Recovery From Distress and Insolvency: A Comparative Analysis Using Accounting Ratios

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ABSTRACT

This study analysed how insolvent firms differ from firms which have successfully recovered from distress. The results show that companies that have recovered from distress are in a position to better manage their gross profit, increase their profitability and exhibit higher interest coverage when compared to insolvent firms. Therefore, managers should focus within turnaround activities on these aspects and introduce appropriate measures to improve the associated accounting ratios. Making a clear distinction between the two states within the prediction model remains difficult and provides evidence that accounting ratios alone are not sufficient in explaining a successful turnaround when compared to the state of insolvency. It seems that there are specific non-accounting measures, not considered within the scope of this study, which may be useful to improve segregation between the two groups of firms.

Key words: **bankruptcy prediction, financial distress, corporate crisis, logistic regression, discriminant analysis**

INTRODUCTION AND PURPOSE OF THE STUDY

The early detection of corporate crisis and insolvencies remains a prominent topic. Any attempts to gain a better understanding of the corporate distress process are valuable and relevant research in this field is therefore merited. The majority of empirical investigations used a bottom-up approach, where prediction models using different statistical techniques were developed based on specific company data (accounting ratios, financial ratios and qualitative variables) as well as the inclusion of macroeconomic indicators and the a-priori distinction of firms into the states bankrupt and non-bankrupt (Butera & Faff, 2006, p. 313 – 314; Du Jardin, 2009). Research has recognized relatively early that this dichotomous (bankrupt/non-bankrupt) thinking is not sufficient to describe the real economic situation. Instead, enterprises can be seen to have different economic and financial states which fluctuate on a continuous scale (Altman, 1968; Edmister, 1972; Ward, 1999; Haber, 2005; Cestari, Risalitti & Pierotti, 2013).

Using the dichotomous states and computing a prediction model implies implicitly that these possible in-between states are replicated and that based on specific approaches, it is possible to create a rating scale which is used to derive probabilities of default (Butera & Faff, 2006, p. 314). Such an approach does not mean, however, that there is a real understanding about how firms experiencing different economic and financial situations move within the continuous scale. It is therefore also of interest to investigate stages in-between the two states of solvent and insolvent, as it is possible to derive information about the behaviour of such firms and to gain insight towards a deeper understanding of the evolution of corporate crises and insolvencies.

As highlighted within the literature review, the amount of empirical research investigating the differences in these in-between stages is relatively low when compared to the amount of studies in the field of bankruptcy prediction as a whole. The motivation for this paper was therefore to conduct a separate study in order to address this area. More specifically, the differences between distressed and then recovered firms and insolvent firms were analyzed using selected accounting ratios, which were shown to be relevant predictors in prior studies. An attempt was then made to develop prediction models, with the aim of assigning a firm into one of these two states using logistic regression and linear discriminant analysis.

The paper is organized as follows: Firstly, an overview is provided regarding relevant prior research, where the different economic states of firms (not only solvent and insolvent) were analysed and compared. Secondly, the data selection process is described, including the variables chosen for the investigation. Within this step, the research hypothesis, research questions and the methodology are presented. Thirdly, the results from statistical pre-analyses are shown. Fourthly, the models that were developed based on logistic regression and linear discriminant analyses are explained and the results are shown. Finally, the paper concludes with a summary of the main results, the limitations of the study, some implications for practical purposes and ideas for further research.

LITERATURE REVIEW

Some papers are presented within this section which did not use a classical distinction of firms into the states of solvent and insolvent. The selection was based on a literature review where 250 papers related to insolvency prediction have been analysed. Lau (1987) developed a five-state model based on multinomial logit analysis, where five different financial states were defined. The model was useful as an instrument in determining the financial position of a firm on a continuous scale. For certain states however, the predictability of the model was difficult and delivered unsatisfactory results (Lau, 1987, 137).

An investigation including merged and acquired companies, as well as chapter 11 and chapter 7 filings, was conducted by Kwabena (1991). Using factor analysis, it was concluded that different types of firms have some common underlying factors, but some factors are dominant for each group. Additionally in this case, the industry of the firm appears to matter. For manufacturing firms, for example, order backlog was seen to be an important aspect. For firms in the service sector, short term borrowings were seen to be relevant (Kwabena, 1991, p. 33 – 34). Ward (1994) defined four states of financial health for his study, analysing the predictability of net income plus depreciation and amortization scaled by total debt (NOF). It was found that NOF is a better measure of economic income than net income and should therefore be favoured as a prediction variable within a multi-state model (Ward, 1994, p. 559).

The study of Poston, Harmon & Gramlich (1994) analysed bankrupt firms, firms in distress and firms in turnaround. The study was not able to achieve a satisfactory distinction between the groups and the use of financial ratios therefore seems questionable for this task. Several versions of Z-scores tended to classify distressed firms as failures and probit models tended to classify failing firms as turnarounds (Poston, Harmon & Gramlich, 1994, p. 54). Non-failed, failed and distressed acquired firms were compared by Wilson, Chong & Peel (1995). They recognized that making a distinction between failed and distressed firms is difficult, leading to the conclusion that these two types of firms have similar characteristics (Wilson, Chong & Peel, 1995, p. 43 – 44). Nevertheless, their neural network application achieved an overall accuracy of 98.2 percent, indicating that a multigroup model could be used successfully for multi-outcome business problems (Wilson, Chong & Peel, 1995, p. 44).

Chatterjee, Dhillon & Ramirez (1996) investigated the behaviour of chapter 11 filings, prepacks and private and public workout firms. They found significant differences in the size and level of debt among the four restructuring methods (Chatterjee, Dhillon & Ramirez, 1996, p. 9 – 10). Firms in workout and prepack showed a significantly higher ratio of EBIDT/Sales than chapter 11 firms. This leads to the conclusion that this type of firm is therefore in less economic distress when compared to chapter 11 firms. A similar study using chapter 7 and chapter 11 firms was conducted by Tucker & Moore (1999). The results show that the tendency to file for chapter 11 increases with the value of intangible assets with favourable business conditions in the industry, and decreases with the associated costs of this procedure (Tucker & Moore, 1999, p. 71 and 74).

The differences between distressed and recovered firms were analysed by Whitaker (1999). The severity of financial distress was negatively related to recovery. This means that firms in distress with high leverage are less likely to achieve a turnaround. Within this context, it was concluded that corrective management actions are a significant determinant for recovery and the increase in market value of the firm relative to its industry (Whitaker, 1999, p. 128 and 132). Using a Cox-proportional hazard model, Turetsky & McEwen (2001) attempted to investigate the failure process using the change of operational cash flow from positive to negative values. They tracked the occurrences of default, dividend reduction and troubled debt restructurings. Similar to Whitaker (1999), they concluded that higher financial leverage is positively associated with default. Higher liquidity levels reduce the probability of default, whereas real growth measured by ROA reduces the likelihood of bankruptcy (Turetsky & McEwen, 2001, p. 337 – 338).

Sudarsanam & Lai (2001) analysed firms identified as being distressed using Taffler´s Z-score and compared them to non-distressed and recovered firms. Distressed firms displayed a decline in performance from the two healthy years pre-distress to the distress year. ROE, ROA, cashflow return to capital employed and cashflow cover for debt were seen to be good indicators for this potential decline. The performance of recovered firms was significantly superior to non-recovered firms in the post-distress years (Sudarsanam & Lai, 2001, p. 190 – 191). Filings firms, acquired firms, merged firms and liquidated firms were compared within the study of Barniv, Agarwal & Leach (2002). Using univariate analysis, certain accounting ratios showed differences between the different types of companies. They achieved relatively high classification accuracy for merged and liquidated firms, but a low level of accuracy for acquired firms (Barniv, Agwarwal & Leach, 2002, p. 509 and 512).

Jones & Hensher (2004) defined three states for their study using non-failed, insolvent and bankrupt firms. Different ratios related to the cash position of the firm showed a strong statistical impact on the probability of a firm belonging to one of the three states (Jones & Hensher, 2004, p. 1029). The application of multinomial logit did not provide logical and consistent signs for all parameter estimations. When using a mixed logit model, they received high classification results, indicating that the variables obtained have a high potential to divide companies into the three defined states (Jones & Hensher, 2004, p. 1033 – 1034). A study was conducted by Sen, Ghandforoush & Stivason (2004) to divide between targets and non-targets for corporate mergers and bankrupt and non-bankrupt firms. The division between bankrupt and non-bankrupt firms functioned reasonably well when using neural network application, but the distinction between the two types of merger targets displayed poor results (Sen, Ghandforoush & Stivason, 2004, p. 229 – 230).

Chancharat, Tian, Davy, McCrae & Lodh (2010) used a hazard model to analyse the differences between active companies, distressed external administration companies and distressed takeovers, mergers or acquisitions. The survival profile of active and distressed takeovers was very similar. This is due to the fact that distressed firms the last mentioned ones exhibited lower leverage, higher capital utilisation efficiency and a larger sized compared to the active companies (Chancharat, Tian, Davy, McCrae & Lodh, 2010, p. 41). The study of Tsai (2013) investigated slightly distressed firms, firms in reorganization or bankruptcy and non-distressed firms. Financial ratios were seen to be statistically insignificant for slightly distressed firms and therefore provide less warning of the occurrence of slight distress than of reorganization and bankruptcy events (Tsai, 2013, p. 56 and 67).

This short review shows that there are certain characteristics which are able to describe and assign firms in different in-between states. Even if some results conclude that a relatively clear differentiation between the different types seems possible, many findings do not support these results. It can be concluded that the event of distress, however it was and is defined in theory and practice, remains an unobservable process. There is therefore sufficient scope for additional research in this field, as there are a number of open questions to be addressed in order to better understand the failure and crisis process of a firm.

DATA DESCRIPTION AND METHODOLOGY

DATABASE

The database for this study consists of Austrian firms from different industries, where financial statements were available for the years 2008 till 2012. The year 2012 was set as the bankruptcy date: Based on this, following definitions were used:

- 2012 as bankruptcy date: t(0)
- 2011 one year to bankruptcy: t(1)
- 2010 two years prior to bankruptcy: t(2)
- 2009 three years prior to bankruptcy: t(3)
- 2008 four years prior to bankruptcy: t(4)

Firms were only chosen where four consecutive years of data (2008 until 2011) were available, in order to receive a respective time series. There are several possible indicators to identify a distressed firm as proposed by literature. However, no common ground exists to explain how this economic state of the firm can be definitively measured. Instead, certain proxies were introduced for this aspect such as two or more consecutive years of operating losses (Poston, Harmon & Gramlich, 1994; Platt & Platt, 2008; Molina & Preve, 2009), current ratio of less than one (Poston, Harmon & Gramlich, 1994), negative balance in the retained earnings accounts (Poston, Harmon & Gramlich, 1994), the first year in which cash flow is less than current maturities of long-term debt

(Whitaker, 1999) or when the interest coverage ratio is lower than 1 (Jostarndt & Sautner, 2008; Pindado, Rodrigues & de la Torre, 2008; Platt & Platt, 2008; Molina & Preve, 2009).

Table 1: **Composition of groups and conditions for identification**

Group number	**Group name**	**Number of firms in initial and validation group**	**Identification of distress**		**Identification of recovery**	
0	Insolvent firms	57/19	Not relevant		Not relevant	
1	Recovered firms	50/9	Negative net income	Negative net income	Positive net income	Positive net income

Within this work, distress was defined as the situation when a firm showed operating losses (negative net income) for two consecutive years, meaning in t(4) and t(3). After that point, the development of net income was observed in order to detect turnaround activities. Firms which had a positive net income in t(2) and t(1) were defined as being recovered from distress. A similar concept was used by Jostarndt & Sautner (2008), but their distress indicator was an interest coverage ratio based on EBIT. Insolvent firms were identified by an insolvency mark and these are entities which went bankrupt under Austrian bankruptcy law. Table 1 summarizes the number of firms in the study and the process of identification concerning the states of distress and recovery.

VARIABLES

As a starting base, 30 accounting ratios and two ratios associated with the age of the firm in years were used. These ratios were selected based on a review of 250 papers related to the topic of bankruptcy and insolvency prediction. These ratios appeared more often than others and should therefore be suitable explanatory variables for differences between the groups of firms. The ratios are presented in the appendix of this work, accompanied by citations of the sources where they had been found in previous research.

The argument for the application of accounting ratios for the detection of distress and insolvencies is based on observations made by Turetsky & McEwen (2001). They provided evidence that such variables contain useful information for the prediction of a firm´s potential to go bankrupt (Turestky & McEwen, 2001, p. 339). This finding was confirmed by Tsai (2013), who found that financial ratios are more closely related to reorganization and bankruptcy events and are therefore suitable for the appraisal of these tasks. Based on this result, it can be concluded that accounting ratios should also be able to act as relevant discriminators for the purposes of this study. It is expected that the two types of firms can be relatively well distinguished and that it is possible to develop a well-functioning classification model.

HYPOTHESIS AND RESEARCH QUESTIONS

The aim of the study is to test the following hypothesis as a consequence of the results of Turetsky & McEwen (2001) and Tsai (2013).

Insolvent firms and firms in successful turnaround can be reliably distinguished with accounting ratios.

Additionally, the following research questions shall be answered:

Which accounting ratios are significant in order to explain differences between recovered and insolvent firms?

How well can both types of firms be distinguished using accounting ratios within statistical prediction models?

METHODOLOGY

In order to detect the potential differences between the two groups of firms, the following methodology was used: Firstly, descriptive statistics and tests for normality of the raw data were computed in order to check outliers and distributional assumptions. Secondly, data was winsorized at the 2 percent level in order to eliminate outliers and to avoid estimation problems within further model building. Thirdly, the best discriminating variables between the two groups were identified using the non-parametric U-test and Kolmogorov-Smirnov test, although parametric tests (t-test and F-test) were applied additionally for informational purposes. Fourthly, the best discriminating ratios were extracted based on the results and a check was made for multicollinearity by applying correlation analysis. Fifthly, with the remaining variables models were computed to discriminate between the two types of firms based on logistic regression and linear discriminant analysis. Lastly, the model performance was evaluated using performance measures such as AUC and Gini-coefficient.

STATISTICAL PRE-ANALYSES AND DISCUSSION

As expected, based on the Kolmogorov-Smirnov test on 5 percent level for almost all data, the normality of data was not a given, which was visible in descriptive statistics due to high skew values. In order to avoid estimation problems, data was winsorized at the 2 percent level as proposed by literature (Löffler & Posch, 2007, p. 15 -19). A check on winsorized data shows that outliers were eliminated, but normality of data was once again not a given for all variables based on p-values within the Kolmogorov-Smirnov test on a 5 percent level (results presented in *table 2*). Logistic regression is based on maximum-likelihood estimation and is theoretically not dependent on normally distributed data, meaning that it should be relatively robust against violations of normality (Press and Wilson, 1978, p. 700; Silva, Stam and Neter, 2002, p. 404). The winsorization itself seems useful, as model accuracy can nevertheless be disturbed to a certain degree by non-normally distributed data (Hopwood, McKeown and Mutchler, 1988, p. 239; Silva, Stam and Neter, 2002, p. 413).

Due to mainly non-normally distributed data, non-parametric tests for differences (U-test and KS-test) were used (Marques de Sá, 2007, p. 201 – 204). For informational purposes, the results of the parametric t-test and F-test are shown in *table 2*. The criterion for inclusion into *table 2* was the appearance of statistically significant differences in one of the two non-parametric tests. NI/TA and NI/S can be seen as ratios of profitability (McKee, 1995; Datta & Iskandar-Datta, 1995) and in median recovered firms exhibited higher values, indicating that they are working more efficiently when compared to insolvent firms. Profitability is a measure of management effectiveness (Dambolena & Khoury, 1980; Edum-Fotwe, Price & Thorpe, 1996) and indicates that good and experienced managers are necessary for a successful turnaround (Whitaker, 1999, p. 132).

NI/S seems to be a stronger predictor as it showed statistical significance in both non-parametric tests. It is also interesting to have a look at the development of these ratios from t(2) to t(1). For insolvent firms, NI/TA decreased from a median value of 3.2 to 1.8 percent and for NI/S, the median value deteriorated from 3.11 to 1.69 percent. Recovered firms display a different behaviour. NI/TA decreased slightly from 2.71 to 2.55 percent and NI/S improved strongly from 2.95 to 4.45 percent. This aspect is an indicator that profitability and efficiency seem to play a key role in successful turnaround strategies and in restructuring (Datta & Iskanda-Datta, 1995, p. 32).

Within all tests for differences, GP/TA showed the strongest ability to differentiate as it exhibited statistically significant values. Recovered firms are much better able to use their total assets for gross profit generation (Doumpos & Zopounidis, 1998). This is visible at the median values of this ratio for both types of firms within *table 2*. Here, the development between t(2) and t(1) is also an interesting indicator. The median value for insolvent firms changes from 62.41 to 52.72 percent and indicates that such companies cannot exploit their assets optimally. In contrast, for recovered firms the median values changes from 67.65 to 81.83 percent. It is a good indicator of turnaround management quality and undermines the above mentioned aspects in connection with NI/TA and NI/S, that an increase in efficiency and profitability are main drivers of successful turnaround strategies.

For t(1), two other interesting ratios were found to be relevant for discrimination between the two groups of firms. Both are related to interest coverage, based on EBIT (EBIT/INT or INT/EBIT). Successful turnarounds display better values for these ratios and therefore have a lower risk of insolvency (Sudarsanam & Lai, 20011; Bhattacharjee, Higson, Holly & Kattuman, 2009; Rose-Green & Lovata, 2013). For insolvent firms, EBIT/INT deteriorated from 3.57 to 1.92 and for successful turnarounds, this ratio decreased only slightly from 4.16 to 4.04. The effect for insolvent firms has two components. Firstly, the ratio deteriorated because the debt-ratio increased. The logical consequence is that interest expenses increased, thereby affecting this ratio negatively. Secondly, due to higher distress risk, the risk premia being charged by banks are increasing. This aspect, combined with the additional loss of tax benefits from debt financing, therefore increases the overall financing cost, which also negatively affects this ratio (Almeida & Philippon, 2007, p. 2579 – 2581).

Several ratios including current assets were significant in t(2). The strongest of these is CA/TA. Insolvent firms showed lower values for the period two years prior to insolvency when compared to recovered firms. Nevertheless, this statistically significant difference diminished totally in t(1), due to the value of the decrease for recovered firms being similar to the decrease in value for insolvent firms. This means that turnaround activities also include tighter management of working capital, which helps to improve cash flow from operations. The differences between distress, successful turnaround and insolvency can therefore be explained by three key factors: firstly, an increase in efficiency and profitability (NI/S and GP/TA); secondly, a much better interest coverage (EBIT/INT) and; lastly, an improvement in working capital management (CA/TA).

Based on these results, the variables identified from *table 2* were used for further analyses. Correlation analysis is used as a last check in the pre-analysis in order to detect multicollinearity. This could be a problem that affects the discriminatory power of models, when such variables are included within prediction models (Ho, 2006, p. 248). Correlation analysis reveals a high positive correlation (0.579) between NI/S_2011 and NI/S_2011 and a high positive correlation (0.563) between S/CA_2010 and CA/S_2010. All values are below 0.7, so that multicollinearity cannot be assumed. The next step was therefore to use the variables and to compute the logistic regression function for t(1) and t(2).

Table 2: **Best discriminating variables based parametric and non-parametric tests**

		Test for Normality	Descriptive Statistics			Parametric Tests for Differences c)		Non-Parametric c) Tests for Differences	
Ratio	**Group**	**KS-Test**	**Mean**	**Median**	**Std.-Dev.**	**t-Test**	**F-Test**	**U-Test**	**KS-Test**
		p-value [b)]	**values**	**values**	**values**	**p-value**	**p-value**	**p-value**	**p-value**
NI/TA_2011	0	0.010	0.030	0.018	0.070	0.144	0.230	0.098	**0.005**
	1	0.000	0.048	0.026	0.058				
NI/S_2011	0	0.000	0.019	0.017	0.197	**0.026**	0.365	**0.028**	**0.008**
	1	0.000	0.131	0.045	0.309				
GP/TA_2011	0	0.000	0.784	0.527	0.964	**0.007**	**0.000**	**0.019**	**0.025**
	1	0.000	1.534	0.818	1.767				
EBIT/INT_2011	0	0.000	39.063	1.917	130.018	**0.026**	**0.000**	**0.041**	0.167
	1	0.000	595.568	4.041	1857.971				
INT/EBIT_2011	0	**.200** [a)]	0.484	0.460	0.397	0.767	0.087	**0.048**	**0.025**
	1	0.000	0.448	0.197	0.826				
TE/TA_2010	0	0.003	0.305	0.259	0.242	0.144	0.298	0.106	**0.030**
	1	0.020	0.374	0.342	0.239				
TD(TA_2010	0	0.003	0.695	0.741	0.242	0.144	0.298	0.106	**0.030**
	1	0.020	0.626	0.658	0.239				
CA/S_2010	0	0.000	0.770	0.363	1.101	0.218	**0.008**	0.454	**0.034**
	1	0.000	0.563	0.425	0.456				
S/CA_2010	0	0.001	3.334	2.757	2.524	0.169	**0.002**	0.454	**0.034**
	1	**0.074**	2.747	2.355	1.719				
CA/TA_2010	0	**.200** [a)]	0.556	0.525	0.271	**0.018**	0.163	**0.029**	**0.014**
	1	0.005	0.675	0.735	0.235				

a. denotes the lower boundary of the real statistical significance

b. bold number for p-values based on KS-test show ratios which are normally distributed

c. bold numbers for p-values show statistically significant differences on the 5 percent level

MODEL DEVELOPMENT AND RESULTS

Only CA/TA was included within the logistic regression function for t(2). It can be observed that the model classifies the initial sample better than the null model (including only a constant), based on the measure of overall accuracy. Therefore, the inclusion of the variable in the null model improved classification accuracy and the model is better at assigning the firms into the two groups than a random guess. Nevertheless, the quality seems questionable for two reasons. Firstly, the R^2 according to Nagelkerke is about 7 percent, which means that only 7 percent of the variation in the dependent variable can be explained. Secondly, the overall accuracy of 63.55 percent is low and a closer look at type I and II errors reveals that a relatively high percentage of firms are assigned into the wrong category.

Two models are presented for t(1), as both are interesting and make interpretations possible. The first model has two variables and can explain approximately 19 percent of the variations, whereas the second model with three variables is able to explain approximately 27 percent. Even if the overall accuracy of the first model is higher when compared to the second model, the second is more interesting, as it has a lower type I error based on the classification matrix for the initial sample. The signs for all of the variables are consistent with expectations and confirm results from prior research.

Table 3: **Summary about statistics and model parameters for logistic regression**

		Test statistics			Model parameters		Null-model	Regression Model
Observation Period	**Variables**	**R^2 (Nagel-kerke)**	**Sign. HL-test**	**Sign. in model**	**Regression coefficient**	**Exp(B)**	**Accuracy in %**	**Accuracy in %**
Model t(2)	Constant Term	0,07	0,40	0,018	-1,280	0,278	53,27	63,55
	CA/TA			0,021	1,861	6,427		
Model t(1) [a]	Constant Term	0,19	0,38	0,003	-0,900	0,406	53,27	64,49
	NI/S			0,037	3,205	24,653		
	GP/TA			0,006	0,513	1,670		
Model t(1) [b]	Constant Term	0,27	0,24	0,001	-1,041	0,353	53,27	62,62
	NI/S			0,035	3,163	23,653		
	GP/TA			0,008	0,489	1,630		
	EBIT/INT			0,171	0,001	1,001		

a. First model for t(1) contains two explanatory variables

b. Second model for t(1) contains three explanatory variables

Firms exhibiting a higher profitability (denoted by NI/S) have a lower probability of insolvency (Begley, Ming & Watts, 1996; Doumpos & Zopounidis, 1998; Kahya & Theodossiou, 1999; Lennox, 1999, Chi & Tang, 2006; Pindado, Rodrigues & de la Torre, 2008). The higher the ratio, the more effectively management has acted (Dambolena & Khoury, 1980). It is also an indicator that firms returned from distress to a "normal" stage within the turnaround process. This suggests that the pre-stages of this process had already been mastered successfully (Pretorius, 2008, p. 419). A higher value for GP/TA is a sign of a firm's health (Doumpos & Zopounidis, 1998, p. 84), an aspect which was confirmed within this study. High values for interest coverage can be positively associated with a firm's health (Chatterjee & Srinivasan, 1992; Nam & Jinn, 2000; Bhattacharjee, Higson, Holly & Kattuman, 2009; Altman, Sabato & Wilson, 2010) and are therefore typical for recovered firms (Sudarsanam & Lai, 2001; Rose-Green & Lovata, 2013).

The three models can be written based on the regression coefficients as shown in equations one to three listed below. A standard 0.5 threshold was set to distinguish between the two groups. For probabilities above this value, a firm is classified as being recovered and otherwise as being insolvent.

$$F_{t(2)} = \frac{1}{1+e^{(1.2801-1.86053*CA/TA)}} \tag{1}$$

$$F_{t(1)a} = \frac{1}{1+e^{(0.90049-3.20491*NI/S-0.51309*GP/TA)}} \tag{2}$$

$$F_{t(1)b} = \frac{1}{1+e^{(1.04145-3.16349*NI/S-0.4885*GP/TA-0.00143*EBIT/INT)}} \tag{3}$$

In order to determine whether regression analysis really measures the states of the dependent variables, a test for objectivity of multivariate linear discriminant functions was computed for t(2) and t(1). The respective results are shown below and based on Mahlanobis distance, the same variables appeared as discriminators as for logistic regression, where the threshold for differentiation was set at zero (a firm showing a lower value than zero was assigned as being insolvent and otherwise as being a successful turnaround):

$$D_{t(2)} = -1.12649 + 1.830586 * CA / TA \quad (4)$$

$$D_{t(1)} = -0.83913 + 2.2419 * NI / S + 0.47889 * GP / TA + 3.676.10^{-4} * EBIT / INT \quad (5)$$

The signs of CA/TA for the first function are in accordance with the results from logistic regression and also with the descriptive statistics. The higher the variable, the more likely a firm will be assigned as successful turnaround. The model is able to explain 5.2 percent of the variation in the dependent variable, which is weaker when compared to the model computed with logistic regression. The second function was able to explain 17.1 percent of the variation and delivered an overall classification accuracy of 65.4 percent (65.4 percent using cross validation) of the cases correctly classified from the initial group. This is a slightly higher value than that obtained with logistic regression, even if non-normality of data and the unequal variance-covariance-matrices (p-vale of 0.0 within Box-test) were taken as a given. Several studies showed that there is sensitivity to linear discriminant analysis in relation to violation of these two aspects and that model development can therefore be affected (Hopwood, McKeown & Mutchler, 1988, p. 292; Klecka, 1989, p. 61; Subhash, 1996, p. 264; Hayden & Porath, 2011, p. 4). The results of this check for objectivity lead to the conclusion that the models developed with logistic regression measure the differences between the two groups of firms (even if classification results are weak), as the discriminant functions provide similar results.

The following table shows results concerning the classification accuracy of the models using out-of-sample (application of the model to a new sample of firms not used for model building) and out-of-time validation (application of the model on data on a different time period) as proposed by Ward (1999, p. 168 - 169) and Sobehart, Keenan & Stein (2001, p. 59 - 61). Additionally, model performance was evaluated using the technique of AUC and Gini-coefficients as recognized methods for this task (Grzybowski & Younger, 1997; Sobehart, Keenan & Stein, 2011; Fawcett, 2006; Anderson, 2007).

Table 4: **Summary of classification accuracies using validation techniques and performance measures for the two best models**

	Logistic Regression t(1)b				Discriminant Analysis t(1)			
	t-1		t-2		t-1		t-2	
	Initial	**Valid. OOS**	**Initial OOT**	**Valid. OOT**	**Initial**	**Valid. OOS**	**Initial OOT**	**Valid. OOT**
AUC	0.602				0.594			
Gini-Coeff.	0.204				0.188			
Accuracy	0.626	0.536	0.477	0.571	0.654	0.500	0.486	0.571
Type I Error	0.175	0.368	0.263	0.421	0.193	0.421	0.246	0.421
Type II Error	0.600	0.667	0.820	0.444	0.520	0.667	0.820	0.444
F-measures	0.500	0.316	0.243	0.455	0.565	0.300	0.247	0.455

OOS = out-of-sample validation
OOT = out-of-time validation

All of the Gini-coefficients showed values under 0.5, meaning that they are not satisfactory and therefore not useful as prediction tools (Anderson, 2007, p. 205). The best results were obtained with the logistic regression model from t(1) using three variables (Gini-coefficient: 0.204) followed by the linear discriminant model from t(1) (Gini-coefficient: 0.188), which are the only ones reported within *table 4* below. The results confirm findings from prior studies, namely that it is difficult to differentiate between insolvent firms and distressed recovered firms, because they seem to have certain similarities which hinder the development of a well-functioning prediction model (Poston, Harmon & Gramlich, 1994; Wilson, Chong & Peel, 1995; Barniv, Agarwal & Leach, 2002). The models were better at predicting insolvent cases, but showed significant weakness in recognizing successful turnarounds, which is similar to results found by Jones & Hensher (2004) and Liou & Smith (2007).

SUMMARY OF THE RESULTS, HYPOTHESIS TESTING AND RESEARCH QUESTIONS

This study showed that making distinctions between the different states of firms is difficult, therefore restricting model development in this field. This confirms results from prior research, where the distinction between certain states was also difficult, in that the models were not able to deliver satisfactory classification results (Lau, 1987; Poston, Harmon & Gramlich, 1994; Barniv, Agarwal & Leach, 2002; Chancharat, Tian, Davy, McCrae & Lodh, 2010, p. 41). Instead, the models classified recovered firms into insolvent firms based on the type II errors obtained, so that a similar bias was found as with Poston, Harmon & Gramlich (1994) concerning the application of different Z-score measures. The explanatory variables do not appear to have the relevant information required to clearly distinguish between the two types of firms (Poston, Harmon & Gramlich, 1994, p. 54).

This study leads to the conclusion that accounting ratios alone are not able to sufficiently describe the two defined states of this study, which is a similar result to prior research (Poston, Harmon & Gramlich, 1994, p. 54; Liou & Smith, 2007, p. 28). They do not seem to be useful in predicting a distressed firm´s potential progression towards bankruptcy as reported in Turetsky & McEwen (2001, p. 339) or in Jones & Hensher (2004, p. 1033), meaning that a contrary result was found within this study. This is also visible in R^2 and Wilks-Lambda measures in the case of model building. A high portion of unexplained variances for the variables remained, suggesting that other potential discriminators also seem to be relevant for this task. Such a finding confirms the recognized view in research that a prediction model should include different types of variables (Grunter, Norden & Weber, 2005; Muller, Steyn-Bruwer & Hamman, 2009; Altman, Sabato & Wilson, 2010; Iazzolino, Migliano & Gregorace, 2013).

The hypothesis of this work must therefore be rejected based on the low Gini-coefficients of the models. Based on Anderson (2007, p. 205,) values below 0.5 are indicators of a weak performance and this threshold was used as a benchmark for testing the hypothesis. Insolvent and recovered firms cannot be properly distinguished. Even if recovered firms exhibited two consecutive years of positive net income, both types of firms seem to have common underlying factors, making a better segregation difficult. This may be due to several limitations of the study, which are highlighted within the next chapter. The rejection of the hypothesis leads to the answer for the second research question; that both types of firms cannot be well differentiated when accounting ratios are used.

Concerning the first research question, it can be stated that NI/S, GP/TA and EBIT/INT are the best discriminating variables one year prior to the event of insolvency. The signs for all of these ratios were in accordance with expectations and the results of prior research. For the period two years prior to bankruptcy, only one variable (CA/TA) was a relevant discriminator, which emphasized the problem of early detection as was visible in different studies. The further away the observation period is from the event of bankruptcy, the worse the prediction results are when using accounting ratios, which is in congruence with findings from prior research (for example in Altman, 1968; Kwon & Wild, 1994; Brabazon & Keenan, 2004; Chi & Tang, 2006; Muller, Steyn-Bruwer & Hamman, 2009).

LIMITATION, IMPLICATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The results of this study have certain limitations:

- A relatively small sample of data was used to develop the models, due to restricted data availability.
- Data was, in most cases, non-normally distributed, which could have an effect on the estimation procedure for logistic regression and discriminant analysis. Even if this is not a problem for logistic regression (Press and Wilson, 1978, p. 700; Silva, Stam and Neter, 2002, p. 404) and instead is a more important problem for discriminant analysis (Hopwood, McKeown & Mutchler, 1988, p. 292; Klecka, 1989, p. 61; Subhash, 1996, p. 264; Hayden & Porath, 2011, p. 4), both methods did not differ substantially in their performance. Nevertheless, the classification accuracy could have been optimized using normally distributed data, but this was not possible due to the lack of sufficient data.
- The definition of distress and recovery could be a biased measure as it is possibly not linked, from a theoretical viewpoint, to the real economic and financial situation of the firm, even if it follows the definitions from prior research. It could therefore be argued that a finer granulation of economic and financial states is necessary in order to better capture the distress process and to obtain better differentiation results.

For research purposes, it is worth investigating the testing of other proxies of distress and whether they could deliver a better segregation between the two groups of firms. Such an attempt would be useful in order to get a better understanding of the distress process and could lead to a common definition of distress for research purposes. It would also be interesting to analyse additional model variables not derived from financial statements (such as industry benchmarks, macroeconomic variables etc.), in order to test their incremental contribution to an improved model performance and classification accuracy.

Based on the results of the studies, it is recommended for practical purposes that managers tighten the purchase process of the firm in order to improve gross profit, which in turn leads to increased profitability. This aspect is also crucial in order to gain sufficient EBIT for the coverage of interest payments. Concerning working capital management, the relation CA/TA can be improved using stricter debtor and inventory management. These combined factors are the main drivers for a successful recovery and turnaround process of a firm and help to prevent insolvency.

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APPENDIX

Table 5: **Independent variables selected for research based on literature review**

Ratios	Computation	References
AGE	Age of the firm in years	Chi & Tang (2006); Chancharat, Tian, Davy, McCrae & Lodh (2010)
Ln(AGE)	Ln(Age of the firm in years)	In accordance to the variable AGE the logarithm was used
SIZE I	Ln(Total Assets)	Dawley, Hoffman & Brockman (2003), Grunert, Norden & Weber (2005), Chi & Tang (2006); Situm (2014)
SIZE II	Ln(Sales)	Opler & Titman (1994); Chancharat, Tian, Davy, McCrae & Lodh (2010); Situm (2014)
CF/TD	Cash Flow (Net Income + Depreciation)/Total Debt	Beaver (1966); Blum (1974); Frydman, Altman & Kao (1985); Ahn, Cho & Kim (2000)
NI/TA	Net Income/Total Assets	Beaver (1966); Bryant (1997); Chava & Jarrow (2004); Ohlson (1980); Zmijeswski (1984)
NI/S	Net Income/Sales	Chalos (1985); Shah & Murtaza (2000); Li & Sun (2011)
EBIT/TA	EBIT/Total Assets	Altman (1968); Frydman, Altman & Kao (1985); Grunert, Norden & Weber (2005)
EBT/TE	Earnings before Taxes /Total Equity	Bruse (1978); Pompe & Bilderbeek (2005); Sarlija & Jeger (2011)
EBIT/S	EBIT/Sales	Sudarsanam & Lai (2001)
EBIT/TD	EBIT/Total Debt	Pacey & Pham (1990); Sudarsanam & Lai (2001): Charitou, Neophytou & Charalambous (2004);
EBITDA/S	EBITDA/Sales	Platt & Platt (2002)
EBITDA/TD	EBITDA/Total Assets	Pacey & Pham (1990); Charitou, Neophytou & Charalambous (2004)
TE/TA	Total Equity/Total Assets	Laitinen & Laitinen (2000); Pompe & Bilderbeek (2005); Grunert, Norden & Weber (2005)
TD/TA	Total Debt/Total Assets	Bryant (1997); Shah & Murtaza (2000); Zmijewski (1984); Yeh, Chi & Hsu (2010); Tsai (2013)
RE/TA	Retained Earnings/Total Assets	Altman (1968); Coats & Fant (1993); Neves & Vieira (2006)
S/TA	Sales/Total Assets	Altman (1968); McKee (2003); Brabazon & Keenan (2004); Tsai (2013)
S/TE	Sales/Total Equity	Bruse (1978)
GP/TA	Gross Profit/Total Assets	Doumpos & Zopounidis (1999); Atiya (2001)
GP/S	Gross Profit/Sales	Ko, Blocher & Lin (2001)
S/FA	Sales/Fixed Assets	Ko, Blocher & Lin (2011); Min & Lee (2005); Chi & Tang (2006); Huang, Tsai, Yen & Cheng (2008)
DEP/TA	Depreciation/Total Assets	Chi & Tang (2006)
TAX/TA	Income Taxes/Sales	Hodges, Cluskey & Bian-Xuan (2005)
INT/S	Interest Expenses/Sales	Min & Lee (2005); Min & Lee (2008)
INT/TD	Interest Expenses/Total Debt	Min, Lee & Han (2006)
EBIT/INT	EBIT/Interest Expenses	Altman, Haldeman & Narayanan (1977); Shah & Murtaza (2000); Brabazon & Keenan (2004); Li & Sun (2011)
INT/EBIT	Interest Expenses/EBIT	In accordance to the references concerning, the reciprocal of EBIT/INT was used
EBITDA/INT	EBITDA/Interest Expenses	Altman, Sabato & Wilson (2010); Iazzolino, Migliano & Gregorace (2013)

Ratios	Computation	References
INT/ EBITDA	Interest Expenses/EBITDA	In accordance to the references concerning, the reciprocal of EBITDA/INT was used
CA/S	Current Assets/Sales	Kim & McLeod (1999); Sen, Ghandforoush & Stivason (2004); Yeh, Chi & Hsu (2010)
S/CA	Sales/Current Assets	Low, Nor & Yatim (2001)
CA/TA	Current Assets/Total Assets	Casey & Bartczak (1985); Frydman, Altman & Kao (1985); Yeh, Chi & Hsu (2010); Iazzolino, Migliano & Gregorace (2013)