THE RELEVANCE OF EMPLOYEE-RELATED RATIOS FOR EARLY DETECTION OF CORPORATE CRISES

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Received: 7 February 2014
Accepted: 27 January 2015

ABSTRACT: *The purpose of this study was to analyse whether employee-related ratios derived from accounts have incremental predictive power for the early detection of corporate crises and bankruptcies. Based on the literature reviewed, it can be seen that not much attention has been drawn to this task, indicating that further research is justified. For empirical research purposes, a database of Austrian companies was used for the time period 2003 to 2005 in order to develop multivariate linear discriminant functions for the classification of companies into the two states; bankrupt and non-bankrupt, and to detect the contribution of employee-related ratios in explaining why firms fail. Several ratios from prior research were used as potential predictors. In addition, other separate ratios were analysed, including employee-related figures. The results of the study show that while employee-related ratios cannot contribute to an improvement in the classification performance of prediction models, signs of these ratios within the discriminant functions did show the expected directions. Efficient usage of employees seems to play an important role in decreasing the probability of insolvency. Additionally, two employee-related ratios were found which can be used as proxies for the size of the firm. This had not been identified in prior studies for this factor.*

Keywords: *bankruptcy prediction, crisis indicators, discriminant analysis, ratio analysis*

JEL Classification: C12, C38, G33

1. INTRODUCTION

Fast-changing environmental conditions increase the challenges faced by enterprises to remain successful in today's markets. The insolvency statistics for Europe show that after the start of financial crisis in 2007/2008, insolvency rates increased and the situation continued to deteriorate thereafter. Nevertheless, the problem of business failures and the potential for insolvency is still an interesting topic within management science, as the damages on a macroeconomic level are significant. Therefore, it is both necessary and useful to direct research towards the early prediction of corporate crises and financial distress. It is generally accepted that prediction models should recognize potential economic and

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financial difficulties as early as possible. The best timing for the detection of crisis is at the strategic crisis stage, which is in practice very difficult to detect, due to the weak signals apparent during this stage (Pretorius, 2008, p. 416; Exler & Situm, 2013, p. 162). This type of crisis is not fully visible in financial statement figures and other non-financial ratios are therefore needed, such as market-based indicators and macroeconomic variables, to make them visible and to achieve stronger and more reliable early warning signals. If this is possible, sufficient time will then remain to induce turnaround activities, which are less costly and far more efficient than in the later stages of crisis.

Even if it is currently recognized that a properly functioning forecasting tool should include a combination of the aforementioned variables (Grunert, Norden & Weber, 2006; Altman, Sabato & Wilson, 2010; Madrid-Guijarro, Garcia-Perez-de-Lema & van Auken, 2011; Iazzolino, Migliano & Gregorace, 2013), the relevance of figures from financial statements as discriminating variables between failed and non-failed firms remains prominent. This paper focuses on this aspect and devotes special attention to accounting ratios related to employee data. An extensive review of 238 papers dealing with the search for potential variables for the differentiation between the two types of firms revealed that such ratios have not received much attention in this field of study.

Therefore, within this research, several ratios related to employees from prior research and several new ratios not found to be analysed in the past were tested to assess their ability to act as prediction variables. An analysis was made based on a database including accounting figures of Austrian firms for the years 2003 and 2004. The aim was to explore how solvent and insolvent firms differ in such ratios and whether the performance of insolvency prediction models based on multivariate linear discriminant analysis could be improved, when these ratios are included with traditional accounting ratios already known as prediction variables.

It was found that several employee-related variables showed discriminatory power between the two types of firms. Nevertheless, this ability could not be exploited to attain improved classification results. Despite this, signs of the variables indicated a direction which was consistent with expectations and can be interpreted economically. Summarized, it can be said that employee-related variables carry certain information which is relevant for discrimination between failed and non-failed firms, but their predictive power is somehow limited and therefore not sufficient in order to be included into a well-functioning forecasting model for bankruptcies.

This paper is organized as follows: First, a literature review is given about the origins of using accounting ratios for the prediction of insolvencies. This is followed by some insights into more recent research, where results concerning the usage of non-financial indicators within bankruptcy prediction are summarized. Additionally, some relevant papers are highlighted with reference to their main conclusions, where employee-related ratios were investigated concerning predictability. Second, three research hypotheses and three research questions are then presented. Third, a description about the database and the selection of samples for empirical tests is given. Fourth, a presentation about the ratios applied within this work is provided, where some of them are based on literature review and some were not found to be used in previous studies. Fifth, the statistical analyses and results are presented, which are necessary to extract the most relevant variables for the construction of an insolvency prediction model. Sixth, the equations obtained for multivariate linear discriminant functions for the different years and combinations of ratios including their performance quality are presented. Seventh, the main conclusions of the result are summarized. At last, implications and limitations of the study are described, and recommendations for future research are given. Within this section the research hypotheses are tested and the research questions are answered.

2. LITERATURE REVIEW

Numerous research papers can be found in the field of business failure prediction which extracted a number of differing variables which are suitable for the prediction of business failures and bankruptcies. The most prominent variables are accounting ratios, which were derived from the financial statements of companies. Early research stated that accounting ratios show the potential to differentiate between bankrupt and non-bankrupt firms (Beaver, 1966; Altman, 1968). Several other papers confirmed these findings based on empirical results (Altman, Haldeman & Narayanan, 1977; Dambolena & Khoury, 1980; Zmijewski, 1984; Casey & Bartczak, 1985; Chalos, 1985; Gombola, Haskins, Ketz & Williams, 1987; Gilbert, Menon & Schwartz, 1990; Platt, Platt & Pedersen, 1994; McKee, 1995; Foster, Ward & Woodroof, 1998; Doumpos & Zopounidis, 1998).

Further research concluded that prediction models using only accounting ratios are inferior to models which combine accounting ratios with other financial and non-financial ratios. Financial ratios could comprise data not available from financial statements and replicate market data of e.g. stock prices, stock volatilities etc. Non-financial ratios can include factors such as management quality or efficiency, which are not directly observable, but can be estimated by appropriate quantitative measures. It is currently generally accepted that insolvency prediction models should include a mix of accounting, financial and non-financial variables as the accuracy of prediction can be increased in contrast to models including only accounting ratios (Thornhill & Amit, 2003; Grunert, Norden & Weber, 2006; Altman, Sabato & Wilson, 2010; Madrid-Guijarro, Garcia-Perez-de-Lema & van Auken, 2011; Iazzolino, Migliano & Gregorace, 2013).

The study by Thornhill & Amit (2003) found that deficiencies in general and financial management can be used as variables to explain why younger firms are more likely to fail. For older firms, failure is more dependent on external forces. A similar conclusion was made by Grunert, Norden & Weber (2006), where the factor of management quality displayed statistical significance to such an extent that this non-financial variable contributed to an improved classification. Furthermore, this research found in general that models incorporating financial and non-financial factors lead to significantly more accurate default probabilities than the single use of either financial or non-financial factors. This result was confirmed by the study of Altman, Sabato & Wilson (2010), where the inclusion of non-accounting data to the basic z-score model significantly improved classification performance. This study concluded that needing a longer time to file accounts after the year end is associated with a higher probability of difficulties. It was also stated that firms which have an audit qualification are more prone to failure, based on the indication that the long-term viability is in some doubt.

The study of Madrid-Guijarro, Garcia-Perez-de-Lema & van Auken (2011) analysed factors affecting the external and internal environment of the firm and their impact on financial distress. They showed that high competition among existing firms in the industry and high bargaining power of customers increase the probability of distress. A higher technological level was negatively associated with bankruptcy. The overall conclusion of the study was that some strategic variables have a close association with financial distress. Iazzolino, Migliano & Gregorace (2013) investigated the contribution of intellectual capital (human capital, structural capital, relational capital) for the purposes of aiding prediction. Intellectual capital showed a contribution for credit risk decisions and was useful for the classification of defaulted and non-defaulted firms. The general conclusion followed that of the aforementioned studies, namely that a scoring model should include financial and non-financial information in order to improve prediction accuracy and model quality.

The inclusion of employee-related ratios – these are ratios where certain variables concerning employees and their associated costs (e.g. number of employees, ln(number of employees), sales/number of employees, EBIT/employee costs etc.) are considered – was not analysed extensively within research. The review of 238 papers related to the task of crises and insolvency prediction revealed that only in a few studies were such ratios included in the starting base (i.e. a catalogue of potential explanatory variables), but hardly any of these were detected as having discriminatory power to divide between failed and non-failed firms. In situations of financial distress or crisis, entrepreneurs try to improve the company´s results through various measures, and cost cutting seems to be one of the most effective measures undertaken in this regard. Firms which recovered from crisis had improved their operating performance through cost rationalization, lay-offs, closures and the integration of business units (Sudarsanam & Lai, 2001; Pretorius, 2008). Unsuccessful enterprises are mostly unable to exploit these opportunities due to different circumstances. This includes the inability to efficiently use employee resources.

The professional and economic use of staff seems important for corporate success and it also depends on management qualities as to how well these aspects are fulfilled. It is possible for companies to increase EBIT via tight control of labor costs (Kim & Gu, 2006). Therefore, ratios associated and related to employee-figures could be seen as a measurement of management efficiency. It is worth attempting to analyse this aspect by using employee-related ratios from prior research, but also with some new ratios which have not been used as potential explanatory variables in previous studies. Before this, some results from papers are presented where employee-related ratios were considered, where differing results were obtained concerning their suitability as predictors for insolvencies and crises.

Bruse (1978) conducted one of the first studies which considered employees for the prediction of the potential growth of a company. He explicitly analysed growing and nongrowing firms in Germany and developed a model that was able to distinguish between these two types of firms. The ratios sales/number of employees and staff costs/sales can be found within his starting catalogue. Only the second ratio showed the ability to forecast corporate growth alongside ratios of liquidity and turnover. Within the work of Gebhardt (1980), three employee-related ratios were defined as starting variables. These were staff costs/sum of costs, staff costs/revenues and value added/staff costs. None of these variables displayed statistical significance within univariate and multivariate analyses and were therefore not considered to act as predictors to distinguish between failed and non-failed firms.

Wilson, Chong & Peel (1995) analysed the ability of the ratio of directors remuneration/employee remuneration to act as a discriminatory variable within a logistic model for the distinction between failed and distressed acquired firms. The resulting negative sign signifies that the more directors earn relative to staff, the more likely it is that a firm can be assigned as distressed acquired. No specific explanation was given within their work for this occurrence. Within the studies of Lennox (1999a and 1999b), the number of employees appeared as a relevant variable for discrimination between failed and non-failed firms. This ratio can be seen as a proxy for the size of the firm. Small firms and indirectly, firms with a low number of employees, are more likely to fail. This aspect confirms results from studies before and after Lennox, where the size of the firm played a crucial role for discrimination between bankrupt and non-bankrupt firms, even if size was sometimes measured by using different variables (Altman, Haldeman & Narayanan, 1977; Ohlson, 1980; Theodossiou, Kahya, Saidi & Phillipatos, 1996; Dawley, Hoffman & Brockman, 2003; Bhattarcharjee, Higson, Holly & Kattuman, 2009; Chancharat, Tian, Davy, McCrae & Lodh, 2010; Pervan & Visic, 2012; Situm, 2014).

Within the work of Whitaker (1999), a more complex ratio was constructed for the prediction of a company's recovery from financial distress. The ratio was defined as number of employees/total assets (following year)/number of employees/total assets (pre-distress year). A decrease in the number of employees can help firms to recover and can therefore provide valuable signals concerning the economic health of a firm. Gudmundsson (2002) investigated the potential role of specific variables for the prediction of bankruptcy in the airline industry. Three non-financial ratios were included in the analyses: Number of pilots per aircraft, number of employees per aircraft and number of hours flown per pilot. Only the second variable showed statistical significance with a positive sign. This meant that non-distressed airlines exhibited a lower value compared to distressed ones. The fewer employees used per aircraft in action, the lower the probability of failure.

Neves & Vieira (2004) found that the ratio percentage of value added for employees and value added per employee were explanatory variables for the discrimination between bankrupt and non-bankrupt companies. The second variable was one of the most significant signals for financial distress. Distressed firms showed much lower values for value added compared to non-distressed firms. The ability of this variable to act as a predictor was also found within the studies of Nam, Kim, Park & Lee (2008) and Lin, Wang, Wu & Chuang (2009). Yim & Mitchell (2007) analysed the ratio of sales/employees within their study to distinguish between failed and non-failed firms in the financial industry. It showed no significance and therefore did not appear as a predictor within their forecasting model. Nam, Kim, Park & Lee (2008) used the growth rate of added value/employee as a potential variable and recognized that it does not have any discriminatory power.

Wetter and Wennberg (2009) analysed the effect of human and social capital on a firm's performance and the ability of related measures to assist in the prediction of bankruptcies. Their conclusion was that these factors have the discriminatory power to divide between successful and unsuccessful firms. Bartual, Garcia, Gimenez & Romero-Civera (2012) began their analyses with two employee-related variables: sales/personnel expenses and sales/(financial expenses + personnel expenses). Only the second variable was statistically significant and therefore suitable to discriminate between failed and non-failed firms. Firms exhibiting a higher value of this ratio are more stable and therefore less vulnerable to problems. Resistance against crises and bankruptcies can be optimized by an increase in sales and the reduction of personnel expenses.

In summary, it can be concluded that the focus in research on employee-related ratios within business failure and insolvency prediction is relatively low when compared to the numerous studies conducted in this field. Due to this lack of analysis concerning these ratios as potential predictors, it is interesting and useful to conduct a separate study where some of the existing, but also some new, as-yet unanalysed ratios is investigated, which were not considered within prior research. From reviewing the literature, it can be expected that some variables will show discrimination ability whereas others will not. This will be the main task of this paper, but also attention will be given to the contribution of each variable concerning the identification of the corporate economic situation.

3. RESEARCH HYPOTHSES AND QUESTIONS

Based on the findings from previous literature, it seems that some financial statement figures and other employee-related ratios have a certain explanatory power for the event of bankruptcy. Firms in financial distress need to implement turnaround activities in order to recover. Employees are a cost factor affecting financial statement figures and it is generally possible from a practical viewpoint to improve different ratios through a reduction of the costs associated with employees. Generally, it is expected that firms with an ineffective use of employees and high staff costs are more likely to become bankrupt.

H1: The higher the proportion between staff costs to sales, the higher the probability of insolvency.

H2: When employee-related ratios are added to prediction models with "traditional" accounting ratios, then the prediction performance of such models can be improved.

H3: The number of employees and associated ratios with the number of employees are potential proxies for the size of the firm.

The third hypothesis is of relevance due to prior studies, where the variable number of employees and ln(number of employees) were found to be proxies for the size of the firm. In previous research, attempts to find other proxies for the size of the firm associated with the number of employees were not made, with the result that this approach is something new in comparison to prior research. Additionally, several research questions shall be answered with the empirical data of this study. First, how can employee-related ratios contribute to early detection of corporate crises and bankruptcies? Second, which of the employee-related ratios are potential predictors for the construction of a business failure prediction model? Last, can the inclusion of such factors be helpful to improve the prediction accuracy of an insolvency prediction model?

4. DATABASE

The database for this study consists of Austrian companies divided into the categories bankrupt and non-bankrupt. The observation period ranges from the years 2003 to 2004. The selected firms were not matched pairwise, as in many other previous studies due to several problems with this selection technique. An attempt was made to obtain a sample which is representative of the whole population. Thomas, Edelman and Crook (2002) propose such an approach. Nevertheless, this procedure also provides problems in terms of statistical estimation. If too few bankrupt firms are present in the sample, then their proportion is underestimated and developed models are much better at detecting non-bankrupt firms. First, a random initial sample was selected for the observation period. Here, 17 bankrupt firms were found from a database for the period 2003 and 2004. Then a random sample of non-bankrupt firms was chosen for the same period for 170 companies. Therefore, the proportion between non-bankrupt and bankrupt firms is 10:1. Similar proportions had also been used within different prior studies (Baetge, Beuter & Feidicker, 1992; Begley, Ming & Watts, 1996; Lennox, 1999a; Lennox, 1999b; Shah & Murtaza, 2000; Paradi, Asmild & Simak, 2004; Hol, 2007; Iazzolino, Migliano & Gregorace, 2013; Chaudhuri, 2013)

Second, a random test sample was obtained in order to assess the performance of the developed models and their ability to be used for practical purposes. Here, 10 bankrupt and 100 non-bankrupt firms were chosen randomly. The composition of the firms within the different samples is presented in *table 1*.

Table 1: *Composition of firms in initial and validation samples*

	2003 [two years prior to bankruptcy]		**2004** [one year prior to bankruptcy]	
	Bankrupt	Non-bankrupt	Bankrupt	Non-bankrupt
initial sample	17	170	17	170
test sample	10	100	10	100

5. METHODOLOGY AND RESEARCH DESIGN

In order to test the research hypotheses and research questions, different statistical tests and applications were applied within this study. First, descriptive statistics for the bankrupt and non-bankrupt companies were computed. Second, a test for normality based on Kolmogorov-Smirnov was applied, in order to determine whether the selected ratios were normally distributed. Normally distributed data are an important theoretical pre-condition for the application of multivariate linear discriminant analysis. Third, the differences in means, medians and variances for the two groups were analysed, in order to detect whether there are differences between the two groups in the variables. This analysis shall determine which of the variables are the most effective for discriminating between bankrupt and non-bankrupt companies. Fourth, a correlation analysis was computed to recognize how the variables are correlated with each other. This application was complemented by a factor analysis, where the loadings of the variables to certain factors were determined.

Last, multivariate linear discriminant functions were computed which are suitable to divide *a posteriori* between failed and non-failed companies two years and one year prior to the event of bankruptcy. In order to test the incremental informational content of employee-related ratios, three types of functions were computed for this purpose. These are functions containing only traditional ratios, only employee-related ratios and a combination of both. The validity of the models was then tested with the companies from the test group. The quality and accuracy of the models was evaluated using appropriate performance measures.

6. SELECTION OF VARIABLES

The variables for the purpose of this study were selected based on their appearance in previous literature. As already stated in this paper, variables related to employees have not been extensively analysed in prior studies. Some traditional ratios and some employee-related were therefore selected. Following accounting variables appeared relatively often in previous studies:

- **Total Equity/Total Assets**
  (Laitinen & Laitinen, 2000; Grunert, Norden & Weber, 2005; Pompe & Bilderbeek, 2005; Shin, Lee & Kim, 2005; Min & Lee, 2005, Muller, Steyn-Bruwer & Hamman, 2009; Bartual, Garcia, Gimenez & Romero-Civera, 2012)
- **Total Debt/Total Assets**
  (Ohlson, 1980; Zmijewski, 1984; Frydman, Altman & Kao, 1985; Pacey & Pham, 1990; Bryant, 1997; Doumpos & Zopounidis, 1998; Andandarajan, Lee & Anandarajan, 2001; Brabazon & Keenan, 2004; Neves & Vieira, 2006; Pervan & Kuvek, 2013; Chaudhuri, 2013).
- **EBIT/Total Assets**
  (Altman, 1968; Gilbert, Menon & Schwartz, 1990; Coats & Fant, 1993; Altman & Saunders, 1998; Grunert, Norden & Weber, 2005; Chen, Marshall, Zhang & Ganesh, 2006; Li & Sun, 2011; Bartual, Garcia, Gimenez & Romero-Civera, 2012; Iazzolino, Migliano & Gregorace, 2013)

- **Ln(Total Assets)**
  (Ohlson, 1980; Frydman, Altman & Kao, 1985; Barniv & Raveh, 1989; Whitaker, 1999; Chi & Tang, 2006; Pervan & Visic, 2012, Situm, 2014)
- **Ln(Sales)**
  (Chancharat, Tian, Davy, McCrae & Lodh, 2010; Situm, 2014)

Additionally, the following ratios were included within this study which were derived partly from previous literature. Also displayed are new ratios which have not been analysed in this form within prior research. Several of them contain figures related to employees.

Table 2: *Additional ratios for analysis*
Ratios on the right side are defined as "new", because these ratios were not found to be considered as potential prediction variables based on an extensive literature review of 238 papers related to the topic of crisis- and insolvency prediction

Ratios found in previous research	"new" ratios not found to be used in previous research
Sales/Total Assets [Altman, 1968; Brabazon & Keenan, 2004; Dietrich, Arcelus & Srinivasan, 2005; Bartual, Garcia, Gimenez & Romero-Civera, 2012; Tsai, 2013]	Ln(Sales/Total Assets)
Ln(Number of Employees) [Situm, 2014]	Ln(Sales/Number of Employees)
Staff Costs/Sales [Bruse, 1978; Gebhardt, 1980]	Ln(Staff Costs/Number of Employees)
EBIT/Sales [Marchesini, Perdue & Bryan, 2005]	EBITDA/Staff Costs
Sales/Staff Costs [inverse relation to the ratio staff costs/sales based on Bruse, 1978; Gebhardt, 1980]	EBIT/Staff Costs

7. STATISTICAL ANALYSES

7.1 Descriptive statistics

Table 3 provides the means, medians and standard deviations for the chosen variables for two years and one year prior to bankruptcy. The mean of total equity/total assets deteriorated for bankrupt firms from 2003 to 2004, which indicates that bankrupt firms incur additional losses as insolvency approaches. Firms in financial trouble are financing their operating business with liabilities, with the result that they are exhibiting much higher leverage ratios in mean and median than solvent firms. Ln(sales), ln(number of employees) and ln(total assets) are all measures associated with the size of the firm. All three variables showed higher means for the solvent firms in comparison to the bankrupt firms for the two observation periods. This indicates that bankrupt firms are in mean, but also in median, smaller than non-bankrupt ones. Staff costs/sales are much lower for solvent firms in mean, which indicates that employee-resources are used more efficiently by financially healthy companies. Higher efficiency of non-bankrupt firms can also be argued by the ratios EBITDA/staff costs, EBIT/staff costs and EBIT/Sales. These variables showed in mean and in median higher values for non-bankrupt than for bankrupt firms.

Table 3: *Descriptive statistics*

		2003 [two years prior to bankruptcy]			**2004** [one year prior to bankruptcy]		
Ratio	**Class**	**Mean**	**Median**	**Stand.-Dev.**	**Mean**	**Median**	**Stand.-Dev.**
Total Equity/ Total Assets	0	-0.062	0.056	0.549	-0.851	-0.330	1.468
	1	0.153	0.177	0.510	0.223	0.193	0.295
Total Debt/ Total Assets	0	1.062	0.944	0.549	1.851	1.330	1.468
	1	0.848	0.823	0.510	0.777	0.807	0.295
Sales/Total Assets	0	2.492	1.694	2.492	1.832	1.238	2.068
	1	1.800	1.386	1.527	1.693	1.301	1.485
ln(Sales/Total Assets)	0	0.225	0.527	1.777	-0.007	0.214	1.271
	1	0.143	0.326	1.171	0.088	0.263	1.102
ln(Sales)	0	11.221	11.235	1.412	11.390	11.549	1.100
	1	12.071	11.988	1.243	12.237	12.031	1.205
ln(Number of Employees)	0	3.418	3.689	1.175	2.687	2.639	1.309
	1	3.834	4.025	1.715	3.749	3.912	1.537
ln(Sales/ Number of Employees)	0	11.221	11.235	1.412	11.390	11.549	1.100
	1	12.071	11.988	1.243	12.237	12.031	1.205
ln(Staff Costs/ Number of Employees)	0	10.346	10.409	0.542	10.481	10.627	0.591
	1	10.676	10.681	0.726	10.690	10.686	0.615
Staff Costs/ Sales	0	3.736	0.325	13.810	0.840	0.367	1.500
	1	0.430	0.274	0.843	0.347	0.262	0.474
Sales/Staff Costs	0	4.188	3.076	4.444	4.198	2.728	6.051
	1	7.130	3.653	11.442	11.982	3.817	34.833
EBITDA/ Staff Costs	0	-0.152	0.107	1.288	-0.503	-0.230	1.514
	1	0.509	0.221	1.571	1.184	0.324	4.072
EBIT/Staff Costs	0	-0.251	0.036	1.284	-0.695	-0.312	1.463
	1	0.021	0.102	2.070	0.770	0.162	3.354
EBIT/Sales	0	-17.311	0.017	71.301	-1.507	-0.058	4.217
	1	-1.254	0.027	15.052	0.043	0.033	0.291

		2003 [two years prior to bankruptcy]			2004 [one year prior to bankruptcy]		
Ratio	**Class**	**Mean**	**Median**	**Stand.-Dev.**	**Mean**	**Median**	**Stand.-Dev.**
EBIT/Total Assets	0	-0.077	0.024	0.292	-0.531	-0.040	0.994
	1	-0.048	0.034	0.909	0.056	0.045	0.163
ln(Total Assets)	0	14.415	14.831	1.126	14.084	14.735	1.783
	1	15.762	15.743	1.807	15.898	15.735	1.742

7.2 Test for normality of data

The test of normality based on Kolmogorov-Smirnov at the 5 percent level is reported in *Table 4*. Normality of data cannot be assumed for the majority of the variables. The only variable which showed normality for both groups and for both time periods is ln(number of employees). Similarly, ln(total assets) showed normal distribution for both groups of firms, but only two periods prior to the event of insolvency. As within this study multivariate linear discriminant analysis has been applied, the occurrence of non-normal data could be a problem for model building, due to the risk that classification accuracy can be affected (Hopwood, McKeown & Mutchler, 1988; Klecka, 1989; Subhash, 1996; Keasey & Watson, 1991). This is not an extreme problem however, when departures from normality are only at a low level (Hopwood, McKewon & Mutchler, 1988; Silva, Stam & Neter, 2002; Feldesman, 2002). For some constellations of probability distribution, a departure can also be beneficial for improved discrimination between both groups, so that better classification accuracies can be achieved in comparison to logistic regression (Pohar, Blas & Turk 2004).

Table 4: *Kolmogorov-Smirnov test for normality of data*
Values in bold denote normally distributed data at 5 percent significance level

		2003 [two years prior to bankruptcy]			2004 [two years prior to bankruptcy]		
Ratio	**Class**	**Statistic**	**Sign.**	**Skewness**	**Statistic**	**Sign.**	**Skewness**
Total Equity/ Total Assets	0	.361	.000	-3.344	.263	.003	-1.724
	1	.253	.000	-4.526	.123	.000	-0.672
Total Debt/ Total Assets	0	.361	.000	3.344	.263	.003	1.724
	1	.253	.000	4.527	.123	.000	0.672
Sales/Total Assets	0	.201	**.065**	1.963	.252	.005	2.010
	1	.120	.000	1.834	.142	.000	1.884
ln(Sales/Total Assets)	0	.209	.046	-2.486	.142	**.200**	-0.571
	1	.113	.000	-1.654	.116	.000	-1.153
ln(Sales)	0	.201	**.067**	-1.587	.182	**.138**	0.275
	1	.072	.030	0.579	.093	.001	0.755
ln(Number of Employees)	0	.135	**.200**	-0.969	.119	**.200**	-0.294
	1	.060	**.200**	0.199	.056	**.200**	0.075

		2003 [two years prior to bankruptcy]			**2004** [two years prior to bankruptcy]		
Ratio	**Class**	**Statistic**	**Sign.**	**Skewness**	**Statistic**	**Sign.**	**Skewness**
ln(Sales/ Number of Employees)	0	.201	**.067**	-1.587	.182	**.138**	0.275
	1	.072	.030	0.579	.093	.001	0.755
ln(Staff Costs/ Number of Employees)	0	.137	**.200**	0.105	.131	**.200**	-1.156
	1	.128	.000	1.373	.101	.000	-0.652
Staff Costs/Sales	0	.519	.000	4.121	.420	.000	3.077
	1	.309	.000	8.385	.234	.000	6.871
Sales/Staff Costs	0	.277	.001	2.441	.370	.000	3.752
	1	.270	.000	5.465	.368	.000	6.974
EBITDA/Staff Costs	0	.365	.000	-3.745	.212	.040	-1.635
	1	.234	.000	4.662	.368	.000	6.120
EBIT/Staff Costs	0	.394	.000	-3.834	.249	.006	-1.869
	1	.313	.000	-5.735	.364	.000	6.536
EBIT/Sales	0	.536	.000	-4.123	.434	.000	-3.350
	1	.478	.000	-12.954	.280	.000	-4.890
EBIT/Total Assets	0	.268	.002	-2.275	.273	.002	-1.929
	1	.370	.000	-11.711	.174	.000	-0.320
ln(Total Assets)	0	.173	**.185**	-0.271	.172	**.196**	-0.690
	1	.067	**.060**	0.155	.076	.017	0.657

The problem of non-normal data appeared in several studies (Hauschildt, Rößler & Gemünden, 1984; Pacey & Pham, 1990; Barniv & McDonald, 1992; Baetge, Beuter & Feidicker, 1992; Lennox, 1999a; Chi & Tang, 2006; Yim & Mitchell, 2007; Samad, Yusof & Shaharudin, 2009), where this aspect was handled differently. Additionally, the approach of logistic regression should be more sound, as it does not demand normally distributed data, but several studies showed that this method is not generally able to deliver superior classification results when compared to multivariate linear discriminant analysis (Gentry, Newbold & Whitford, 1985; Gombola, Haskins, Ketz & Williams, 1987; Barniv & Raveh, 1989; Pacey & Pham, 1990; Barniv & McDonald, 1992; Neophytou & Mar Molinero, 2004; Kim & Gu, 2006).

The aim of this study is not to develop a forecasting model. This study aims to test the potential prediction power of employee-related ratios in order to differentiate between bankrupt and non-bankrupt firms. Despite the non-normality of data being a given, multivariate linear discriminant analysis can nevertheless be used for such an attempt (Feldesman, 2002; Neophytou & Mar Molinero, 2005; Kim & Gu, 2006). Therefore, further progress was conducted without outlier deletion techniques or attempts concerning the normalization of data. Nevertheless, it must be kept in mind that this theoretical pre-condition is generally violated and that this may be attributable to weaker model quality and classification results. This aspect is also discussed within the section covering the limitations of the study.

7.3 Tests for differences in means and variances

A test for differences in means and in variances at 5 percent level can be applied to detect the variables with the highest potential as discriminators between the two groups of companies. Mainly due to non-normally distributed data additionally, a U-test was considered (Ho, 2006, p. 357 and 368). In this case it is the more suitable method for decision and evaluation, and the results from the two aforementioned methods are displayed for informational purposes. The results are presented in the *Tables 5* and *6*. Many more variables can be found for the period one year prior to bankruptcy, which indicates that the signalling power increases as the event of bankruptcy approaches. This is in congruence with the generally accepted view that early detection is much more difficult (i.e. the signals are much weaker or less forthcoming) when the distance in time to the event of bankruptcy increases (Altman, 1968; Blum, 1974; Altman, Haldeman & Narayanan, 1977; Dambolena & Khoury, 1980; Mensah, 1984; Barniv & McDonald, 1992; Lennox 1999a; Laitinen & Laitinen, 2000; Chi & Tang, 2006; Korol & Korodi, 2011). According to the results, certain variables remain, which could act as potential predictors for the models.

Table 5: *Parametric and non-parametric test for differences two years prior to bankruptcy*
Values in bold denote statistically significant differences at the 5 percent level

	2003 [two years prior to bankruptcy]					
	t-test		**Levene-test**		**U-Test**	
Variables	**T**	**Sign.**	**F**	**Sign.**	**U**	**Sign.**
Equity/Total Assets	-1.646	0.102	0.118	0.731	914.000	**0.013**
Total Debt/Total Assets	1.644	0.102	0.119	0.730	914.000	**0.013**
Sales/Total Assets	1.664	0.098	5.483	**0.020**	1252.000	0.364
ln(Sales/Total Assets)	0.261	0.794	1.377	0.242	1252.000	0.364
ln(Sales)	-2.654	**0.009**	0.031	0.860	955.000	**0.021**
ln(Number of Employees)	-0.974	0.331	2.806	0.096	1237.500	0.329
ln(Sales/Number of Employees)	-2.654	**0.009**	0.031	0.860	955.000	**0.021**
ln(Staff Costs/ Number of Employees)	-1.817	0.071	0.136	0.713	916.000	**0.013**
Staff Costs/Sales	3.139	**0.002**	41.265	**0.000**	1176.000	0.206
Sales/Staff Costs	-1.050	0.295	1.877	0.172	1176.000	0.206
EBITDA/Staff Costs	-1.677	0.095	0.161	0.689	1014.000	**0.043**
EBIT/Staff Costs	-0.531	0.596	0.099	0.754	1132.000	0.141
EBIT/Sales	-2.482	**0.014**	25.694	**0.000**	1086.000	0.092
EBIT/Total Assets	-0.130	0.897	0.027	0.870	1200.000	0.250
ln(Total Assets)	-3.010	0.003	1.869	0.173	720.000	**0.001**

All of the significant variables in 2003 based on U-test (the only exception is ln(staff costs/number of employees) are also statistically significant at the 5 percent level in 2004. This indicates that these ratios are able to provide much earlier warning signals concerning the economic situation of the firm. In 2004, four additional ratios showed discriminatory power to make a distinction between the two types of firms (ln(number of employees), EBIT/staff costs, EBIT/sales and EBIT/total assets). All other ratios are insignificant and can therefore be excluded from further analysis. A more profound insight can be achieved using correlation and factor analysis.

Table 6: *Parametric and non-parametric test for differences one year prior to bankruptcy*
Values in bold denote statistically significant differences at the 5 percent level

	2004 [one year prior to bankruptcy]					
	t-test		**Levene-test**		**U-Test**	
Variables	**T**	**Sign.**	**F**	**Sign.**	**U**	**Sign.**
Equity/Total Assets	-8.194	**0.000**	119.091	**0.000**	574.000	**0.000**
Total Debt/Total Assets	8.194	**0.000**	119.091	**0.000**	574.000	**0.000**
Sales/Total Assets	0.353	0.724	1.818	0.179	1377.000	0.749
ln(Sales/Total Assets)	-0.334	0.739	0.827	0.364	1377.000	0.749
ln(Sales)	-2.784	**0.006**	0.639	0.425	853.000	**0.005**
ln(Number of Employees)	-2.748	**0.007**	0.430	0.513	870.500	**0.007**
ln(Sales/Number of Employees)	-2.784	**0.006**	0.639	0.425	853.000	**0.005**
ln(Staff Costs/ Number of Employees)	-1.340	0.182	0.067	0.796	1202.000	0.253
Staff Costs/Sales	3.065	**0.003**	23.353	**0.000**	1051.000	0.064
Sales/Staff Costs	-0.918	0.360	1.858	0.175	1051.000	0.064
EBITDA/Staff Costs	-1.693	0.092	0.375	0.541	846.000	**0.005**
EBIT/Staff Costs	-1.781	0.077	0.097	0.756	770.000	**0.002**
EBIT/Sales	-4.795	**0.000**	77.533	**0.000**	846.000	**0.005**
EBIT/Total Assets	-6.968	**0.000**	110.293	**0.000**	734.000	**0.001**
ln(Total Assets)	-4.085	**0.000**	0.667	0.415	699.000	**0.000**

7.4 Correlation analysis and factor analysis

The complete results of correlation analysis based on Pearson for the two years prior to the event of bankruptcy can be found in the appendix of this work. Within *Tables 7* and *8*, the correlations for the most relevant variables based on U-test are reported. The general results show some highly positive and significant correlations between variables, which imposes multicollinearity. This occurrence can affect the discrimination power of models when such variables are included within prediction models (Hosmer & Lemeshow, 2000; Thomas, Edelman & Crook, 2002; Silva, Stam & Neter, 2002; Wooldridge, 2006; Asteriou & Hall, 2007). Multicollinearity can therefore be assumed for the following constellations:

- Ln(sales) and ln(sales/number of employees) for both years
- Total equity/total assets and EBIT/total assets for 2004
- EBITDA/staff costs and EBIT/staff costs for 2004

This implies that not all of these variables should be used for model building, because information redundancy is taken as a given. Besides this, there are several negative correlations which are potentially interesting for model building.

Table 7: *Correlation analysis for two years prior to bankruptcy*
Values in bold denote statistically significant correlations at the 1 percent level

	Equity/Total Assets	Total Debt/Total Assets	ln(Sales)	ln(Sales/Number of Employees	ln(Staff Costs/ Number of Employees)	EBITDA/Staff Costs	ln(Total Assets)
Equity/Total Assets	1	**-1.000**	**.273**	**.273**	.087	**.343**	**.316**
Total Debt/Total Assets		1	**-.273**	**-.273**	-.087	**-.343**	**-.316**
ln(Sales)			1	**1.000**	**.547**	**.370**	**.334**
ln(Sales/Number of Employees)				1	**.547**	**.370**	**.334**
ln(Staff Costs/ Number of Employees)					1	.066	**.239**
EBITDA/Staff Costs						1	**.331**
ln(Total Assets)							1

Table 8: *Correlation analysis for one year prior to bankruptcy*
Values in bold denote statistically significant correlations at the 1 percent level

	Equity/Total Assets	Total Debt/Total Assets	ln(Sales)	ln(Number of Employees)	ln(Sales/Number of Employees	EBITDA/Staff Costs	EBIT/Staff Costs	EBIT/Sales	EBIT/Total Assets	ln(Total Assets)
Equity/Total Assets	1	**-1.000**	**.194**	**.237**	**.194**	.080	.103	**.488**	**.775**	**.360**
Total Debt/Total Assets		1	**-.194**	**-.237**	**-.194**	-.080	-.103	**-.488**	**-.775**	**-.360**
ln(Sales)			1	**-.253**	**1.000**	.285	**.251**	**.238**	**.198**	**.321**
ln(Number of Employees)				1	**-.253**	**-.273**	**-.242**	.076	.125	**.633**
ln(Sales/Number of Employees)					1	**.285**	**.251**	**.238**	**.198**	**.321**
EBITDA/Staff Costs						1	**.952**	**.172**	**.231**	.085
EBIT/Staff Costs							1	**.187**	**.276**	.048
EBIT/Sales								1	**.453**	.097
EBIT/Total Assets									1	**.195**
ln(Total Assets)										1

Further insight into the ability of the ratios is provided with factor analysis based on Varimax-rotation. For the period two years prior to bankruptcy, two factors were extracted. These factors are able to explain over 70.7 percent of the variances between the related variables. Ln(sales) shows a high loading on the first factor, which is the same for the ratio ln(sales/number of employees). As the first ratio is associated with the size of the firm, this factor could be assigned as a "size factor". Therefore the second ratio seems to be a good proxy for this aspect too. This is also valid for the variable ln(staff costs/number of employees).

The second factor is driven mainly by the variable equity/total assets ratio, which indicates that this factor can be assigned as the "capital structure". Here, total debt/total assets is loaded with the same value as the equity-ratio, but with a negative sign, which was expected based on correlation analysis. The relation between EBITDA/staff costs, which could be assigned as a measure of efficiency, is also loaded on this factor, so that here the aspects of profitability and efficiency are additionally included. It is interesting to note that ln(total assets) is mainly loaded on the second factor, even if it is a measure of size.

Table 9: *Factor analysis for two years prior to bankruptcy*

	Factors	
	1	**2**
Cumulated explained variances in %	35.9935564	70.7114292
Equity/Total Assets		,964
Total Debt/Total Assets		-,964
ln(Sales)	,924	,238
ln(Sales/Number of Employees)	,924	,238
ln(Staff Costs/Number of Employees)	,757	
EBITDA/Staff Costs	,309	,512
ln(Total Assets)	,374	,441

The results of factor analysis for one year prior to bankruptcy exhibited four factors. The first factor is related to "capital structure and profitability", where the equity-ratio showed the highest loading. The second and fourth factor can both be associated with the "size of the firm". It is interesting to note that ln(total assets) gained a higher value one year prior to the event of bankruptcy and showed a much higher loading. Here it is dominant and responsible for the formation of the fourth factor. The third factor shows "efficiency" in the usage of staff within the firm, where it is measured by different types of earnings. The general conclusion of factor analysis is in congruence with the results from correlation analysis in that certain variables will not appear within the models due to multicollinearity, even if they showed discriminatory power based on the U-test. To answer which variables these will be, several multivariate linear discriminant analyses based on a step-wise method were applied.

Table 10: *Factor analysis for one year prior to bankruptcy*

	Factors			
	1	**2**	**3**	**4**
Cumulated explained variances in %	30.3933421	51.9858626	72.080472	88.8199957
Equity/Total Assets	.938			.210
Total Debt/Total Assets	-.938			-.210
ln(Sales)	.134	.978	.132	
ln(Number of Employees)	.129	-.282	-.196	.872
ln(Sales/Number of Employees)	.134	.978	.132	
EBITDA/Staff Costs		.152	.971	
EBIT/Staff Costs	.119	.105	.972	
EBIT/Sales	.659	.156		
EBIT/Total Assets	.865		.184	
ln(Total Assets)	.150	.309		.901

8. MODEL BUILDING

Resulting from the preliminary analyses, it is now possible to construct prediction models based on multivariate linear discriminant analysis for the two periods prior to bankruptcy. This method is used here to determine the prediction ability of employee-related ratios as potential indicators for the distinction between bankrupt and non-bankrupt firms. It cannot be expected that the models obtained will provide good classification results nor that they will show a good model quality, due to the violations of certain theoretical assumptions for the correct application of linear discriminant analysis. Within this research, the technique of Mahlanobis distance is used for the construction of the classification functions, where a stepwise method is applied. First, only "traditional" ratios will be used for model building, which do not have any association with the number of employees or to staff costs. Second, models fed with all variables will be computed so that the incremental informational content of employee-related ratios for the task of prediction can be assessed. Third, only models containing employee-related variables were calculated in order to determine the predictive ability of these ratios. Last, the models were then tested on the firms of the validation group, in order to evaluate their potential for practical purposes and to assess model stability.

The relevant statistical ratios concerning pre-analysis for discriminant models are shown in *Table 11*. Based on Box-test, the significances are less than 0.05 for the first two model types, meaning that equality of variance-co-variance matrices cannot be assumed (Burns & Burns, 2008, p. 598). This is a violation of another theoretical pre-condition for the application of linear discriminant analysis, which can affect the prediction accuracy of classification functions (Feldesman, 2002). The only exception is apparent in the model using only employee-related ratios for the period 2003 and 2004. Here, this pre-condition was fulfilled so that a better model fit could be expected. Based on the Wilks-Lambda model, quality of discriminant functions can be assessed. The significances are all below 0.05, so that the discriminant functions are significantly discriminating between the two groups of firms. A classification with the functions is more reliable than a random assignment of the firms into the two groups.

Even if this aspect is taken as a given, based on the value of Wilks-Lambda there remains a large proportion of unexplained variances between the two groups of firms. For the model containing only "traditional" ratios/all ratios in 2004, the unexplained variance was about 73.4 percent, which is much lower than for the other models. This result indicates that the chosen ratios are not in the position to fully explain or describe how bankrupt and non-bankrupt firms differ in this regard. There is the need to consider additional ratios and variables, which need not be accounting ratios at all, so that model quality and performance can be improved. This conclusion is in congruence with the generally accepted views in research (Grunert, Norden & Weber, 2006; Muller, Steyn-Bruwer & Hamman, 2009; Altman, Sabato & Wilson, 2010; Madrid-Guijarro, Garcia-Perez-de-Lema & van Auken, 2011; Iazzolino, Migliano & Gregorace, 2013).

Table 11: *Pre-analysis for discriminant models*

	Models with "traditional" ratios		Models with all ratios		Models with "employee-related" ratios	
	2003	**2004**	**2003**	**2004**	**2003**	**2004**
Box-M	5.079	155.604	5.079	155.604	.511	2.335
Sign.	.026	.000	.026	.000	.479	.527
Wilks Lambda	.953	.734	.953	.734	.963	.894
Sign.	.003	.000	.003	.000	.009	.000

The related discriminant functions are shown in the following equations. These are the models with the best model fit. The abbreviations are defined as T = traditional model, A = all ratios model and E = employee-related model and the numbers in parenthesis denote the respective year:

$$Z_{T(2003)} = -6.568 + 0.435 \times \ln(Total\ Assets) \quad (1)$$

$$Z_{T(2004)} = 1.271 + 4.044 \times \frac{Total\ Equity}{Total\ Assets} \quad (2)$$

$$Z_{A(2003)} = Z_{T(2003)} \quad (3)$$

$$Z_{A(2004)} = Z_{T(2004)} \quad (4)$$

$$Z_{E(2003)} = -6.249 + 0.537 \times ln\left(\frac{Sales}{Number\ of\ Employees}\right) \quad (5)$$

$$Z_{E(2004)} = -12.165 + 0.849 \times ln\left(\frac{Sales}{Number\ of\ Employees}\right) + 0.664 \times ln(Number\ of\ Employees) \quad (6)$$

As can be seen above, functions two and four, but also one and three are the same. With discriminant analysis, it was not possible to include an additional employee-related ratio to total equity/total assets (in 2004) and to ln(total assets) (in 2003) in order to improve the prediction accuracy of the model. The classification results for initial and validation sample are presented in the *Tables 12* and *13*. Generally, the functions did not provide satisfactory results, which is attributable to the factors of non-normally distributed data, inequality of covariance matrices (for the first two model types) and the composition of the samples itself, which will be discussed in a later section. Here, it must once again be pointed out that these aspects were ignored, as the purpose of this study was not to construct a prediction model. The aim is rather to investigate the predictive power of employee-related ratios for the distinction between bankrupt and non-bankrupt firms.

Table 12: *Classification results of discriminant models for initial sample*
Models with "traditional" ratios and models with all ratios contain the same combination of prediction variables for the respective year, so that there is no difference in the classification results between these two types of discriminant functions

			2003 [two years prior to bankruptcy]		**2004** [one year prior to bankruptcy]	
			Assignment		**Assignment**	
	bankrupt non-bankrupt		**bankrupt**	**non-bankrupt**		
Models with "traditional" ratios	Number of firms	bankrupt	11	6	9	8
		non-bankrupt	54	116	8	162
	%	bankrupt	64.71%	35.29%	52.94%	47.06%
		non-bankrupt	31.76%	68.24%	4.71%	95.29%
Models with all ratios	Number of firms	bankrupt	11	6	9	8
		non-bankrupt	54	116	8	162
	%	bankrupt	64.71%	35.29%	52.94%	47.06%
		non-bankrupt	31.76%	68.24%	4.71%	95.29%
Models with "employee-related" ratios	Number of firms	bankrupt	11	6	11	6
		non-bankrupt	66	104	50	120
	%	bankrupt	64.71%	35.29%	64.71%	35.29%
		non-bankrupt	38.82%	61.18%	29.41%	70.59%

The most relevant measurement for practical purposes is a type I error, which occurs when a bankrupt firm is assigned by the model as being non-bankrupt. Therefore, it is of interest to minimize this type of error. Models with high type I error are normally not suitable for practical purposes. In the case of the models developed, it can be seen that type I errors are relatively high, which is implied by the fact that the cut-off value between the two types of firms was set at zero. A firm having a lower value than zero was assigned as being bankrupt and otherwise it was assigned as non-bankrupt. Literature provides different methods of adjusting this cut-off point in order to minimize type I error, which will not be examined further within this work as it is not the purpose of this study.

Nevertheless, it is of interest to analyse the signs of the ratios within the equations, as they can provide some information about the probability of bankruptcy. Within equation one, the signs are consistent with expectations. The size of the firm was found in many studies to be a good discriminator between bankrupt and non-bankrupt firms (Ohlson, 1980; Theodossiou, Kahya, Saidi & Philippatos, 1996; McKee, 2007; Fitzpatrick & Ogden, 2011; Situm, 2014), and it is unsurprising that this variable also appeared as a discriminator within this study. Firms which are great in size are much less likely to go into bankruptcy.

The sign of total equity/total assets for equations two and four is also consistent with findings from prior literature (Laitinen & Laitinen, 2000; Grunert, Norden & Weber, 2005; Muller, Steyn-Bruwer & Hamman, 2009). Companies with a higher portion of equity are less likely to fail. The discriminatory power of this ratio in 2004 is not surprising, based on the preliminary U-test and its significance.

Table 13: *Classification results of discriminant models for validation sample*
Models with "traditional" ratios and models with all ratios contain the same combination of prediction variables for the respective year, so that there is no difference in the classification results between these two types of discriminant functions

			2003 [two years prior to bankruptcy]		**2004** [one year prior to bankruptcy]	
			Assignment		**Assignment**	
bankrupt non-bankrupt			**bankrupt**	**non-bankrupt**	**bankrupt**	**non-bankrupt**
Models with "traditional" ratios	Number of firms	bankrupt	4	6	5	5
		non-bankrupt	33	67	6	94
	%	bankrupt	40.00%	60.00%	50.00%	50.00%
		non-bankrupt	33.00%	67.00%	6.00%	94.00%
Models with all ratios	Number of firms	bankrupt	4	6	5	5
		non-bankrupt	33	67	6	94
	%	bankrupt	40.00%	60.00%	50.00%	50.00%
		non-bankrupt	33.00%	67.00%	6.00%	94.00%
Models with "employee-related" ratios	Number of firms	bankrupt	7	3	6	4
		non-bankrupt	40	60	29	71
	%	bankrupt	70.00%	30.00%	60.00%	40.00%
		non-bankrupt	40.00%	60.00%	29.00%	71.00%

The fifth equation, ln(sales/number of employees), appeared with a positive sign. This ratio indirectly replicates the size of the firm based on factor analysis, so that the direction of the sign follows the expectation. A higher value for this ratio improves the score of the discriminant functions and tends towards the assignment of a company as non-bankrupt.

Therefore, the greater the size of the firm, the less likely it will become bankrupt. This result is in congruence with the findings concerning the model comprising the traditional ratios. In equation six, ln(sales/number of employees) showed a positive sign. It can be defined as a measure of efficiency. The more sales with fewer employees that can be achieved, the more efficiently a firm can be said to be working. This efficiency contributed positively to discriminant value. Firms with higher efficiency are less likely to fail. Ln(number of employees) is a proxy for the size of the firm and therefore has a similar function to ln(total assets). Firms with a higher number of employees are greater in size and therefore have a lower probability of failure. This aspect is in congruence with results from previous literature (Situm, 2014). Therefore, the positive sign of this ratio satisfies expectations.

A significantly better comparison of the models can be reached when certain performance measures are computed (calculations were based on Metz, 1978; Fawcett, 2006; Anderson, 2007; Ooghe & Spaenjers, 2010). Based on AUC, it can be seen that the models one year prior to bankruptcy have a higher performance when compared to the models two years prior to bankruptcy. It is interesting to note that the results for validation sample in 2004 are quite good, and for the model with "traditional" ratios (and also for the model with all variables), they are better than for the initial sample. Nevertheless, type I error remains relatively high, but could be adjusted appropriately to achieve better results. The model containing only employee-related ratios in 2004 was slightly weaker in performance, but showed a better ability to correctly assign bankrupt firms due to lower type I error. The overall accuracy of this model in 2004 was relatively weak, which means that the model produced high type II errors. It must be emphasized again that the model with all variables is the same as the model with traditional ratios. Stepwise discriminant analysis was not able to include any of the employee-related variables in order to improve prediction accuracy. This occurrence leaves doubt about the incremental informational content of employee-related ratios for bankruptcy prediction.

Table 14: *Performance measures for the models*
Values in bold denote statistically insignificant values

	2004 [one year prior to bankruptcy]					
	Models with "traditional " ratios		**Models with all ratios**		**Models with "employee-related" ratios**	
	Initial	**Validation**	**Initial**	**Validation**	**Initial**	**Validation**
AUC	80,14%	83,60%	80,14%	83,60%	79,34%	76,60%
Accuracy	91,44%	90,00%	91,44%	90,00%	70,05%	70,00%
Type I Error	47,06%	50,00%	47,06%	50,00%	35,29%	40,00%
Type II Error	4,71%	6,00%	4,71%	6,00%	29,41%	29,00%

2003 [two years prior to bankruptcy]						
	Models with "traditional " ratios		**Models with all ratios**		**Models with "employee-related" ratios**	
	Initial	Validation	Initial	Validation	Initial	Validation
AUC	50.59%	43.90%	50.59%	43.90%	54.19%	58.10%
Accuracy	67.91%	64.55%	67.91%	64.55%	61.50%	60.91%
Type I Error	35.29%	60.00%	35.29%	60.00%	35.29%	30.00%
Type II Error	31.76%	33.00%	31.76%	33.00%	38.82%	40.00%

For the period two years prior to bankruptcy, the models delivered a weaker performance and in contrast to the models in 2004, the results for validation sample are weak. The AUC measures were all relatively low and not statistically significant. Therefore, none of the models in 2003 are suitable for practical purposes in the apparent combination. They mainly exhibited Gini coefficients below 0.5, and based on this measure their usefulness can be dismissed (Anderson, 2007, p. 205). It is assumed that it would also be possible here to adjust cut-off values to achieve an improved performance. It is noticeable that accuracies in 2003 are much lower than for 2004, which indicates that the informational content of the ratios is not strong enough for early detection of corporate crises. This is true for all analysed ratios in the course of this study. Such a statement also confirms the results from previous literature that the signalling power of predictors is weaker as the distance to the event of bankruptcy increases (Altman, 1968; Dambolena & Khoury, 1980; Lennox, 1999a; Laitinen & Laitinen, 2000; Chi & Tang, 2006; Korol & Korodi, 2011).

9. CONCLUSIONS

The results of this study provide some interesting conclusions concerning the suitability of employee-related ratios for the task of prediction. The models developed within this study did not show a satisfactory performance, which is attributable to different factors which will be highlighted within the next chapter. The signalling power for the period two years prior to bankruptcy was limited and the performance of the models was clearly inferior to the models developed for the period one year prior to bankruptcy. Such an observation confirms the results from numerous prior research. It is remarkable that the model based on traditional ratios in 2004 provided a better performance in terms of classifying the firms from validation sample than it did from initial sample. This provides evidence that the model does have a certain discriminatory power and stability which could be exploited if cut-off values are appropriately adjusted in order to minimize type I error. Even if this is possible, it does not seem useful to make this attempt, as the function contains only one variable, in that it is a univariate approach. Several problems are associated with such a model, which deny a proper practical application.

The results show that it was not possible to increase the prediction performance of the models when employee-related ratios were incorporated within the models. It must be mentioned here that it was not possible to build a model containing traditional and employee-related ratios due to statistical restrictions. Models built solely on employee-related ratios are inferior with respect to their predictive power when compared to models using traditional ratios and a combination between classical and employee-related ratios. Generally, their ability to act as predictors seems questionable based on these results, although several ratios showed discriminatory power grounded on the tests for differences.

The signs of the independent variables within the discriminant functions are all in congruence with expectations. A closer look at the weightings and interpretation of the discriminators helps to draw some useful conclusions. The size of the firms seems to play an important role in the distinction between bankrupt and non-bankrupt firms, because this factor was implicitly inherent within the different functions replicated by different variables. Based on the results from factor analysis, the following proxies were found which were all related to the size of the firm. The final two proxies had not been found and attributed to this factor in previous studies until now.

- ln(total assets)
- ln(number of employees)
- ln(staff costs/number of employees)
- ln(sales/number of employees)

From a theoretical viewpoint, it is assumed that firms with a greater size have a greater chance of survival due to different factors such as less business risk per dollar of assets invested, easier access to borrowing markets or more tax offsets per dollar of assets (Castanias, 1983, p. 1628 – 1629; Theodossiou, Kahya, Saidi & Philippatos, 1996, p. 704). These theoretical statements were confirmed within different studies, resulting in firms with a greater size having a lower probability of bankruptcy (Ohlson, 1980; Chatterjee & Srinivasan, 1992; Theodossiou, Kahya, Saidi & Philippatos, 1996; Dawley, Hoffman & Brockman, 2003; Chava & Jarrow, 2004; Chi & Tang, 2006; Hol, 2007; Pervan & Visic, 2012; Situm, 2014). The same result was found within this study.

The factor of efficiency appeared within this study, but it was not as important a factor as expected. Ln(sales/number of employees) appeared as an independent variable within the functions containing only employee-related variables for the periods one and two years prior to bankruptcy. The respective weightings are relatively low, with the result that the contribution of the values to the score of the function is marginal. An argument can be made that the data set was not concentrated on a specific industry. Certain industries need comparatively much more employees than others to generate sales and results. Such an aspect cannot be directly associated with inefficiency to the extent that this can explain the small weightings of the related ratios. Despite this, the signs suggest that firms with a higher efficiency are less likely to fail. This result confirms the findings of previous studies (Chen, Marshall, Zhang & Ganesh, 2006; Yeh, Chi & Hsu, 2010). It is also a sign that firms are stable at the operational level, meaning that the pre-conditions for stabilization and profit generation are taken as a given (Sudarsanam & Lai, 2001).

The capital structure of the firm was replicated with the ratio of total equity/total assets, which was also a predictor in other studies (Laitinen & Laitinen, 2000; Grunert, Norden & Weber, 2005; Pompe & Bilderbeek, 2005; Shin, Lee & Kim, 2005; Min & Lee, 2005, Bahiraie, Akma bt Ibrahim & Azhar, 2009; Muller, Steyn-Bruwer & Hamman, 2009; Bartual, Garcia, Gimenez & Romero-Civera, 2012). The interesting finding from this study is that it appeared alone within the discrimination functions without any other supporting ratios for one year prior to bankruptcy. This is not surprising as this was also visible from the results of means and medians from descriptive statistics. This result supports the generally accepted view that companies with a high (positive) equity ratios are less likely to fail. Nevertheless, it is interesting that the ratio did not provide an early warning signal two years prior to bankruptcy. This aspect could be attributable to the database however, as the differences in means and medians for this ratio in 2003 were relatively low.

The overall conclusion of this work is that employee-related ratios cannot provide additional information which could be exploited for the task of prediction. Therefore, their inclusion within bankruptcy prediction models is neither recommendable nor beneficial.

10. IMPLICATIONS, LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

10.1 Research hypotheses

The first hypothesis assumed that the higher the ratio of staff costs/sales, the higher the probability of insolvency. This statement can be confirmed by the findings of this study. The ratio was much higher in mean for bankrupt firms when compared to non-bankrupt firms. Nevertheless, the medians were not dispersed so much that the differences were not statistically significant based on the results from U-test. Therefore, it was also not considered within further model building, as it cannot provide incremental explanatory power to divide between the two types of firm. Consequently, hypothesis one must be rejected.

The second hypothesis assumed that a combination of traditional and employee-related ratios could improve the classification performance of prediction models. This hypothesis must be rejected based on the performance measures of the derived functions and the classification results. Employee-related ratios did not show incremental information content which could be exploited for improved prediction accuracy, even if some of them showed discriminatory power.

The third hypothesis assumed that the number of employees and related ratios could act as proxies for the size of the firm. This hypothesis can be accepted to a significant degree. Based on factor analyses, several ratios concerning employee-related figures were loaded on size factor. The ratios were ln(staff costs/number of employees) for two years, ln(sales/number of employees) for both years and ln(number of employees) for one year prior to bankruptcy. Therefore, these ratios showed the potential to act as proxies for the size of the firm. The first two variables had not been found in previous studies as proxies for the size of the firm, which is therefore a new finding from this study.

10.2 Research questions

The contribution of employee-related ratios for the task of prediction is limited due to the results of this study and the chosen variables did not show signalling power, which could have been exploited for improved classification accuracy of the models. Employee-related ratios are inferior concerning their ability to act as crisis indicators. Therefore, they did not contribute to the early detection of bankruptcies. Only some of the employee-related ratios were able to act as discriminators between the two types of firms. The respective variables mainly characterized the factors of size and efficiency. The size of the firm was found to be a relevant predictor within numerous previous studies and the theoretical considerations have already been highlighted within this work. Efficiency can be a relevant factor for the distinction between bankrupt and non-bankrupt firms, but the discriminatory power is somewhat limited. This may be attributable to the fact that the study included different industries with varying dependencies on the number of employees required for business success. Nevertheless, the inclusion of such factors was not able to improve the prediction quality of the models.

10.3 Limitations and recommendations for future research

The results of this study are based on a database of Austrian companies for the period 2003 to 2004. As a consequence, certain limitations concerning the generalizability of the results must be stated. Therefore, additional research for different countries and observation periods would be necessary to develop a more profound statement about the potential of employee-related ratios to assist in bankruptcy prediction.

The classification performance of the developed models was not satisfying. Here, several problems appeared which potentially affected classification accuracy. First, the theoretical pre-conditions for application of multivariate linear discriminant analysis were mostly violated by the database and the selected ratios. Several distributions showed a strong departure from normality, meaning that the proper application of multivariate linear discriminant analysis was theoretically not taken as a given. Additionally, the equalities of variance-co-variance matrices based on Box-test were not given, with the result that another important requirement was violated (this point was not true for the models including only employee-related ratios). These two aspects together can explain a significant proportion of the misclassifications assigned by the discriminant functions and the poor model quality. These points are additionally the reason why such a high proportion of unexplained variances remained, based on Wilks-Lambda.

Despite this, it was possible to realize the effect of employee-related ratios on the probability of insolvency based on the signs within the functions. All signs showed the expected direction. Therefore, multivariate linear discriminant analysis can be applied as an analytical tool to answer specific research questions, even if the theoretical pre-conditions for proper application of this method are violated. It remains a valuable instrument for researchers in order to analyse further ratios which could potentially be of interest in explaining the differences between bankrupt and non-bankrupt firms. Nevertheless, due to the restriction problems, it does not appear to be the correct instrument for the future development of a perfectly functioning forecasting tool and the foundation of a theory for the explanation of crises and insolvencies.

The proportion between bankrupt and non-bankrupt firms was unequal, with the result that different prior probabilities were incorporated within the models. Even if the event of insolvency was overrepresented in the initial sample when compared to the real insolvency rate of the whole population, the models understated the event of bankruptcy as they showed a much higher ability to detect non-bankrupt firms. This is a general problem of sampling for the purpose of business failure prediction, which can only be overcome when a much larger sample size is used (Thomas, Edelman & Crook, 2002, p. 122; Anderson, 2007, p. 350), which was not possible within this study due to restricted data size.

Finally, the models were not adjusted concerning their cut-off values. The threshold for classification was set at zero, but it is possible for optimization of model performance to adjust this value with appropriate techniques. This means a reduction of type I error with an accompanied increase in type II error. Based on the results for performance measures, such an adjustment only makes sense for the model in 2004, which includes the traditional ratios, but makes no sense due to its univariate character. None of the other models developed are useful for practical purposes and are not suitable as crisis indicators.

APPENDIX

Table 15: *Correlation analysis for the year 2003 (two years prior to the event of bankruptcy)*
*) statistically significant correlations at the 5 percent level
**) statistically significant correlations at the 1 percent level

	EquityTotalAssets	TotalDebt/TotalAssets	Sales/TotalAssets	ln(SalesTotal/Assets)	ln(Sales)	ln(Number of Employees)	ln(Sales/Number of Employees	ln(Staff Costs/Number of Employees)	Staff Costs/Sales	Sales/Staff Costs	EBITDA/Staff Costs	EBIT/Staff Costs	EBIT/Sales	EBIT/TotalAssets	ln(TotalAssets)
Total EquityTotalAssets	1	-1.000**	.026	.113	.273**	.214**	.273**	.087	-.339**	.064	.343**	.342**	.340**	.160*	.316**
Total Debt/ TotalAssets		1	-.026	-.113	-.273**	-.214**	-.273**	-.087	.339**	-.064	-.343**	-.343**	-.340**	-.160*	-.316**
Sales/TotalAssets			1	.747**	.225**	.066	.225**	-.122	-.119	.249**	-.103	.080	.119	.060	-.291**
ln(SalesTotal/ Assets)				1	.287**	.242**	.287**	-.105	-.419**	.185*	-.154*	.327**	.495**	.071	-.256**
ln(Sales)					1	-.194**	1.000**	.547**	-.375**	.604**	.370**	.324**	.362**	.239**	.334**

	EquityTotalAssets	TotalDebt/TotalAssets	Sales/TotalAssets	ln(SalesTotal/Assets)	ln(Sales)	ln(Number of Employees)	ln(Sales/Number of Employees	ln(Staff Costs/Number of Employees)	Staff Costs/Sales	Sales/Staff Costs	EBITDA/Staff Costs	EBIT/Staff Costs	EBIT/Sales	EBIT/TotalAssets	ln(TotalAssets)
ln(Number of Employees)						1	-.194**	-.237**	-.120	-.201**	-.041	.124	.134	.165*	.629**
ln(Sales/Number of Employees)							1	.547**	-.375**	.604**	.370**	.324**	.362**	.239**	.334**
ln(Staff Costs/ Number of Employees)								1	.037	.024	.066	.015	-.036	.010	.239**
Staff Costs/Sales									1	-.086	-.304**	-.320**	-.906**	-.163*	-.091
Sales/Staff Costs										1	.122	.047	.066	.063	.115
EBITDA/Staff Costs											1	.586**	.302**	.223**	.331**
EBIT/Staff Costs												1	.588**	.217**	.122
EBIT/Sales													1	.120	.043
EBIT/TotalAssets														1	.275**
ln(TotalAssets)															1

Table 16: *Correlation analysis for the year 2004 (one year prior to the event of bankruptcy)*
*) statistically significant correlations at the 5 percent level
**) statistically significant correlations at the 1 percent level

	EquityTotalAssets	TotalDebt/TotalAssets	Sales/TotalAssets	ln(SalesTotal/Assets)	ln(Sales)	ln(Number of Employees)	ln(Sales/Number of Employees	ln(Staff Costs/Number of Employees)	Staff Costs/Sales	Sales/Staff Costs	EBITDA/Staff Costs	EBIT/Staff Costs	EBIT/Sales	EBIT/TotalAssets	ln(TotalAssets)
Total EquityTotalAssets	1	-1,000**	-,089	-,046	,194**	,237**	,194**	,179*	-,266**	-,014	,080	,103	,488**	,775**	,360**
Total Debt/ TotalAssets		1	,089	,046	-,194**	-,237**	-,194**	-,179*	,266**	,014	-,080	-,103	-,488**	-,775**	-,360**
Sales/TotalAssets			1	,802**	,334**	-,104	,334**	,050	-,181*	,307**	-,130	-,083	,082	,040	-,356**
ln(SalesTotal/Assets)				1	,218**	,078	,218**	-,074	-,347**	,180*	-,206**	-,138	,207**	,072	-,402**
ln(Sales)					1	-,253**	1,000**	,402**	-,505**	,482**	,285**	,251**	,238**	,198**	,321**
ln(Number of Employees)						1	-,253**	,077	,035	-,253**	-,273**	-,242**	,076	,125	,633**

	EquityTotalAssets	TotalDebt/TotalAssets	Sales/TotalAssets	ln(SalesTotal/Assets)	ln(Sales)	ln(Number of Employees)	ln(Sales/Number of Employees	ln(Staff Costs/Number of Employees)	Staff Costs/Sales	Sales/Staff Costs	EBITDA/Staff Costs	EBIT/Staff Costs	EBIT/Sales	EBIT/TotalAssets	ln(TotalAssets)
ln(Sales/Number of Employees)							1	,402**	-,505**	,482**	,285**	,251**	,238**	,198**	,321**
ln(Staff Costs/ Number of Employees)								1	,126	-,251**	-,166*	-,192**	-,098	,004	,380**
Staff Costs/Sales									1	-,160*	-,173**	-,166*	-,783**	-,310**	-,096
Sales/Staff Costs										1	,377**	,409**	,039	,053	-,003
EBITDA/Staff Costs											1	,952**	,172*	,231**	,085
EBIT/Staff Costs												1	,187*	,276**	,048
EBIT/Sales													1	,453**	,097
EBIT/TotalAssets														1	,195**
ln(TotalAssets)															1

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