2001). An empirical investigation of firm longevity: A model of the ex ante predictors of financial distress. *Review of Quantitative Finance and Accounting, 16(4)*, 323–343.
Vlachos, D., & Tolias, Y. A. (2003). Neuro-fuzzy modeling in bankruptcy prediction. *Yugoslav Journal of Operations Research, 13(2)*, 165–174.
Ward, T. J. (1999). A review of financial distress research methods and recommendations for future research. *Academy of Accounting and Financial Studies Journal, 3(1)*, 160–178.
Ward, T. J. (1994). An empirical study of the incremental predictive ability of Beavers´ naïve operating flow measure using four-state ordinal models of financial distress. *Journal of Business Finance & Accounting, 21(4)*, 547–561.

Whitaker, R. B. (1999). The early stages of financial distress. *Journal of Economics and Finance, 23(2)*, 123–133.
Whittred, G., & Zimmer, I. (1984). Timeliness of financial reporting and financial distress. *The Accounting Review, 59(2)*, 287–295.
Wilson, N., Chong, K. W., & Peel, M. J. (1995). Neural network simulation and the prediction of corporate outcomes: Some empirical findings. *International Journal of Economics of Business, 2(1)*, 31–50.
Yeh, C.-C., Chi, D.-J., & Hsu, M.-F. (2010). A hybrid approach of DEA, rough set and support vector machines for business failure prediction. *Expert Systems with Applications, 37(2)*, 1535–1541.
Youn, H., & Gu, Z. (2010). Predict US restaurant firm failures: The artificial neural network model versus logistic regression model. Tourism and Hospitality Research, 10(3), 171–187.
Zhang, G., Hu, M. Y., Patuwo, E. B., & Indro, D. C. (1999). Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research, 116(1)*, 16–32.
Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research, 22, Supplement*, 59–82.

Appendix

Table 1A

Summary of potential discriminatory variables selected for the study

The table shows the variables used within this study. They were categorized into factors based on the findings from Chen & Shimerda (1981), Laurent (1979), Min & Lee (2008) and Pohlman & Hollinger (1981).

Factor	Ratios	Computation	References
AGE	AGE	Age of the firm in years	Chancharat et al. (2010); Chi & Tang (2006); Dakovic, Czado & Berg (2010); Hensher, Jones & Greene (2007)
SIZE	SIZE I	Ln(Total Assets)	Chi & Tang (2006); Datta & Iskandar-Datta (1995); Grunert, Norden & Weber (2005); Hensher, Jones & Greene (2007)
CASH FLOW	CF/TD	Cash Flow (Net Income + Depreciation)/Total Debt	Ahn, Cho & Kim (2000); Beaver (1966); Blum (1974); Frydman, Altman & Kao (1985)
PROFITABILITY	NI/TA	Net Income/Total Assets	Beaver (1966); Beaver (1968); Chava & Jarrow (2004); Libby (1975); Norton & Smith (1979); Ohlson (1980); Zmijeswski (1984)
	NI/S	Net Income/Sales	Chalos (1985); Li & Sun (2011); Shah &Murtaza (2000);
	EBIT/TA	EBIT/Total Assets	Altman (1968); Callejon et al. (2013); Chen et al. (2006); Frydman, Altman & Kao (1985); Gilbert, Menon & Schwartz (1990); Grunert, Norden & Weber (2005); Li & Sun (2011);
	EBITDA/TA	EBITDA/Total Assets	Altman. Sabato & Wilson (2010); Platt & Platt (2008)
	EBIT/S	EBIT/Sales	Marchesini, Perdue & Bryan (2004); Sudarsanam & Lai (2001)
	EBITDA/S	EBITDA/Sales	Platt & Platt (2002)
	EBIT/TD	EBIT/Total Debt	Charitou, Neophytou & Charalambous (2004); Neophytou & MarMolinero (2004); Kim & Gu (2006); Sudarsanam & Lai (2001)
	EBITDA/TD	EBITDA/Total Debt	Chaudhuri (2013)
	GP/TA	Gross Profit/Total Assets	Atiya (2001); Doumpos & Zopounidis (1999)
	GP/S	Gross Profit/Sales	Ko, Lin & Blocher (2001)
	STAFF/S	Staff Costs/Sales	Bruse (1978); Gebhardt (1980); Situm (2015b)
CAPITAL STRUCTURE	TE/TA	Total Equity/Total Assets	Bartual et al. (2012); Grunert, Norden & Weber (2005); Pompe & Bilderbeek (2005)
	TD/TA	Total Debt/Total Assets	Chen et al. (2006); Frydman, Altman & Kao (1985); Kim & Partington (2015); Ohlson (1980); Shah & Murtaza (2000); Turetsky & McEwen (2001); Zmijewski (1984)
	RE/TA	Retained Earnings/Total Assets	Altman, Sabato & Wilson (2010); Altman (1968); Coats & Fant (1993); Gilbert, Menon & Schwartz (1990); Hensher, Jones & Greene (2007); Iazzolino, Migliano & Gregorace (2013)
ACTIVITY	S/TA	Sales/Total Assets	Altman (1968); Bartual et al. (2012); Gombola et al. (1987); Santos et al. (2006); Stanisic, Mizdrakovic & Knezevic (2013); Tsai (2013)
	S/TE	Sales/Total Equity	Bruse (1978)
COVERAGE	EBIT/INT	EBIT/Interest Expenses	Butera & Faff (2006); Marchesini, Perdue & Bryan (2004); Min, Lee & Han (2006)
	EBITDA/INT	EBITDA/Interest Expenses	Altman, Sabato & Wilson (2010); Iazzolino, Migliano & Gregorace (2013)
TURNOVER	CA/TA	Current Assets/Total Assets	Aktan (2011); Chen & Du (2010); Pervan, Pervan & Vukoja (2011); Sun (2007); Yeh, Chi & Hsu (2010)
	CA/S	Current Assets/Sales	Butera & Faff (2006); Sun (2007); Sen, Ghandforoush & Stivason (2004); Yeh, Chi & Hsu (2010)

Table 2A

Statistical pre-analysis – The age of the firm and accounting ratios for the period two years after distress

The table shows the results of descriptive statistics, test for normal distribution and the test for differences on a univariate basis for the types of firms (0 = unsuccessfully recovered; 1 = successfully recovered; 2 = healthy). The test for normality was based on Shapiro-Wilks (SW) as proposed by Raykov & Marcoulides (2008, p. 81) due to the relatively low number of cases per group. To determine the best discriminating variables, parametric-tests (t-test, ANOVA) and non-parametric tests (U-test, H-test) were applied (Freund & Perles, 2013, p. 465 and 471). ANOVA and H-Test were applied to investigate whether the ratios are statistically significant across all groups (Ho, 2006, p. 51 and 372). In order to achieve more accurate results, regarding the groups between which the results are effectively attributed, t-test and U-test were applied for each combination between the three groups of firms.

		SW-test	Descriptive statistics			0 vs. 1	0 vs. 2	1 vs. 2		0 vs. 1	0 vs. 2	1 vs. 2	
Ratio	Group	p-value	Mean	Median	Std.-Dev.	t-test			ANOVA	U-test			H-Test
AGE	0	0.000**	27.305	18.000	32.135	0.642	0.494	0.175	0.515	0.860	0.751	0.989	0.964
	1	0.000**	30.211	15.500	32.614								
	2	0.000**	23.297	18.000	18.722								
SIZE	0	0.067	16.127	15.975	1.382	0.526	0.194	0.077	0.174	0.811	0.119	0.082	0.172
	1	0.020*	15.931	15.913	1.748								
	2	0.375	16.528	16.946	1.455								
CFTD	0	0.229	0.042	0.043	0.097	0.000**	0.026*	0.357	0.006**	0.000**	0.000**	0.930	0.000**
	1	0.000**	0.269	0.193	0.282								
	2	0.000**	0.426	0.174	1.032								
NITA	0	0.000**	-0.039	-0.010	0.071	0.000**	0.000**	0.268	0.000**	0.000**	0.000**	0.601	0.000**
	1	0.000**	0.087	0.065	0.080								
	2	0.000**	0.111	0.062	0.120								
NIS	0	0.000**	-0.115	-0.010	0.409	0.000**	0.001**	0.409	0.000**	0.000**	0.000**	0.305	0.000**
	1	0.000**	0.164	0.059	0.384								
	2	0.000**	0.236	0.085	0.491								
EBITTA	0	0.000**	-0.021	0.002	0.062	0.000**	0.000**	0.831	0.000**	0.000**	0.000**	0.919	0.000**
	1	0.000**	0.102	0.075	0.093								
	2	0.001**	0.098	0.075	0.126								
EBITDATA	0	0.106	0.042	0.044	0.071	0.000**	0.000**	0.861	0.000**	0.000**	0.000**	0.957	0.000**
	1	0.000**	0.141	0.124	0.098								
	2	0.002**	0.137	0.116	0.133								
EBITS	0	0.000**	-0.008	0.003	0.108	0.000**	0.573	0.316	0.293	0.000**	0.000**	0.591	0.000**
	1	0.000**	0.107	0.075	0.106								
	2	0.000**	-0.155	0.069	1.607								
EBITDAS	0	0.000**	0.078	0.043	0.155	0.008**	0.412	0.294	0.263	0.000**	0.014*	0.708	0.002**
	1	0.000**	0.158	0.115	0.154								
	2	0.000**	-0.116	0.121	1.607								
EBITTD	0	0.000**	-0.025	0.003	0.078	0.000**	0.231	0.716	0.189	0.000**	0.000**	0.438	0.000**
	1	0.000**	0.190	0.115	0.196								
	2	0.000**	0.284	0.106	1.582								
EBITDATD	0	0.494	0.058	0.056	0.090	0.000**	0.266	0.720	0.244	0.000**	0.000**	0.384	0.000**
	1	0.000**	0.255	0.206	0.218								
	2	0.000**	0.348	0.174	1.601								
GPTA	0	0.295	0.717	0.745	0.367	0.074	0.956	0.132	0.128	0.452	0.453	0.176	0.368
	1	0.000**	0.891	0.733	0.636								
	2	0.006**	0.712	0.610	0.466								
		SW-test	Descriptive statistics			0 vs. 1	0 vs. 2	1 vs. 2		0 vs. 1	0 vs. 2	1 vs. 2	
Ratio	Group	p-value*)	Mean	Median	Std.-Dev.	t-test			ANOVA	U-test			H-Test
GPS	0	0.000**	0.675	0.767	0.321	0.365	0.758	0.237	0.445	0.321	0.845	0.280	0.463
	1	0.000**	0.731	0.899	0.314								
	2	0.000**	0.654	0.644	0.327								
STAFFS	0	0.008**	0.396	0.362	0.254	0.117	0.491	0.245	0.381	0.157	0.159	0.897	0.267
	1	0.010*	0.323	0.304	0.225								
	2	0.000**	0.557	0.270	1.580								
TETA	0	0.227	0.192	0.163	0.243	0.005**	0.004**	0.894	0.007**	0.002**	0.007**	0.739	0.003**
	1	0.034*	0.346	0.354	0.304								
	2	0.308	0.354	0.273	0.269								
TDTA	0	0.227	0.808	0.837	0.243	0.005**	0.004**	0.894	0.007**	0.002**	0.007**	0.739	0.003**
	1	0.034*	0.654	0.646	0.304								
	2	0.308	0.646	0.727	0.269								
RETA	0	0.003**	0.009	0.026	0.199	0.003	0.000	0.31	0.000*	0.000	0.000	0.62	0.000

	1	0.003**	0.147	0.132	0.264	**	**	2	*	**	**	4	**
	2	0.002**	0.197	0.160	0.201								
STA	0	0.000**	1.528	0.983	1.387	0.911	0.270	0.221	0.494	0.825	0.852	0.629	0.898
	1	0.000**	1.501	1.233	1.144								
	2	0.009**	1.255	1.090	0.864								
STE	0	0.000**	16.183	4.537	65.368	0.345	0.630	0.361	0.490	0.384	0.618	0.703	0.669
	1	0.000**	6.877	3.215	16.693								
	2	0.000**	10.782	2.965	26.571								
EBITINT	0	0.000**	-670.102	0.282	3.218.792	0.100	0.069	0.181	0.205	0.000**	0.000**	0.946	0.000**
	1	0.000**	4,854.754	9.236	26,185.135								
	2	0.000**	412.512	9.474	1.917.847								
EBITDAINT	0	0.000**	-148.465	2.248	746.210	0.129	0.086	0.191	0.248	0.000**	0.000**	0.940	0.000**
	1	0.000**	4,889.612	13.069	26,179.951								
	2	0.000**	529.396	13.461	2,546.530								
CATA	0	0.015*	0.514	0.541	0.272	0.031*	0.078	0.792	0.062	0.035*	0.117	0.577	0.086
	1	0.003**	0.624	0.648	0.256								
	2	0.485	0.611	0.618	0.226								
CAS	0	0.000**	0.944	0.344	1.737	0.437	0.482	0.180	0.279	0.179	0.084	0.644	0.201
	1	0.000**	0.735	0.481	0.672								
	2	0.000**	1.252	0.505	2.309								

**) statistical significance on the 1 percent level; *) statistical significance on the 5 percent level

Table 3A

Statistical pre-analysis – Inflation adjusted accounting ratios, industry-compared accounting ratios and industry GDP_{growth} for the period two years after distress

The table is structured based on the same assumptions as were made in table 2 A. The first eight variables are profitability ratios, based on accounting ratios adjusted for inflation. The inflation rate for the period one year prior to insolvency was taken on average to be 3.3 percent. The next seven variables illustrate the relationship between a firm's accounting ratios and the median of the respective industry in which the firm operates. The next three variables are inflation-adjusted profitability ratios, which are compared to industry medians. The variable GDP_{growth} is assumed, which measures the contribution of the industry the firm is operating in to the gross value added of the economy. Finally, the variable Goodwill is shown, which was assigned as a dummy variable and given a value of "1" if the firm exhibited goodwill on the balance sheet. Otherwise it received a value of "0".

		SW-test	Descriptive statistics			0 vs. 1	0 vs. 2	1 vs. 2		0 vs. 1	0 vs. 2	1 vs. 2	
Ratio	Group	p-value*)	Mean	Median	Std.-Dev.	t-test			ANOVA	U-test			H-Test
$NITA_{infl.}$	0	0.000**	-0.057	-0.028	0.069	0.000**	0.000**	0.268	0.000**	0.000**	0.000**	0.601	0.000**
	1	0.000**	0.066	0.045	0.078								
	2	0.000**	0.090	0.043	0.118								
$NIS_{infl.}$	0	0.000**	-0.131	-0.028	0.402	0.000**	0.001**	0.409	0.000**	0.000**	0.000**	0.305	0.000**
	1	0.000**	0.142	0.039	0.377								
	2	0.000**	0.213	0.065	0.482								
$EBITTA_{infl.}$	0	0.000**	-0.039	-0.016	0.061	0.000**	0.000**	0.831	0.000**	0.000**	0.000**	0.919	0.000**
	1	0.000**	0.082	0.055	0.091								
	2	0.001**	0.077	0.055	0.124								
$EBITDATA_{infl.}$	0	0.106	0.023	0.025	0.070	0.000**	0.000**	0.861	0.000**	0.000**	0.000**	0.957	0.000**
	1	0.000**	0.120	0.103	0.097								
	2	0.002**	0.116	0.096	0.131								
$EBITS_{infl.}$	0	0.000**	-0.027	-0.016	0.106	0.000**	0.573	0.316	0.293	0.000**	0.000**	0.591	0.000**
	1	0.000**	0.086	0.055	0.104								
	2	0.000**	-0.171	0.049	1.577								
$EBITDAS_{infl.}$	0	0.000**	0.058	0.024	0.153	0.000**	0.412	0.294	0.263	0.000**	0.014*	0.708	0.002**
	1	0.000**	0.137	0.094	0.152								
	2	0.000**	-0.133	0.101	1.577								
$EBITTD_{infl.}$	0	0.000**	-0.043	-0.016	0.076	0.000**	0.231	0.716	0.189	0.000**	0.000**	0.438	0.000**
	1	0.000**	0.168	0.095	0.192								
	2	0.000**	0.260	0.085	1.553								
$EBITDATD_{infl.}$	0	0.494	0.038	0.036	0.088	0.000**	0.266	0.720	0.244	0.000**	0.000**	0.384	0.000**
	1	0.000**	0.232	0.183	0.214								
	2	0.000**	0.32	0.152	1.571								

			3										
EBITTA$_{ind.}$	0	0.000**	-0.361	0.022	0.941	0.000**	0.000**	0.969	0.000**	0.000**	0.000**	0.683	0.000**
	1	0.000**	1.401	0.799	1.545								
	2	0.002**	1.388	1.177	1.749								
EBITS$_{ind.}$	0	0.000**	-0.181	0.064	2.061	0.000**	0.562	0.324	0.307	0.000**	0.000**	0.514	0.000**
	1	0.000**	2.051	1.245	2.251								
	2	0.000**	-3.336	1.042	33.624								
EBITDAS$_{ind.}$	0	0.000**	0.875	0.411	1.678	0.017*	0.408	0.291	0.260	0.001**	0.033*	0.668	0.006**
	1	0.000**	1.782	1.179	2.110								
	2	0.000**	-1.320	0.938	18.012								
GPS$_{ind.}$	0	0.001**	1.318	1.209	0.866	0.779	0.712	0.876	0.924	0.643	0.664	0.981	0.875
	1	0.000**	1.363	1.211	0.794								
	2	0.002**	1.390	1.316	0.916								
		SW-test	**Descriptive statistics**			**0 vs. 1**	**0 vs. 2**	**1 vs. 2**		**0 vs. 1**	**0 vs. 2**	**1 vs. 2**	
Ratio	**Group**	**p-value*)**	**Mean**	**Median**	**Std.-Dev.**	**t-test**			**ANOVA**	**U-test**			**H-Test**
STAFFS$_{ind.}$	0	0.000**	2.662	1.961	3.041	0.292	0.737	0.340	0.545	0.099	0.141	0.881	0.195
	1	0.000**	2.078	1.209	2.743								
	2	0.000**	3.063	1.376	7.447								
TETA$_{ind.}$	0	0.429	1.028	0.813	1.330	0.020*	0.013*	0.091	0.003**	0.008**	0.008**	0.591	0.008**
	1	0.016*	1.672	1.790	1.490								
	2	0.000**	2.958	1.436	4.490								
STA$_{ind.}$	0	0.000**	1.848	0.621	3.763	0.599	0.477	0.756	0.737	0.761	0.738	0.978	0.936
	1	0.000**	1.522	0.816	2.770								
	2	0.000**	1.358	0.820	2.233								
EBITTA$_{infl. ind.}$	0	0.000**	-0.590	-0.158	0.956	0.000**	0.000**	0.919	0.000**	0.000**	0.000**	0.673	0.000**
	1	0.000**	1.118	0.575	1.435								
	2	0.001**	1.086	0.899	1.641								
EBITS$_{infl. ind.}$	0	0.000**	-0.522	-0.234	2.033	0.000**	0.561	0.324	0.307	0.000**	0.000**	0.563	0.000**
	1	0.000**	1.660	0.887	2.172								
	2	0.000**	-3.627	0.634	33.004								
EBITDAS$_{infl. ind.}$	0	0.000**	0.656	0.225	1.628	0.015*	0.407	0.291	0.260	0.001**	0.027*	0.688	0.004**
	1	0.000**	1.545	0.911	2.043								

	2	0.000**	-1.502	0.807	17.685								
GDP_{growth}	0	0.000**	0.787	1.000	0.414	0.238	0.704	0.123	0.259	0.245	0.701	0.138	0.258
	1	0.000**	0.688	1.000	0.467								
	2	0.000**	0.821	1.000	0.389								

Table 4A

Model building results for accounting ratios & inflation-adjusted accounting ratios

In *part A*, the model quality is determined by the explained variance, computed as the square of the canonical correlation coefficient (Burns & Burns, 2008, p. 599; Raykov & Marcoulides 2008, p. 351). Within *part B and C*, the model accuracy is displayed using true positives and true negatives, divided by the total number of cases (Fawcett, 2006, p. 862; Metz, 1978, p. 284). The highlighted results are valid for the standard cut-off value of zero. The models were developed using data from two years after distress and were applied to this time period and to the time period of one year after distress. *Part D* shows the results in order to evaluate the performance of the models based on AUC and Gini-coefficients (Agarwal & Taffler, 2007, p. 291; Grzybowsky & Younger, 1997, p. 822). *Part E and F* provide the median discriminant values obtained by the models for each type of corporate health. Finally, *part G* shows the best performing discriminating variables, with their related signs and weightings.

	Application of accounting ratios		**Application of inflation adjusted accounting ratios**	
Part A: Measures	**0 vs. 1**	**0 vs. 2**	**0 vs. 1**	**0 vs. 2**
Explained Variance (in %)	43.031	38.161	43.031	38.161
Wilks Lambda (Sign.)	0.000**	0.000**	0.000**	0.000**
Box´s M (Sign.)	0.000**	0.000**	0.000**	0.000**
Part B: Application on two years after distress (t+2)				
Accuracy (in %)	91.892	87.209	91.892	87.209
Type I error (in %)	2.128	4.255	2.128	4.255
Type II error (in %)	12.500	23.077	12.500	23.077
Part C: Application on one year after distress (t+1)				
Accuracy (in %)	44.144	45.349	47.748	43.023
Type I error (in %)	63.830	55.319	72.340	68.085
Type II error (in %)	50.000	53.846	37.500	43.590
Part D: Performance measures				
$AUC_{(t+2)}$	0.982**	0.922**	0.982**	0.922**
$\text{Gini-Coefficient}_{(t+2)}$	0.964	0.844	0.964	0.844
$AUC_{(t+1)}$	0.455	0.488	0.455	0.488
$\text{Gini-Coefficient}_{(t+1)}$	-0.090	-0.023	-0.090	-0.023
Part E: Statistics for classification values (t+2)				
Median discriminant-value (0)	- 0.928	- 0.809	- 0.928	- 0.810
Median discriminant-value (1)	0.991	-	0.992	-
Median discriminant-value (2)	-	0.512	-	0.511
Part F: Statistics for classification values (t+1)				
Median discriminant-value (0)	0.127	0.135	0.431	0.348
Median discriminant-value (1)	-0.043	-	0.258	-
Median discriminant-value (2)	-	- 0.142	-	0.071
Part G: Explanatory variable				
NIS	1.880	1.874	-	-
$NIS_{infl.}$	-	-	1.916	1.910
EBITTA	19.035	12.958	-	-
$EBITTA_{infl.}$	-	-	19.397	13.204
TETA	1.085	1.467	1.085	1.467
Constant	-1.116	-1.013	- 0.718	- 0.732

**) statistical significance on the 1 percent level; *) statistical significance on the 5 percent level

Table 5A

Model building results for accounting ratios, inflations-adjusted accounting ratios & industry-related ratios

This table is structured under the same logic as *table 6A*. The difference is that here, additional industry-related ratios have been integrated in order to determine their contribution towards the correct assignment of companies into their related stages of corporate health.

	Application of accounting ratios & industry-related ratios		**Application of inflation adjusted accounting ratios & industry-related ratios**	
Part A: Measures	**0 vs. 1**	**0 vs. 2**	**0 vs. 1**	**0 vs. 2**
Explained Variance (in %)	43.226	40.192	43.225	39.908
Wilks Lambda (Sign.)	0.000**	0.000**	0.000**	0.000**
Box´s M (Sign.)	0.000**	0.000**	0.000**	0.000**
Part B: Application on two years after distress (t+2)				
Accuracy (in %)	92.793	88.372	92.793	87.209
Type I error (in %)	2.128	2.128	2.128	4.255
Type II error (in %)	10.938	23.077	10.938	23.077
Part C: Application on one year after distress (t+1)				
Accuracy (in %)	47.748	45.349	52.252	52.326
Type I error (in %)	57.447	55.319	65.957	55.319
Type II error (in %)	48.438	53.846	34.375	38.462
Part D: Performance measures				
$AUC_{(t+2)}$	0.977**	0.932**	0.977**	0.930**
$\text{Gini-Coefficient}_{(t+2)}$	0.955	0.865	0.955	0.860
$AUC_{(t+1)}$	0.476	0.498	0.509	0.540
$\text{Gini-Coefficient}_{(t+1)}$	-0.049	-0.005	0.019	0.080
Part E: Statistics for classification values (t+2)				
Median discriminant-value (0)	- 0.943	- 0.843	- 0.934	- 0.816
Median discriminant-value (1)	0.949	-	0.946	-
Median discriminant-value (2)	-	0.811	-	0.824
Part F: Statistics for classification values (t+1)				
Median discriminant-value (0)	0.105	0.152	0.306	0.211
Median discriminant-value (1)	0.069	-	0.456	-
Median discriminant-value (2)	-	- 0.126	-	0.309
Part G: Explanatory variables				
NIS	1.780	1.989	-	-
$NIS_{infl.}$	-	-	1.812	2.012
EBITTA	18.039	1.921	-	-
$EBITTA_{infl.}$	-	-	18.375	1.537
TETA	1.012	1.419	1.013	1.379
$EBITS_{ind.}$	0.083	-	-	-
$EBITTA_{ind.}$	-	0.854	-	-
$EBITS_{ind.\ infl.}$	-	-	0.086	-
$EBITTA_{ind.\ Infl.}$			-	0.909
Constant	-1.131	-1.021	- 0.725	- 0.714

**) statistical significance on the 1 percent level; *) statistical significance on the 5 percent level