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Inability of Gearing-Ratio as Predictor for Early Warning Systems

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Abstract

Background: Research in business failure and insolvency prediction provides numerous potential variables, which are in the position to differentiate between solvent and insolvent firms. Nevertheless, not all of them have the same discriminatory power, and therefore their general applicability as crisis indicators within early warning systems seems questionable. **Objectives:** The paper aims to demonstrate that gearing-ratio is not an appropriate predictor for firm failures/bankruptcies. **Methods/Approach:** The first and the second order derivatives for the gearing-ratio formula were computed and mathematically analysed. Based on these results an interpretation was given and the suitability of gearing-ratio as a discriminator within business failure prediction models was discussed. These theoretical findings were then empirically tested using financial figures from financial statements of Austrian companies for the observation period between 2008 and 2010. **Results:** The theoretical assumptions showed that gearing-ratio is not a suitable predictor for early warning systems. This finding was confirmed with empirical data. **Conclusions:** The inclusion of gearing-ratio within business failure prediction models is not able to provide early warning signals and should therefore be ignored in future model building attempts.

Keywords: capital structure; gearing-ratio; business failure prediction; crisis indicators

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Introduction

The financial world changed dramatically due to the impacts of financial crisis and these changes also affected the awareness concerning the topic of risk. Market participants recognized that the reliability of current risk management systems failed in many cases. The trust in markets deteriorated and liquidity received the highest priority in financial management. Financial intermediaries restricted the access to funds by stronger regulations and implemented more accurate appraisal processes for prospectus financing of corporate customers. Summarized it can be said that it is all about risk. Potential investments and credit grantings are assessed with much more caution and it is to detect potential disturbances and disruptions much earlier than in the past.

Therefore, the need for qualified early warning systems increased, which are able to detect corporate crises as early as possible, so that appropriate turnaround activities can be implemented much more successfully. The question is, which variables should be taken into account for this purpose and which are having sufficient information content for the manager, but also for the shareholders and other stakeholders, in order to detect unfavourable economic and financial developments? The purpose of this paper is to analyse the ability of gearing-ratio and its derivatives of first and second order concerning prediction potential within early warning systems. Such a system is defined as a strategic management tool, which is able to deliver early warning signals based on the observations of some reliable and understandable crisis indicators (Müller-Stewens, 2007).

Due to the already described findings the importance for such systems is increasing enormously and will in future gain more attention. It is generally recognized that companies with a good functioning business model and a sound strategy are more likely to be successful. Additionally, these pre-conditions are mostly the guarantee for a success on operational level (Ansoff and Sullivan, 1993; Exler and Situm, 2013). Corporate strategy and its connection to environmental conditions are important drivers for the probability of insolvency (Madrid-Guijarro, Garcia-Perez-de-Lema and van Auken, 2011). The best point to detect a potential crisis is therefore at the strategic level, which emphasizes the growing importance of reliable and good functioning strategic controlling tools for corporates (Brouthers and Roozen, 1999; Exler and Situm, 2013; Exler and Situm, 2014).

The attempt within this research was to analyse the specific behaviour of gearing-ratio and to determine, whether it is a potential indicator for early warning systems. This paper is organized as follows: First, a literature review is given about different models and variables used in credit assessments, which were applied in practice for the development of bankruptcy and financial distress prediction models. Second, a theoretical framework is presented based on gearing-ratio in order to describe its inability as potential crisis indicator for early warning systems. Here also research hypotheses and research questions were posted. Third, the theoretical findings were tested with selected statistical applications on a data base consisting of financial statements of Austrian companies. Based on the results of preliminary statistics it was concluded, whether gearing-ratio and its derivatives of first and second order are suitable predictors for bankruptcy prediction. Additionally, business failure prediction models using multivariate linear discriminant analysis and logistic regression for the periods one and two years prior to bankruptcy using relevant explanatory variables were computed and tested. Fourth, the results were discussed followed by a test of research hypotheses and answering the research questions. The paper closes with a summary about the main findings, provides some recommendations for further research and implications for future model building.

Literature review

Early warning system methods

The early stages of business failure prediction started with simple evaluation of accounting ratios using univariate discriminant analysis, whereas the most prominent work is attributed to Beaver (1966). The weakness of this approach is that a company can be classified as solvent using one variable, but may be assigned as insolvent using another variable. This problem was solved by Altman (1968), who introduced multivariate linear discriminant analysis for business failure prediction. His original model contained five variables, which were in the position to divide between solvent and insolvent companies. He also recognized that the economic situation of a company could not be solely determined by two dichotomous states (solvent and insolvent). After Altman (1968) several authors applied multivariate linear discriminant analysis to develop early warning systems (Edmister, 1972; Altman, Haldeman and Narayanan, 1977; Houghton and Woodliff, 1987; Dietrich, Arcelus and Srinivasan, 2005). Other forms of discriminant analysis like the quadratic form or the non-parametric form were also used for prediction purpose, but they disappeared relatively quickly, as they did not provide better results compared to the linear version (Altman et al., 1977; Gombola, Haskins, Ketz and Williams, 1987; Barniv and Raveh, 1989; Barniv and McDonald, 1992).

Ohlson (1980) introduced logistic regression, so that it was possible to determine probabilities for each company concerning its membership to a certain group. Several studies were conducted with this new method, whereas many of them analysed its prediction performance compared to discriminant analysis. Some authors found logistic regression to be superior over discriminant analysis (Lau, 1987; Pacey and Pham, 1990; Pervan, Pervan and Vukoja, 2011), whereas others received better results for the latter application (Yim and Mitchell, 2007; Muller, Steyn-Bruwer and Hamman, 2009). Other investigations provided equal or similar performance quality for both methods (Gombola et al., 1987; Boritz, Kennedy and de Mirande e Albuquerque, 1995; Hwang, Cheng and Lee, 2007; Gepp and Kumar, 2008).

The introduction of neural network applications brought a methodological progress as it was possible to model non-linear behaviour similar to the human brain. Based on some results it seemed that this method is superior to logistic regression and discriminant analysis (Anandarajan, Lee and Anandarajan, 2001; Charitou, Neophytou and Charalambous, 2004; Neves and Vieira, 2006; Yim and Mitchell, 2007), but this superiority was not confirmed within other studies (Fanning and Cogger, 1994; Pompe and Bilderbeek, 2005; Chen, Marshall, Zhang and Ganesh, 2006). During the last decades researchers applied many other methods, whereas different results were obtained concerning their usefulness for prediction task. Only some of them can be named here for illustration like recursive partioning and decision trees (Frydman, Altman and Kao, 1985; Muller et al., 2009), survival and hazard models (Fanning and Cogger, 1994; Gepp and Kumar 2008) or support vector machines (Lin, Liang and Chen, 2011; Li and Sun, 2011).

Prediction variables used in early warning systems

The universe of potential predictors in early warning systems, which are in the position to discriminate between failed and non-failed (or solvent and insolvent) companies is big and they can be categorized into variables from financial statements, statistical values, variables about the company and its environment in context with its economic situation, market data and other variables (Du Jardin, 2009; Pretorius, 2008). A basic argument for the application of certain variables may be attributed to the information content. The higher the information load a variable can provide, the more relevant and helpful the respective variable could be for prediction purposes. There is some doubt about the application of accounting ratios within this context as such figures can be manipulated by managers according to generally accepted accounting principles in order to disguise the real economic condition of the firm (Keasey and Watson, 1991; Sharma, 2001; Tsai, 2013). Additionally, it seems that accounting ratios are not carrying sufficient information content, which could be exploited for an improved prediction of crises or insolvencies (Chava and Jarrow, 2004; Grunert, Norden and Weber, 2005; Pretorius, 2008).

The deficiencies of accounting ratios could be overcome by incorporation of non-financial and market-based variables. They seem to have additional information, which is beneficial for early detection purposes. Several studies discovered the value of such information and concluded that a well-functioning early warning systems must contain a combination of accounting, market-based and non-financial indicators (Grunert et al., 2005; Muller et al., 2009; Altman, Sabato and Wilson, 2010; Iazzolino, Migliano and Gregorace, 2013). Such a consideration is not solving the problem of non-stationarity, which means that a model developed with historical data must not automatically be applicable on future or other time periods (Gombola et al., 1987; Begley, Ming and Watts 1996; Liou and Smith, 2007; Nam, Kim, Park and Lee, 2008). This problem seems to be mainly affected by macroeconomic factors, therefore also macroeconomic variables should be implemented within early warning systems, in order to solve this problem too (Keasey and Watson, 1991; Liou and Smith, 2007; Nam et al, 2008). Even if there is knowledge about all of these aspects, research is still not in the position to answer the questions, which combination of the different types of variables can provide an "optimal" model, which method shall be applied to construct such a model and how it could be connected to a theory of insolvency prediction, which is also suitable to fit into the framework of already existing and generally accepted theories of finance.

Gearing-ratio usage in early warning systems

Gearing-ratio is within this work defined as the relation between total-book value of debt to the total book-value of equity. From viewpoint of capital structure theory it seems appealing that such a relation could be a good indicator to describe the financial viability of a company. A higher gearing-ratio is increasing borrower´s interest charges and claims on firm´s cash flows (Saunders and Cornett, 2011, p. 335). Therefore, its suitability for business failure prediction should also be given. Under trade-off theory a company will try to optimize its capital structure in order to minimize total cost of capital. It is economically interesting to substitute expensive equity with cheaper debt until a point, where the tax benefits outweigh potential costs associated with financial distress and bankruptcy (Leland and Toft, 1996; Hennessy and Whited, 2005; Hackbarth, Miao and Morellec, 2006). This is having certain consequences on the cost of capital and the value of the firm, which will not be discussed within this paper in detail. The purpose within this theoretical section is to analyse the ability of gearing-ratio as an early warning predictor for the detection of business failures and bankruptcies. These analyses are conducted using comparative statics.

The starting point of the analysis is the definition of gearing-ratio presented in equation one (based on Schmidt, Terberger, 1996, pp. 240-241).

$$\text{Gearing} = g = \frac{\text{TotalDebt}}{\text{TotalEquity}} = \frac{TD}{TE} = \frac{DR}{ER} = f(D,E) \quad (1)$$

TD Total Debt
TE Total Equity
DR Debt-Ratio
ER Equity-Ratio

Based on Figure 1 it must be differentiated, whether equity remains positive or negative. It is visible that both curves are not connected for the case, when equity-ratio is zero. The determinant of Hessian matrix is $-1/E^4$ and remains in all cases of equity-ratio (positive and negative values) negative. In this situation, the function is having a saddle point. Such a saddle point delivers a great problem concerning mathematical properties for gearing-ratio function. This means that the function cannot be steadily differentiated. This is also the fact, why *figure 1* shows two mirror-inverted curves which are not connected with each other.

The next equations show the derivatives of first and second order for the defined gearing-ratio.

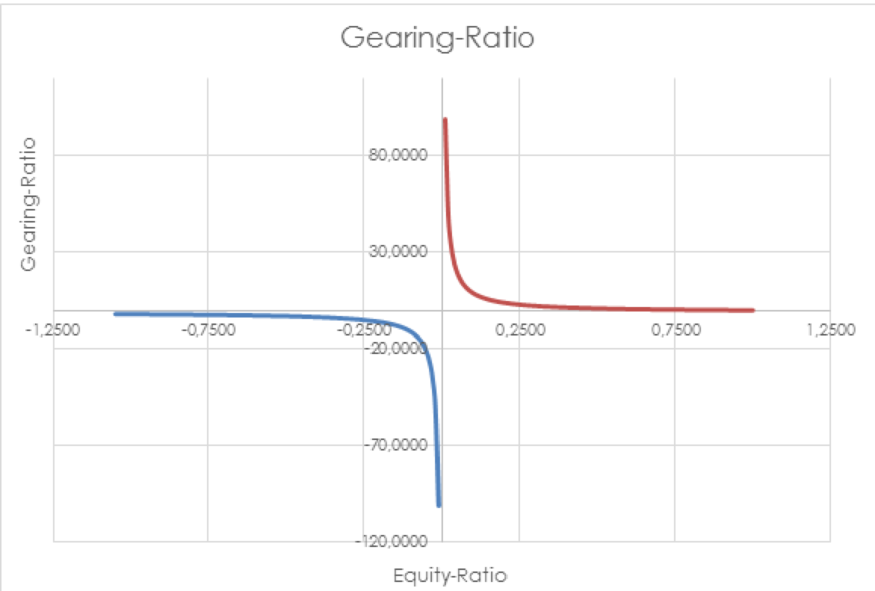
$$grad\ f(D,E) = \left[\frac{\partial f(DR,ER)}{\partial DR}, \frac{\partial f(DR,ER)}{\partial ER}\right] = \left[\frac{1}{ER}, -\frac{DR}{ER^2}\right] \qquad \text{(D1 \& D2)}$$

$$\frac{\partial f(DR,ER)}{\partial DR} - \frac{\partial f(DR,ER)}{\partial ER} = \frac{1}{ER} + \frac{DR}{ER^2} \qquad \text{(D3)}$$

$$\frac{\partial f(DR,ER)}{\partial ER} - \frac{\partial f(DR,ER)}{\partial DR} = -\frac{DR}{ER^2} - \frac{1}{ER} \qquad \text{(D4)}$$

$$\text{Hessian} f(D,E) = \begin{bmatrix} \frac{\partial^2 f(DR,ER)}{\partial DR^2} & \frac{\partial^2 f(DR,ER)}{\partial DR \partial ER} \\ \frac{\partial^2 f(DR,ER)}{\partial ER \partial DR} & \frac{\partial^2 f(DR,ER)}{\partial ER^2} \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{ER^2} \\ -\frac{1}{ER^2} & \frac{2DR}{ER^3} \end{bmatrix} \qquad \text{(D5 \& D6)}$$

Figure 1
Graphical Illustration of Gearing-Ratio



Source: Graph based on own computations

The static analysis concerning the first order derivatives confirms the behaviour of gearing-ratio, when the relations between equity- and debt-ratio are changing. The main implications can be summarized as follows:

- An increase in equity-ratio on the right side of *figure 1* is decreasing gearing-ratio. This is equivalent to the situation, when debt-ratio decreases.

- An increase in debt-ratio on the left side of *figure 1* is decreasing gearing-ratio (value of gearing-ratio changes from low negative to high negative).

More interesting are the results obtained from second order derivatives, because they are providing evidence, about how strong the signal effects of changes in equity- and debt-ratio are, when a certain gearing-ratio is given. The major findings are:

- When equity-ratio is already highly positive, then a small increase in debt-ratio is not having a great impact on gearing-ratio. This implies that in such situations the signalling power is not very high.
- Another situation occurs, when equity-ratio is at a lower positive level. Here a small increase in debt-ratio is having a much higher effect on gearing-ratio. In these situations the signalling power is much higher and therefore potentially useful for prediction purposes.
- When equity-ratio is already highly negative, then a small increase in debt-ratio is having a weak effect on gearing-ratio. Under this situation the signalling power is low.
- In cases, where equity-ratio is only in a low negative band, an increase in debt-ratio is providing high signalling power as it is having a much greater effect on gearing-ratio.

Based on the mathematical analysis and the interpretations given following hypotheses are stated, which will be tested based on empirical data:

- Gearing-ratio is not a suitable predictor for business failure prediction and no reliable early warning indicator.
- Derivatives of first order from gearing-ratio are not suitable predictors for business failure prediction and no reliable early warning indicators.
- Derivatives of second order from gearing-ratio are not suitable predictors for business failure prediction and no reliable early warning indicators.

Additionally certain questions shall be answered within this study. The first one is to determine, why gearing-ratio is not in the position to act as an early warning indicator. Second, it is of interest, which of the chosen variables selected from results of prior research, are having the highest discriminatory power between bankrupt and non-bankrupt firms. At last, it is to answer, whether ratios associated with the capital structure of the company are having sufficient information content to explain, why a firm´s performance is deteriorating.

Methodology

Data set

In order to test the results from theoretical discussion an empirical investigation was applied. Data were obtained from a data base containing figures from financial statements of Austrian companies for the time period between 2008 and 2010. The year 2010 was set as the „bankruptcy date" and the previous years as the „periods before bankruptcy". Following definitions were used within this paper:

- Period one year prior to bankruptcy – 2009 (t-1)
- Period two years prior to bankruptcy – 2008 (t-2)

These definitions were used, because the purpose was to test how the signalling and prediction power of the potential explanatory variables is varying over time.

Generally, prior research found that the prediction accuracy of models is increasing as the event of bankruptcy is approaching (Zenzerovic, 2011; Hauser and Booth, 2011; Li and Sun, 2011; Lin et al., 2011). This is also assumed to be the case within this research. The selection of samples for model building is a difficult task, because several biases can arise. Many papers set up their initial sample based on a matched pairing. Normally bankrupt cases are searched and then similar non-bankrupt firms per each case are retrieved. A common problem here is choice-based-sampling, which results when due to matching of firms to samples a.) the prior probabilities of the proportion between bankrupt and non-bankrupt companies are not replicating those of the whole population and b.) the process of random sample selection is violated (Zmijewski, 1984; Platt and Platt, 2002; Thomas, Edelman and Crook, 2002; Skogsvik and Skogsvik, 2013).

Therefore, for the sample selection the following procedure was used: First, the bankruptcy date was set at 2010. Based on this, potential bankrupt firms were selected from the database, for which financial statement figures for two consecutive years were available. For (t-1) 65 potential firms were identified. For these firms financial statement figures for the year (t-2) were searched, whereas only 44 out of 65 companies exhibited financial data for this observation period. Therefore, the final sample of bankrupt firms consisted of 44 firms. They were then split randomly into half. The first half (22 firms) was assigned to initial group and the second half (22 firms) was reserved for validation group.

Second, non-bankrupt firms were randomly selected for comparison to bankrupt firms. Here also the requirement for availability of financial statement figures for two consecutive years had to be fulfilled. Within this paper explicitly no matched sampling was applied due to the previously described problems. Instead, it was tried to replicate the proportions between failed and non-failed firms apparent in the whole population for companies in Austria for the bankruptcy date. Nevertheless literature shows that an underrepresentation of bankrupt firms can cause that models cannot identify the characteristics of them (Thomas et al., 2002, p. 122). Data for insolvency rates were taken from Creditreform Wirtschaftsforschung Austria (2011) for the year 2010. The respective insolvency rate was 1.63 percent. This means that 163 firms out of 10,000 went bankrupt in this year. Based on this measure it would be necessary to identify 1,350 non-bankrupt firms in order to replicate the prior probability of bankruptcy and non-bankruptcy inherent of the whole population. Such a proportion does not make sense, so that the approach of Zmijewski (1984) was used. Within his work a proportion between non-bankrupt and bankrupt firms of 20:1 was chosen. Based on this relation the distribution of the initial and validation sample can be found in *table 1*.

Table 1
Distributions of bankrupt and non-bankrupt firms for the observation period

	Initial sample		Validation sample	
	Bankrupt	**Non-bankrupt**	**Bankrupt**	**Non-bankrupt**
2009 (t-1)	22	440	22	420
2008 (t-2)	22	440	22	420

Source: Author's illustration

Variable selection

An analysis of literature reveals the already mentioned aspect that researchers found copious potential variables as potential predictors. Nevertheless, certain variables appeared more often and are well suited under theoretical and explanatory implications to act as crisis indicators in early warning systems. EBIT/TA appeared the first time in the study of Altman (1968) and was also found to be relevant in other studies too (Begley et al., 1996; Grunert et al., 2005; Iazzolino et al., 2013). It is replicating the profitability of the firm and showed empirically that insolvent firms are exhibiting lower values for this ratio.

Capital structure analyses revealed the relevance of the ratios TD/TA (Ohlson, 1980; Charitou et al., 2004; Neves and Vieira, 2006) and TE/TA (Laitinen and Laitinen 2000; Grunert et al., 2005; Muller et al., 2009) for prediction purposes. Generally, it can be concluded that firms with a higher equity-ratio (lower debt-ratio) are less likely to fail. The ability of gearing-ratio for prediction purposes was also analysed within prior studies, but in contrast to the previously mentioned ratios its frequency of appearance was low (Casey and Bartczak, 1985; Jones and Hensher, 2004; Prasad and Puri, 2005; Chi and Tang, 2006; Chen and Du, 2009).

Summarized following ratios were selected for further investigations based on popularity in literature and on results from prior research:

- Equity-Ratio = Total Equity/Total Assets
- Debt-Ratio = Total Debt/Total Assets
- Gearing-Ratio
- Return on Assets = EBIT/Total Assets

Statistical methods

To assess, whether the selected ratios are potential predictors of business failure, statistical pre-analyses must be applied. First, tests for normal distribution and descriptive statistics for the chosen ratios, gearing-ratio and its shown derivatives were computed for the two groups of companies. Second, tests for differences in means and variances were calculated to determine, whether the independent variables are having the potential as discriminators between the different groups of firms. Theoretically only ratios should be included, which are normally distributed and are showing statistically significant differences for the variables between the two groups of firms. Third, a correlation analysis and principal component analysis (PCA) were applied to detect, on which factors the variables are loaded and whether information redundancies are apparent. This is relevant to detect, which variables are having common characteristics and could be suitable for model building. At last, two prediction models based on multivariate linear discriminant analysis and multiple logistic regressions were developed, in order to derive classification functions for insolvency prediction for the two periods before bankruptcy.

Results

A first check was made on the assumption about normal distribution of data. Especially for discriminant analysis it seems to be relevant that normally distributed data is available, because this is a theoretical pre-condition for proper application of this method (Klecka, 1980, p. 61; Hopwood, McKeown and Mutchler, 1988; Subhash, 1996, p. 263). Nevertheless, several results provided evidence that a weak violation of normality assumptions is not affecting the prediction accuracy of the final model that much, so that some departures can be argued (Hopwood et al., 1988; Silva, Stam and Neter, 2002). In some cases departures are beneficial for better discrimination in means, which can lead to better classification results compared to logistic regression (Pohar, Blas and Turk, 2004). Logistic regression is using maximum-likelihood estimation for data and is theoretically not dependent on normally distributed data, so that this statistical method is relatively robust against this violation (Press and Wilson, 1978; Silva et al., 2002). Nevertheless, its model accuracy can be disturbed to a certain degree by non-normally distributed data (Hopwood et al., 1988; Silva et al., 2002).

The p-values based on Kolmogorov-Smirnov statistic are all below 0.05 percent, so that null hypotheses must be rejected. For none of the variables normality of data can be assumed for both observation periods. The values of skewness reveal extreme deviations from normality for the majority of the variables for both observation periods. Therefore, it must be concluded that the application of multivariate linear discriminant analysis is theoretically not justified based on these results. It seems that logistic regression should be more suitable for prediction task as these deviations from normality should not influence the estimations procedure of this method significantly. In order to test this statement nonetheless linear discriminant functions were computed for both observation periods in addition to logistic regression functions.

Descriptive statistics reveal some interesting aspects for the purpose of early prediction of bankruptcies. The ratio TE/TA deteriorated in mean from t-2 to t-1 for the bankrupt companies. This indicates that firms in distress are incurring additional losses as the event of insolvency approaches. Similarly, the profitability denoted as EBIT/TA is worsen and implicates that firms in difficulties cannot efficiently use their assets for revenue generation. The development of gearing-ratios shows an inconsistent behaviour, which undermines the theoretical framework of this paper. The mean gearing-ratio was lower for t-1 compared to t-2. This implies that gearing was decreasing, which is not consistent with the behaviour of TD/TA. Thirteen out of the 22 bankrupt firms had a negative equity-ratio in t-1, whereas only nine out of 22 had a negative ratio in t-2. Even if debt financing increased for the bankrupt cases, this was not visible in the mean gearing-ratio. Therefore gearing-ratio is providing inconsistent and not reliable signals, which are not beneficial for the construction of early warning systems.

The means that the different derivatives of gearing ratio are also inconsistent in their signalling power as expected by the presented theoretical framework. For example D1 denotes the change in gearing-ratio, when debt-ratio is increasing. In this situation the value of D1 is approaching infinity for positive values of equity-ratio, whereas its limit is going towards zero for negative values of equity-ratio. In t-2 the value of D1 for the bankrupt firms was in mean about 7.255, whereas it decreased in t-1 to the value of 2.971. This is a statistical problem of mean, as already mentioned the number of bankrupt firms exhibiting a negative equity-ratio increased from t-2 to t-1. This implies that D1 is offsetting two behaviours of gearing ratio, whereas the strongest effect in mean is superior and determines the main signal concerning the respective ratio. D2 determines the change in gearing-ratio, when equity-ratio is increasing. Here it does not matter, whether equity-ratio is positive or negative. The derivative is always having a negative sign. Therefore, companies having a certain portion of positive equity show the same value for D2 like companies having the same portion of negative equity. Under this occurrence the signalling power of this variable is restricted.

Table 2
Test for normal distribution and descriptive statistics for variables

Ratio	Group	(t-1)				(t-2)			
		Kolmogorov-Smirnov		**Descriptive Statistics**		**Kolmogorov-Smirnov**		**Descriptive Statistics**	
		Statistic	**Sign.**	**Mean**	**Std.-Dev.**	**Statistic**	**Sign.**	**Mean**	**Std.-Dev.**
TE/TA	0	,333	,000	-1,178	2,402	,283	,000	-0,222	0,700
	1	,247	,000	0,337	0,543	,243	,000	0,326	0,493
TD/TA	0	,332	,000	2,177	2,402	,283	,000	1,222	0,701
	1	,244	,000	0,654	2,402	,240	,000	0,665	0,493
Gearing	0	,243	,002	1,975	7,885	,242	,002	6,245	25,512
	1	,442	,000	11,182	110,663	,461	,000	18,496	206,923
EBIT/TA	0	,333	,000	-0,376	0,903	,326	,000	-0,135	0,480
	1	,164	,000	0,054	0,144	,135	,000	0,076	0,139
D1	0	,243	,002	2,971	7,888	,242	,002	7,255	25,519
	1	,443	,000	12,628	117,844	,462	,000	20,526	222,980
D2	0	,303	,000	-65,243	126,485	,397	,000	-666,738	2050,375
	1	,494	,000	-13151,526	265906,396	,506	,000	-46410,907	838357,088
D3	0	,304	,000	68,225	133,049	,394	,000	674,231	2069,428
	1	,494	,000	14015,157	283773,581	,507	,000	50028,514	907150,042
D4	0	,304	,000	-68,225	133,049	,394	,000	-674,231	2069,428
	1	,494	,000	-14015,157	283773,581	,507	,000	-50028,514	907150,042
D5	0	,304	,000	-68,225	133,049	,394	,000	-674,231	2069,428
	1	,494	,000	-14015,157	283773,581	,507	,000	-50028,514	907150,042
D6	0	,353	,000	1953,877	5708,096	,470	,000	83702,330	402000,291
	1	,510	,000	62014169,444	1297448676,260	,514	,000	365160308,690	7184692957,894
Gearing + D1	0	,243	,002	4,946	15,774	,242	,002	13,500	51,030
	1	,443	,000	23,811	228,502	,461	,000	39,022	429,895
Gearing - D1	0	,502	,000	-0,996	0,016	,497	,000	-1,009	0,030
	1	,476	,000	-1,446	7,318	,481	,000	-2,030	16,281
Gearing + D2	0	,303	,000	-63,268	120,085	,400	,000	-660,493	2031,536
	1	,494	,000	-13140,343	265797,421	,506	,000	-46392,411	838156,156
Gearing - D2	0	,304	,000	67,219	133,044	,394	,000	672,983	2069,357
	1	,494	,000	13162,708	266015,372	,506	,000	46429,403	838558,023
Gearing + D1 - D2	0	,305	,000	70,190	139,743	,392	,000	680,238	2088,480
	1	,493	,000	13175,336	266131,623	,506	,000	46449,929	838775,168
Gearing + D2 - D1	0	,303	,000	-66,240	126,487	,397	,000	-667,748	2050,376
	1	,494	,000	-13152,971	265913,669	,506	,000	-46412,937	838373,295

Note: Results based on own computations; group 0 = bankrupt firms and group 1 = non-bankrupt firms
Source: Author's calculation

D3 was defined as increase in debt-ratio and a decrease in equity-ratio. Here a similar problem like for D2 occurs. For every value of equity-ratio the value of D2 remains positive. This can also be observed for D4 and D5, whereas the values always remain negative. Therefore, the same conclusion is valid as already posted for D2. D6 is showing a similar behaviour like D1 and is not providing appropriate signals, which could be used for early detection of crises. The combinations of gearing-ratio with the different derivatives are also not helpful for prediction purposes, as for these similar problems like for the derivatives are vacant.

The differences in means were analysed based on t-test for independent samples at a 5 percent significance level. The results indicate that only three ratios in t-2 showed statistically significant differences in means between the two groups. The ratios are TE/TA, TD/TA and EBIT/TA. The same ratios also showed a discriminatory power for the period t-1. For all the other explanatory variables the differences in means were not statistically significant for both periods, so that the null hypotheses for these must be accepted. This provides a first result that the three mentioned ratios could be useful as potential discriminators within prediction models.

Table 3
Tests for differences in means and variances

	t-1				t-2			
	Differences in Means		Differences in Variances		Differences in Means		Differences in Variances	
	F	Sig.	F	Sig.	F	Sig.	F	Sig.
TE/TA	88,390***	**,000**	88,390***	**,000**	24,761***	**,000**	24,761***	**,000**
TD/TA	89,182***	**,000**	89,182***	**,000**	25,528***	**,000**	25,528***	**,000**
Gearing	,152	,697	,152	,697	,077	,782	,077	,782
EBIT/TA	68,031***	**,000**	68,031***	**,000**	32,455***	**,000**	32,455***	**,000**
D1	,147	,701	,147	,701	,078	,781	,078	,781
D2	,053	,818	,053	,818	,065	,798	,065	,798
D3	,053	,818	,053	,818	,065	,799	,065	,799
D4	,053	,818	,053	,818	,065	,799	,065	,799
D5	,053	,818	,053	,818	,065	,799	,065	,799
D6	,050	,823	,050	,823	,057	,812	,057	,812
Gearing + D1	,150	,699	,150	,699	,077	,781	,077	,781
Gearing - D1	,083	,774	,083	,774	,086	,769	,086	,769
Gearing + D2	,053	,818	,053	,818	,065	,798	,065	,798
Gearing - D2	,053	,818	,053	,818	,065	,798	,065	,798
Gearing + D1 - D2	,053	,818	,053	,818	,065	,798	,065	,798
Gearing + D2 - D1	,053	,818	,053	,818	,065	,798	,065	,798

Note: *** statistically significant at the 1 percent level
Source: Author's calculation

Additionally a test for differences in variances was applied. For this a Levene-test on the 5 percent significance level was computed. The results in *table 3* show that variances between the groups for the ratios TE/TA, TD/TA and EBIT/TA are statistically significant for both observation periods. The results from both tests therefore confirm the previous statement that bankrupt and non-bankrupt firms are different substantially in their capital structure and profitability, and that these three ratios are suitable early warning indicators for prediction purposes. None of the other variables were significant, which is confirming the results from differences in means. Such a finding is supporting again the theoretical assumptions that gearing-ratio and its derivatives are not providing reliable signals concerning crises and are therefore not potential explanatory variables for model building. For a deeper understanding and better interpretation some additional tests were conducted.

To detect the relations between the different variables a correlation analysis based on Pearson was applied. Due to size of the matrix only the correlations for the potential prediction variables are shown within *table 4*. As it can be seen gearing-ratio did not show any statistically significant correlations to the other variables, but it had significant and high positive and negative correlations to all of its derivatives for all two observation periods. This means that for all of the positively correlated derivatives multicollinearity is given. This implies that they can be substituted with gearing-ratio and are not relevant to be considered for further investigation. Their incremental information content over gearing-ratio is not given, so that an inclusion of the derivatives within prediction models would not result in an improved prediction performance. The highly negative correlations of the remaining derivatives could principally be interesting for prediction purposes, but based on the preliminary results about differences in means and variances their discriminatory power is not given.

The ratios TE/TA and TD/TA are significantly and relatively strong correlated with EBIT/TA, which is a profitability ratio. These ratios exhibited discriminatory power based on the tests for differences in means and variances. The high positive correlation between TE/TA and EBIT/TA imposes multicollinearity. This means that information redundancy is vacant and that both variables are carrying similar information. Therefore it could be sufficient to eliminate one of these variables for model building.

Table 4
Correlation analysis for potential prediction variables

Variables	t-1			
	TE/TA	**TD/TA**	**Gearing**	**EBIT/TA**
TE/TA	1	**-.998******	-.024	**.694******
TD/TA		1	.021	**-.693******
Gearing			1	.013
EBIT/TA			.013	1
	t-2			
TE/TA	1	**-.996******	-.045	**.318******
TD/TA		1	.038	**-.316******
Gearing			1	-.012
EBIT/TA				1

Note: *** statistically significant at 1 percent level
Source: Author's calculation

As last preliminary test, a PCA was applied based on Varimax-rotation. Within *table 5* the results from rotated component matrix and the cumulated explained variances are shown. For both observation periods two factors were relevant, whereas the same variables were loaded on the related factors. The first factor is dominated by gearing-ratios and its derivatives, so that this factor could be assigned as "gearing factor". It shows a high redundancy in data. It is therefore not necessary to consider all of the positively loaded variables for the explanation of capital structure based on gearing-ratio. This result is not surprising as it confirms the findings from correlation analysis. Even if this factor is able to explain about 80 percent of variance, the related variables did not show any ability to act as potential predictors for bankruptcy.

Table 5
Principal component analysis based on Varimax-rotation

Variables	t-1		t-2	
	Factor		**Factor**	
	1	**2**	**1**	**2**
explained variance (%)	79.559	96.889	79.019	93.484
TE/TA		.972		.972
TD/TA		-.972		-.972
Gearing	.991		.981	
EBIT/TA		.843		.528
D1	.992		.983	
D2	-.999		-.999	
D3	.999		.999	
D4	-.999		-.999	
D5	-.999		-.999	
D6	.999		.989	
Gearing + D1	.992		.982	
Gearing + D2	-.999		-.999	
Gearing - D2	.999		.999	
Gearing + D1 - D2	.999		.999	
Gearing + D2 - D1	-.999		-.999	

Source: Author's calculation

Model building

Grounded on the previous analyses following remarks can be concluded:

First, due to non-normally distributed data and extreme skewness the application of linear discriminant analysis is theoretically not given. Such a violation can extremely affect the prediction accuracy of this technique. Nevertheless, linear discriminant analysis was computed in order to test, whether these deviations from normality are really influencing the accuracy and whether the performance compared to logistic regression, which should not be that sensitive against deviations from normality, is inferior.

Second, gearing-ratio and its derivatives did not show any discriminatory power based on the tests for differences in means and variances. The related ratios also did not have significant and strong correlations to the other variables of interest within this study. Based on PCA the variables were loaded on one single factor, where none of the other variables was loaded on. From these findings it can be concluded that the propositions from theoretical framework are supported and that gearing ratio and its derivatives are not suitable early warning indicators at all.

Third, the greatest potential for prediction purposes can be seen in the ratios TE/TA and EBIT/TA, which had been found in numerous studies as relevant discriminators between the two types of firms (for example Laitinen and Laitinen, 2000; Pompe and Bilderbeek, 2005; Grunert et al., 2005; Iazzolino et al., 2013). Nevertheless, based on PCA it can be concluded that not both of the ratios will appear as predictors within the models, because of information redundancy.

Fourth, TD/TA also showed a potential as predictor. It exhibited a high negative loading on the second factor for both observation periods and a strong negative and significant correlation to EBIT/TA. TD/TA seems to include certain information, which is not given in EBIT/TA, so that both measures in combination could have the potential to increase signalling power concerning bankruptcy prediction.

In the first step a multivariate linear discriminant analysis for the two observation periods based on the initial sample was applied, which is based on the technique of Mahlanobis distance (Table 6). A first important pre-test is Box-Test in order to evaluate whether the covariance matrices are equal (null hypothesis). Both significances are below 0.05, so that the null hypotheses for both observation periods must be rejected. This result indicates another violation for the application of linear discriminant analysis, which can also affect the model quality and the classification accuracy (Klecka, 1980, p. 61; Subhash, 1996, p. 264). The model quality can be assessed by a check on Wilks-Lambda. The significances for the models of both observation periods are less than 0.05, so that they can significantly discriminate between the two groups of firms.

Table 6
Box-test for equality of covariances and Wilks-Lambda of discriminant function

		t-1	t-2
Box-Test	Box-M	457,185***	136,691***
	Approximation	147,113	43,984
	df1	3	3
	df2	15428,517	15428,517
	Significance	,000	,000
Wilks-Lambda	Wilks-Lambda	0,825***	0,910***
	Chi-Square	88,078	88,078
	Significance	0,000	0,000

Note: *** statistically significant at 1 percent level
Source: Author's work

Following equations show the linear functions based on Fisher for t-1 and t-2, whereas the two ratios TD/TA and EBIT/TA appeared as expected from previous analysis.

$$Z_{(t-2)} = 1.718 - 1.635x_1 + 5.989x_2 \quad (2)$$

$$Z_{(t-1)} = 3.504 - 2.089x_1 + 3.401x_2 \quad (3)$$

X_1 = TD/TA
X_2 = EBIT/TA

The signs of the ratios within the equations are consistent with results from previous research. Companies having a high debt-ratio are more likely to receive a low Z-score and are therefore more likely to fail. Firms with a high profitability are less likely to fail. The classification results based on initial sample are reported within *table 7*. Both functions provided a high type I error (a bankrupt firms was assigned as non-bankrupt). About 54.5 percent of the cases had been assigned into the wrong category. Type II error is much lower and reached values between 1.8 (for t-1) and 6.4 (t-2) percent. Therefore, these models rather predict non-bankrupt than bankrupt firms and are not reliable prediction instruments. Although, it must be mentioned that they were not adjusted concerning cut-off value. It could be possible with appropriate techniques to find a cut-off values, where type I error can be minimized, but this is not the purpose of this paper. For prediction of the two states all Z-scores below zero were assigned as bankrupt and Z-scores above zero were assigned as non-bankrupt.

The application of the functions on validation sample of this research brought following results, which are also reported in *table 7*. The prediction results for the non-bankrupt firms showed better results for both observation periods. The problem of high type I error remains vacant for these models, so that for practical application they cannot be used, when cut-off values are not adjusted to minimize type I error. The potential occurrences concerning model quality are highlighted in the discussion of this work.

Table 7
Classification results with discriminant functions

				t-1		t-2	
Initial Sample	Class			Prediction		Prediction	
				0	1	0	1
	Original	absolute	0	10	12	10	12
			1	8	432	28	412
		%	0	45.5	54.5	45.5	54.5
			1	1.8	98.2	6.4	93.6
Validation Sample	Class			Prediction		Prediction	
				0	1	0	1
	Original	absolute	0	8	14	11	11
			1	3	417	22	398
		%	0	36.4	63.6	50.0	50.0
			1	0.7	99.3	5.2	94.8

Source: Author's work

Based on the preliminary findings logistic regression should provide a better model with a better classification accuracy compared to discriminant analysis as several theoretical pre-conditions for the latter were violated. For model building, the two known ratios TD/TA and EBIT/TA were used. The test for model quality provided significances less than 0.05, so that null hypotheses can be rejected. The developed models are well suited for classification and provide significantly better results than a random classification of the firms into the two categories.

Table 8
Model quality, goodness of fit and R² for logistic regression analysis

		Model Quality			Goodness of Fit			R²	
		-2 Log-Likelihood	Chi-Square	Sign.		Chi-Square	Sign.		Value
t-1	Intercept only	176,894			Pearson	603,542***	,000	Nagelkerke	0,270
	Final	135,467***	41,427	,000	Deviation	135,467	1,000	McFadden	0,234
t-2	Intercept only	176,894			Pearson	377,058	,998	Nagelkerke	0,130
	Final	157,312***	19,582	,000	Deviation	157,312	1,000	McFadden	0,111

Note: *** statistically significant at 1 percent level
Source: Author's work

The goodness of fit within *table 8* shows for the period t-1 a significance of 0.000, so that the related model was not able to adjust the data well. In contrast, the model for t-2 shows a significance of 0.998, which means the model was well estimated. Nevertheless, the R² for both models based on Nagelkerke were relatively low, so that only a small portion of the variances between the figures can be explained with the estimated values. For derivation of logistic function the bankrupt group was used as reference group. The results from parameter estimation are reported in *table 9*. As it can be seen the significance for the ratio TD/TA was above 0.05 percent, so that its contribution for explanation of the differences between the two groups was limited. Nevertheless, the variable was included within the logistic regression functions.

Table 9
Parameter estimation for logistic regression

Observation Period		B	Standard-error	Wald	df	Sign.
t-1	Constant Term	-3.609***	.379	90.653	1	.000
	TD/TA	.468	.348	1.812	1	.178
	EBIT/TA	-5.170***	1.371	14.213	1	.000
t-2	Constant Term	-3.338***	.366	83.264	1	.000
	TD/TA	.512	.346	2.195	1	.138
	EBIT/TA	-3.157**	1.227	6.618	1	.010

Note: *** statistically significant at 1 percent level; ** 5% level
Source: Author's illustration

Based on the estimations, following classification functions were obtained. Their signs concerning contribution for assignment of a firm into one of two categories are like for discriminant analysis consistent with results from prior research. Companies having a higher debt-ratio are more likely to be classified as bankrupt. The higher the profitability of a firm is the less likely a bankruptcy can occur.

$$F_{(t-2)} = \frac{1}{1+e^{(3.338-0.512x_1+3.157x_2)}} \tag{4}$$

$$Z_{(t-1)} = \frac{1}{1+e^{(3.609-0.468x_1+5.170x_2)}} \tag{5}$$

$X_1 =$ TD/TA
$X_2 =$ EBIT/TA

Table 10
Classification results with logistic regression

				t-1		t-2	
Initial Sample	Class			Prediction		Prediction	
				0	1	0	1
	Original	absolute	0	4	18	2	20
			1	1	439	1	439
		%	0	18.2	81.8	9.1	90.9
			1	0.2	99.8	0.2	99.8
Validation Sample	Class			Prediction		Prediction	
				0	1	0	1
	Original	absolute	0	4	18	1	21
			1	2	418	1	419
		%	0	18.2	81.8	4.5	95.5
			1	0.5	99.5	0.2	99.8

Note: Results based on own computations
Source: Author's illustration

The classification results for logistic regression in *table 10* show that the logistic functions did not provide better results compared to discriminant analysis. Type I error is much higher than for discriminant analysis, but type II error is lower. Therefore, logistic regression is better detecting non-bankrupt firms. This is valid for initial and validation sample. This result is surprising, as it was expected that logistic regression should provide much better classification results, as almost all theoretical pre-conditions for the application of discriminant analysis had been violated. Within both methods gearing-ratio and its derivatives did not appear as relevant predictors for bankruptcy. This was expected based on the preliminary results and was also confirmed in case of model building.

Results

Hypothesis and research questions

The results of the study provided empirical evidence that the assumptions within the theoretical framework can be confirmed. Gearing-ratio and its derivatives of first and second order are not containing sufficient information, so that they cannot be used as discriminators within business failure prediction models, which are constructed with statistical methods. Their signalling power and directions are not consistent with expectations. Therefore, the ratio and its derivatives did not show discriminatory power, which can be used to divide between the two groups of companies within this study. All of the hypotheses of this work can be accepted without any restrictions.

This also gives the hint to the research questions. The first question was to answer, why gearing-ratio is not in the position to act as an early warning indicator. Gearing-ratio provided inconsistent behaviour for bankrupt firms. This aspect is problematic for a statistical purpose as this occurrence is disturbing means and variances, which are both relevant for discrimination between the two groups of firms. The curves of gearing functions can explain this problem visually and the mathematical computations show the problem that the function of gearing-ratio is not differentiable for the situation, where equity ratio is zero. Moreover, the drawback is that firms already exhibiting a negative gearing ratio can improve their gearing ratio by incurring additional losses or increasing their leverage. Additionally, the derivatives showed an inconsistent behaviour, so that they were also not in the position to act as reliable crisis indicators. These results do not confirm the findings from prior research, where gearing-ratio appeared as prediction variable (Casey and Bartczak, 1985; Jones and Hensher, 2004; Chi and Tang, 2006; Chen and Du, 2009).

The second question concerned, which of the chosen variables from prior research had the highest discriminatory power between the two types of firms. The statistical analysis clearly brought that TE/TA and TD/TA, but also EBIT/TA had the greatest potential to differentiate between bankrupt and non-bankrupt firms. Therefore, the findings from prior research concerning these three ratios were confirmed within this study (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Laitinen and Laitinen, 2000; Grunert et al., 2005; Zenzerovic, 2011; Pervan and Kuvek, 2013). It can also be concluded that firms with higher debt-ratio and lower profitability are more likely to go into bankruptcy. Such a result implies that a potential theory of bankruptcy prediction should be associated with these variables.

The last question referred to ratios associated with capital structure of the firm and their informational content to explain deteriorating performance of firms. The two relevant variables were TD/TA and EBIT/TA. As expected one ratio describing the capital structure of the firm appeared as potential predictor. EBIT/TA is a measure of profitability and appeared in addition to capital structure ratio (TE/TA or TD/TA) within different previous studies (Chen et al., 2006; Pervan, Pervan and Vukoja, 2011). Profitability ratios can be used as a proxy for the measurement of management efficiency (Dambolena and Khoury, 1980; Pervan and Visic, 2012) and are therefore interesting explanatory variables. It is interesting to note that EBIT/TA had a high positive correlation to TE/TA and was also loaded positively on the same factor based on PCA. It seems that EBIT/TA contains some information, which is also inherent in equity-ratio, so that it can to a certain degree replicate the latter.

Testing models' assumptions

The pre-conditions for application of discriminant analysis were all violated within this work. These violations could be assumed as responsible for the weak classification results concerning bankrupt firms. Type I error was very high, whereas the models classified non-bankrupt firms quite well. Nevertheless, the results were not that bad compared to logistic regression, which was assumed to be more appropriate for model building. This assumption was not confirmed with the apparent results. It seems that strong deviations from normality of data are influencing the estimation procedure of logistic regression and are affecting the classification accuracy of logistic functions. This result is consistent with some other prior studies (Hopwood et al., 1988; Silva et al., 2002). Therefore, it cannot be concluded that logistic regression is superior for model building in contrast to discriminant analysis, which is in congruence with several findings from previous research (Casey and Bartczak, 1985; Gombola et al., 1987; Boritz et al., 1995; Hwang, Cheng and Lee, 2007; Yim and Mitchell, 2007; Gepp and Kumar, 2008; Muller et al., 2009).

Moreover, the unequal distribution between bankrupt and non-bankrupt firms seems to influence the classification results of both models. Discriminant analysis was more successful in detecting bankrupt firms compared to logistic regression, whereas latter showed a greater ability to detect non-bankrupt firms. Therefore, this must be seen as a big limitation of this study. Additionally it must be emphasized that equal costs of misclassification were assumed for determining the cut-off point. It could be possible to optimize type I error by appropriate adjustment of cut-off point. Under this assumption the model quality could be improved, so that an application for practical purposes would be possible. This was not the purpose of this paper and could be a topic for further research.

Models' performance

For better comparison of model quality different performance measures were computed, which are shown in *table 11* (computations were based on Fawcett, 2006; Ooghe and Spaenjers, 2009). As already reported the models better predicted non-bankrupt as bankrupt firms, so that type I errors were extremely high due to the already described problem about cut-off value. Despite of this, the overall accuracy of the models for all observation periods remained relatively high. This is also visible at AUC-values, which were high and all statistically significant. This means that the models are classifying better than a random assessment. Here once again the superiority of logistic regression for bankruptcy prediction cannot be confirmed.

Table 11
Performance measures for the models

	t-1				t-2			
	Discriminant Analysis		Logistic Regression		Discriminant Analysis		Logistic Regression	
	Initial	Validation	Initial	Validation	Initial	Validation	Initial	Validation
AUC	0.898	0.883	0.831	0.820	0.873	0.955	0.830	0.952
Gini-Coeff.	0.797	0.767	0.662	0.640	0.746	0.911	0.660	0.905
Accuracy	0.957	0.962	0.959	0.955	0.913	0.925	0.955	0.950
Type I Error	0.545	0.636	0.818	0.818	0.545	0.500	0.909	0.955
Type II Error	0.018	0.007	0.002	0.005	0.064	0.052	0.002	0.002
F-measures	0.977	0.980	0.979	0.977	0.954	0.960	0.977	0.974

Note: Results based on own computations
Source: Author's illustration

Conclusion

When analysing current literature and empirical results one can find that there are numerous potential financial and non-financial variables, which are all having a predictive power to a certain degree (Pretorius, 2008). Within this paper it was shown that a potential discriminator (gearing-ratio) found in previous studies did not have the ability to act as crisis or early warning indicator. So the results from prior research were not confirmed. This would suggest the concentration of further research on predictors, which had been mostly found to be good indicators in previous papers and maybe to focus investigation additionally on elimination of variables, which appeared as predictors in previous research, but which are theoretically not in the position to explain or detect deterioration of corporate economic health. This proposal is a contrary approach to the most existing methods applied in business failure prediction research. Generally, empirical research is focused on the collection of a representative data base, formulates potential predictors, applies certain statistical tests and obtains a model incorporating the best discriminating variables.

With such a contrary approach it will be possible to contract the universe of potential predictors into a group of meaningful and suitable indicators, on which further research can be focused.

The used statistical methods within this work showed a certain ability to discriminate between bankrupt and non-bankrupt firms, whereas the model accuracies are highly influenced by the selection of an appropriate cut-off value. Despite of this the derived financial ratios showed discriminatory power for one and two years prior to bankruptcy, which is supporting the evidence that they are meaningful early warning indicators. Moreover, their relevance is interesting for practical purposes, because they were able to provide relatively good results for the period two years prior to bankruptcy. The great contribution of such a finding is that the earlier potential crises can be detected, the quicker and more effective turnaround activities can be implemented. Even if the models provide a better classification for non-bankrupt firms, their value must be seen in the early signalling character, which can give the hint that the firm could be potentially endangered. The developed models can in this form not be used for practical purposes, but with an appropriate adjustment cut-off values its assessment qualities can be improved substantially. Such a project could be conducted with future research. Additionally the models could be expanded by incorporation of additional powerful and maybe non-financial ratios in order to improve model quality and prediction accuracy.

References

1. Ansoff, H. I., Sullivan, P. A. (1993), "Optimizing profitability in turbulent environment: A formula for strategic success", Long Range Planning, Vol. 26, No. 5, pp. 11-23.
2. 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, Vol. 6, No. 2, pp. 1-33.
3. Altman, E. I., Haldeman, R. G., Narayanan, P. (1977), "ZETATM Analysis: A new model to identify bankruptcy risk of corporations", Journal of Banking and Finance, Vol. 1, No. 1, pp. 29-54.
4. Altman, E. I. (1968), "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", The Journal of Finance, Vol. 23, No. 4, pp. 589-609.
5. 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, Vol. 10, No. 2, pp. 69-81.
6. Barniv, R., McDonald, J. B. (1992), "Identifying financial distress in the insurance industry: A synthesis of methodological and empirical issues", The Journal of Risk and Insurance, Vol. 59, No. 4, pp. 543 – 573.
7. Barniv, R., Raveh, A. (1989), "Identifying financial distress: A new nonparametric approach", Journal of Business Finance & Accounting, Vol. 16, No. 3, pp. 361-383.
8. Beaver, W. H. (1966), "Financial ratios as predictors of failure", Journal of Accounting Research, Vol. 4, pp. 71-111.
9. 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, Vol. 1, No. 4, pp. 267-284.
10. Boritz, J. E., Kennedy, D. B., de Miranda e Albuquerque, A. M. (1995), "Predicting corporate failure using a neural network approach", Intelligent Systems in Accounting, Finance and Management, Vol. 4, No. 2, pp. 95-111.

11. Brouthers, K. D., Roozen, F. A. (1999), "Is it time to start thinking about strategic accounting?„ Long Range Planning, Vol. 32, No. 3, pp. 311-322.
12. Casey, C., Bartczak, N. (1985), "Using operating cash flow data to predict financial distress: Some extensions", Journal of Accounting Research, Vol. 23, No. 1, pp. 384-401.
13. Charitou, A., Neophytou, E., Charalambous, C. (2004), "Predicting corporate failure: Empirical evidence for the UK", European Accounting Review, Vol. 13, No. 3, pp. 465-497.
14. Chava, S., Jarrow, R. A. (2004), "Bankruptcy prediction with industry effects", Review of Finance, Vol. 8, No. 4, pp. 537-569.
15. Chen, J., Marshall, B. R., Zhang, J., Ganesh, S. (2006), "Financial distress prediction in China", Review of Pacific Basin Financial Markets and Policies, Vol. 9, No. 2, pp. 317-336.
16. Chen, W. S., Du, Y. K. (2009), "Using neural networks and data mining techniques for the financial distress prediction model", Expert Systems with Applications, Vol. 36, No. 2, pp. 4075-4086.
17. Chi, L. C., Tang, T. C. (2006), "Bankruptcy prediction: Application of logit analysis in export credit risks", Australian Journal of Management, Vol. 31, No. 1, pp. 17-27.
18. Creditreform Wirtschaftsforschung Austria (2011), "Insolvenzen in Europa: Jahr 2010/11", available at: http://www.creditreform.at/fileadmin/user_upload/Oesterreich/Downloads/Insolvenz/Insolvenzen_in_Europa_2010.pdf (13 January 2014).
19. Dambolena, I. G., Khoury, S. J. (1980), "Ratio stability and corporate failure", The Journal of Finance, Vol. 35, No. 4, pp. 1017-1026.
20. 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, Vol. 76, No. 2, pp. 179-194.
21. Du Jardin, P. (2009), "Bankruptcy prediction models: How to choose the most relevant variables?", Bankers, Markets & Investors, No. 98, pp. 39-46.
22. Edmister, R. O. (1972), „An empirical test of financial ratio analysis for small business failure prediction", Journal of Financial and Quantitative Analysis, Vol. 7, No. 2, pp. 1477-1493.
23. Exler, M. W., Situm, M. (2014), „Indikatoren zur Früherkennung von Unternehmenskrisen in der Beraterpraxis: Ansatzpunkte zur Etablierung eines internen Frühwarnsystems", Krisen-, Sanierungs- und Insolvenzberatung, Vol. 10, No. 2, pp. 53-59.
24. Exler, M. W., Situm, M. (2013), "Früherkennung von Unternehmenskrisen: Systematische Einteilung von Krisenfrüherkennungsindikatoren zu den unterschiedlichen Krisenphasen eines Unternehmens", Krisen-, Sanierungs- und Insolvenzberatung, Vol. 9, No. 4, pp. 161-166.
25. 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, Vol. 3, No. 4, pp. 241-252.
26. Fawcett, T. (2006), "An introduction to ROC analysis", Pattern Recognition Letters, Vol. 27, No. 8, pp. 861-874.
27. Frydman, H., Altman, E. I., Kao, D. L. (1985), "Introducing recursive partitioning for financial classification: The case of financial distress", The Journal of Finance, Vol. 40, No. 1, pp. 269-291.

28. Gepp, A., Kumar, K. (2008), "The role of survival analysis in financial distress prediction", International Research Journal of Finance and Economics, Vol. 16, pp. 13-34.
29. Gombola, M. J., Haskins, M. E., Ketz, E. J., Williams, D. D. (1987), "Cash flow in bankruptcy prediction", Financial Management, Vol. 16, No. 4, pp. 55-65.
30. Grunert, J., Norden, L., Weber, M. (2005), "The role of non-financial factors in internal credit ratings", Journal of Banking & Finance, Vol. 29, No. 2, pp. 509-531.
31. Hackbarth, D., Miao, J., Morellec, E. (2006), "Capital structure, credit risk, and macroeconomic conditions", Journal of Financial Economics, Vol. 82, pp. 519-550.
32. Hauser, R. P., Booth, D. (2011), "Predicting bankruptcy with robust logistic regression", Journal of Data Science, Vol. 9, pp. 565-584.
33. Hennessy, C. A., Whited, T. M. (2005), "Debt dynamics", The Journal of Finance, Vol. 60, No 3, pp. 1129-1165.
34. Hopwood, W., McKeown, J., Mutchler, J. (1988), "The sensitivity of financial distress prediction models to departures from normality", Contemporary Accounting Research, Vol. 5, No. 1, pp. 284-298.
35. Houghton, K. A., Woodliff, D. R. (1987), "Financial ratios: The prediction of corporate ´success´ and failure", Journal of Business Finance & Accounting, Vol. 14, No. 4, pp. 537-554.
36. Hwang, R. C., Cheng, K. F., Lee, J. C. (2007), "A semiparametric method for predicting bankruptcy", Journal of Forecasting, Vol. 26, No. 5, pp. 317-342.
37. Keasey, K., Watson, R. (1991), "Financial distress prediction models: A review of their usefulness", British Journal of Management, Vol. 2, No. 2, pp. 89-102.
38. Iazzolino, G., Migliano, G., Gregorace, E. (2013), "Evaluating intellectual capital for supporting credit risk assessment: An empirical study", Investment Management and Financial Innovations, Vol. 10, No. 2, pp. 44-54.
39. Jones, S., Hensher, D. A. (2004), "Predicting firm financial distress: A mixed logit model", The Accounting Review, Vol. 79, No. 4, pp. 1011-1038.
40. Klecka, W. R. (1980). "Discriminant analysis", Newbury Park: Sage.
41. Laitinen, E. K., Laitinen, T. (2000), "Bankruptcy prediction : Application of the Taylor´s expansion in logistic regression", International Review of Financial Analysis, Vol. 9, No. 4, pp. 327-349.
42. Lau, A. H. L. (1987), "A five-state financial distress prediction model", Journal of Accounting Research, Vol. 25, No. 1, pp. 127-138.
43. Leland, H. E., Toft, K. B. (1996), "Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads", The Journal of Finance, Vol. 51, No. 3, pp. 987-1019.
44. Li, H., Sun, J. (2011), "Predicting business failure using forward ranking-order case-based reasoning", Expert Systems with Applications, Vol. 38, No. 4, pp. 3075-3084.
45. Lin, F., Liang, D., Chen, E. (2011), "Financial ratio selection for business crisis prediction", Expert Systems with Applications, Vol. 38, No. 12, pp. 15094-15102.
46. Liou, D. K., Smith, M. (2007), "Macroeconomic variables and financial distress", Journal of Accounting, Business & Management, Vol. 14, pp. 17-31.
47. Madrid-Guijarro, A., Garcia-Pèrez-de-Lema, D., van Auken, H. (2011), "An analysis of non-financial factors associated with financial distress", Entrepreneurship & Regional Development, Vol. 23, No. 3-4, pp. 159-186.
48. Muller, G. H., Steyn-Bruwer, B. W., Hamman, W. D. (2009), "Predicting financial distress of companies listed on JSE – A comparison of techniques", South African Journal of Business & Management, Vol. 40, No. 1, pp. 21-32.

49. Müller-Stewens, G. (2007). "Früherkennungssysteme", in Köhler, R., Küpper, H. U., Pfingsten, A. (ed.), „Handwörterbuch der Betriebswirtschaft", Schaeffer-Pöschl, Stuttgart, pp. 558-580.
50. Nam, C. W. et al. (2008), "Bankruptcy prediction using a discrete-time duration model incorporating temporal macroeconomic dependencies", Journal of Forecasting, Vol. 27, No. 6, pp. 493-506.
51. Neves, J. C., Vieira, A. (2006), "Improving bankruptcy prediction with hidden layer learning vector quantization", European Accounting Review, Vol. 15, No, 2, pp. 253-271.
52. Ohlson, J. A. (1980), "Financial ratios and the probabilistic prediction of bankruptcy", Journal of Accounting Research, Vol. 18, No. 1, pp. 109-131.
53. Ooghe, H., Spaenjers, C. (2009), "A note on performance measures for business failure prediction models", Applied Economics Letter, Vol. 17, No. 1, pp. 67-70.
54. Pacey, J. W., Pham, T. M. (1990), "The predictiveness of bankruptcy models: Methodological problems and evidence", Australian Journal of Management, Vol. 15, No. 2, pp. 315-337.
55. Pervan, I., Kuvek, T. (2013), "The relative importance of financial ratios and nonfinancial variables in predicting of insolvency", Croatian Operational Research Review, Vol. 4, No. 1, pp. 187-198.
56. Pervan, I., Pervan, M., Vukoja, B. (2011), "Prediction of company bankruptcy using statistical techniques – Case of Croatia", Croatian Operational Research Review, Vol. 2, No. 1, pp. 158-167.
57. Pervan, M., Visic, J. (2012), "Influence of firm size on its business success", Croatian Operational Research Review, Vol. 3, No. 1, pp. 213-223.
58. Platt, H. D., Platt, M. B. (2002), "Predicting corporate financial distress: Reflections on choice-based sample bias", Journal of Economics and Finance, Vol. 26, No. 2, pp. 184-199.
59. Pohar, M., Blas, M., Turk, S. (2004), "Comparison of logistic regression and linear discriminant analysis: A simulation study", Metdološki Zvezki, Vol. 1, No. 1, pp. 143-161.
60. Pompe, P. P. M., 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, Vol. 13, No. 2, pp. 95-112.
61. Prasad, D., Puri, Y. R. (2005), "Does combining alternate bankruptcy prediction models improve forecasting accuracy?", The International Journal of Finance, Vol. 17, No. 3, pp. 3581-3602.
62. Press, J. S., Wilson, S. (1978), "Choosing between logistic regression and discriminant analysis", Journal of American Statistical Association, Vol. 73, No. 364, pp. 699-705.
63. Pretorius, M. (2008), "Critical variables of business failure: A review and classification framework", South African Journal of Economic and Management Sciences, Vol. 11, No. 4, pp. 408-430.
64. Saunders, A., Cornett, M. (2011). "Financial institutions management: A risk management approach", 7th edition, New York: Mc-Graw-Hill.
65. Schmidt, R., Terberger, E. (1996). „Grundzüge der Investitions- und Finanzierungstheorie", 3rd edition, Wiesbaden: Gabler.
66. Sharma, D. S. (2001), "The role of cash flow information in predicting corporate failure: The state of the literature", Managerial Finance, Vol. 27, No. 4, pp. 3-28.

67. Silva, A. P. D., Stam, A., Neter, J. (2002), "The effects of misclassification costs and skewed distributions in two-group classification", Communications in Statistics – Simulation and Computation, Vol. 31, No. 3, pp. 401-423.
68. Skogsvik, K., Skogsvik, S. (2013), "On the choice based sample bias in probabilistic bankruptcy prediction", Investment Management and Financial Innovations, Vol. 10, No. 1, pp. 29-37.
69. Subhash, S. (1996). "Applied multivariate techniques", New York: John Wiley & Sons.
70. Thomas, L. C., Edelman, D. B., Crook, J. N. (2002). "Credit scoring and its applications", Philadelphia: Society for Industrial and Applied Mathematics.
71. Tsai, B. H. (2013), "An early warning system of financial distress using multinomial logit models and a bootstrapping approach", Emerging Markets Finance & Trade, Vol. 49, No. 2, pp. 43-69.
72. Yim, J., Mitchell, H. E. (2007), "Predicting financial distress in the Australian financial service industry", Australian Economic Papers, Vol. 46, No. 4, pp. 375-388.
73. Zenzerovic, R. (2011), "Credit scoring models in estimating the creditworthiness of small and medium and big enterprises", Croatian Operational Research Review, Vol. 2, No. 1, pp. 143-157.
74. Zmijewski, M. E. (1984), "Methodological issues related to the estimation of financial distress prediction models", Journal of Accounting Research, Vol. 22, pp. 59-82.

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