Recovery from distress and insolvency: A comparative analysis using accounting ratios

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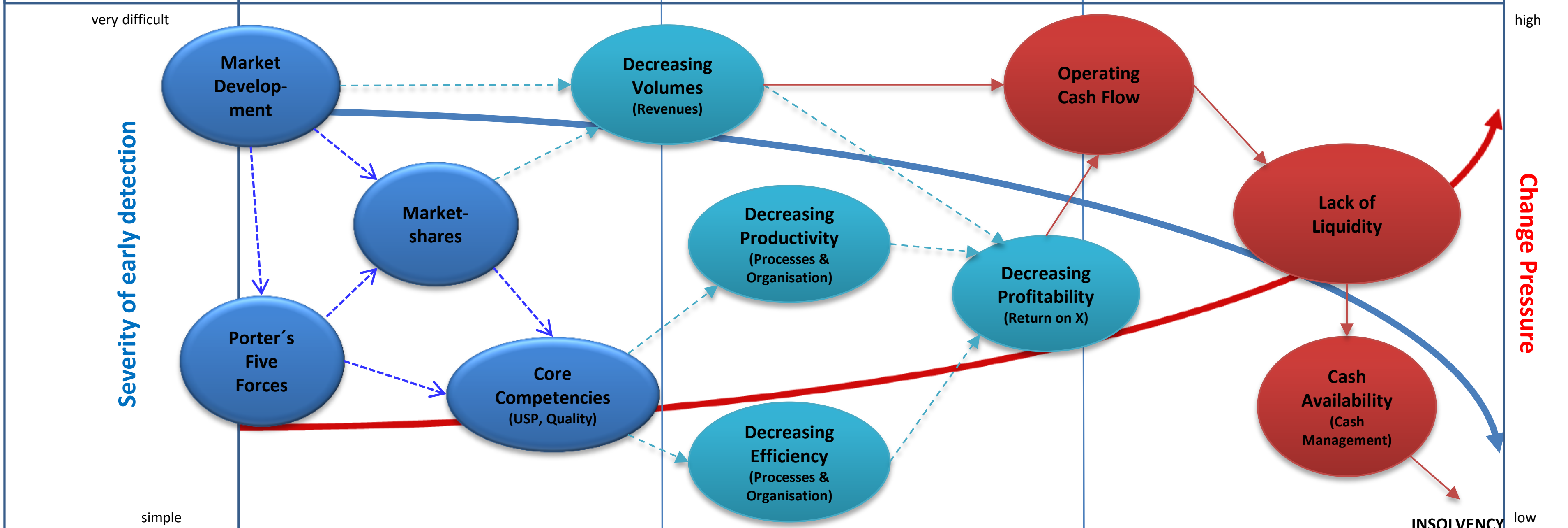
Introduction
Motivation for the study

- Majority of studies in bankruptcy and insolvency prediction is grounded on the investigation of two **dichotomous states** (solvent/insolvent)
- Models developed on such data implicitly assume that the different **degrees** of „corporate health" in between the dichotomous states are considered too
- However, actually there is a low knowledge base of how corporate crises develop or evolve **over time** and how the different stages of „corporate health" can be **identified** and **measured**
- A relatively **low number of studies** was conducted in order to deliver progress towards this aspect and to provide additional knowledge

The evolution of corporate crises
A potential model for explanation

Type of Crisis:	Strategic Crisis	Revenue Crisis	Liquidity Crisis



Types of Crisis Indicators:	Performance Indicators	Financial Indicators	
Indicators:	• Increasing fluctuation in personnel • Increase of illness • Delay in delivery against customers • Increasing commodity prices • Increasing production time • Increasing failure rates • Decreasing rate of innovation • Increasing number of unrealized offers	• Decreasing equity ratio/increasing debt ratio • Decreasing revenues • Decreasing earnings • Decreasing gross profit • Missing cooperation between production and sales • Delays in delivery • Decreasing volumes	• Delay in interest- and principal payments • Overdrawn credit lines • Covenant breach • Decreasing cash flow from operations • Increasing pressure from debtholders • Delivery against cash payment

Literature review

Empirical evidence (1/2)

- *Lau (1987)* constructed a five-state model to create a continuous scale to determine the financial position of a firm; however, for certain states the logit model delivered unsatisfactory results
- *Anyane-Ntow (1991)* applied factor analysis on chapter 11 and 7 firms as well as on merged and acquired firms and found that they are having common characteristics, but some factors are dominant for each group
- *Poston, Harmon & Gramlich (1994)* analysed bankrupt firms, firms in distress and firms in turnaround and did not receive satisfactory classification results even if they tried different versions of Z-scores
- *Wilson, Chong & Peel (1995)* investigated non-failed, failed and distressed acquired firms and concluded that the distinction between failed and distressed is difficult due to similar characteristics; nevertheless, their neural network showed a high overall accuracy, indicating that a multigroup model could be used successfully for multi-outcome business problems
- *Chatterjee, Dhillon & Ramirez (1996)* analysed chapter 11, prepacks, private and public workouts and found differences in size and level of debt among these restructuring methods.
- *Tucker & Moore (1999)* used chapter 7 and 11 firms and concluded that the tendency to file for chapter 11 increases with the value of intangible assets and the business conditions in the respective industry of the firm, whereas the probability is decreasing with the associated costs of the procedure.
- *Whitaker (1999)* investigated distressed and recovered firms and found that the severity of financial distress was negatively related to recovery; firms in distress with a high leverage level are less likely to achieve turnaround

Literature review
Empirical evidence (2/2)

- *Turetsky & McEwen* (2001) used a Cox-proportional hazard model to capture the failure process using cash flow from positive to negative values; similar to *Whitaker (1999)* they concluded that financial leverage is associated with default and higher liquidity reduces the probability of default
- *Sudarsanam & Lai* (2001) identified distressed firms using Taffler´s Z-score and compared to non-distressed and recovered ones; the performance of recovered firms was significantly superior to non-recovered firms
- *Barniv, Agarwal & Leach* (2002) used filings, acquired, merged and liquidated firms; a good distinction was possible between merged and liquidated, but it was not possible to differentiate between acquired firms
- *Jones & Hensher (2004)* defined three states within their studies and received partially inconsistent signs within their models; using logit model they achieved good results and reported a high potential to divide companies into the three states
- *Sen, Ghandforoush & Stivason (2004)* divided between targets and non-targets for corporate mergers and bankrupt and non-bankrupt firms; the distinction between the two types of mergers showed poor results, whereas a segregation between bankrupt and non-bankrupt showed quite good results
- *Chancharat, Tian, Davy, McCrae & Lodh (2010)* used a hazard model to analyse differences between active companies, distresses external administration firms and distressed takeovers, mergers or acquisitions; it was difficult to differentiate between active and distressed takeovers
- *Tsai (2013)* investigated slightly distressed, firms in reorganization or bankruptcy and non-distressed firms; financial ratios were statistically insignificant for slightly distressed firms and therefore provide less warning compared to reorganization or bankruptcy

Literature review

Potential indicators to assign firms into different economic and financial stages

- Two or more consecutive years of **operating losses** *(Poston, Harmon & Grmalich, 1994; Moline & Preve, 2009; Platt & Platt, 2008;)*
- **Current ratio** of less than one in a year *(Poston, Harmon & Gramlich, 1994)*
- Negative balance in **retained earnings** *(Poston, Harmon & Gramlich, 1994)*
- **Interest coverage** ratio lower than one *(Jostarndt & Sautner, 2008; Molina & Preve, 2009; Pindado, Rodrigues & de la Torre, 2008; Platt & Platt, 2008)*

Conclusion:

Actually there is **no common definition** for the stage of „**financial distress**" or other stages of „**corporate health**".

Data description and methodology

Database and variables (1/2)

- Financial statement data of **Austrian firms** from different industries for the period 2008 – 2012

- Bankruptcy was based on the definitions from Austrian **insolvency law**

<u>2012 was the bankruptcy data:</u>

- 2011 = one year prior to bankruptcy
- 2010 = two years prior to bankruptcy
- 2009 = three years prior to bankruptcy
- 2008 = four years prior to bankruptcy

- 30 **accounting variables** and two ratios associated with the **age** of the firms were used as potential explanatory variables based on results from prior research *(for example Altman, 1968; Beaver, 1966; Chava & Jarrow, 2004; Grunert, Norden & Weber, 2005; Ohlson, 1980; Pompe & Bilderbeek, 2005 or Zmijewski, 1984)*

Data description and methodology
Database and variables (2/2)

- Distress was defined as the event of **two consecutive years of negativ net income** (Poston, Harmon & Gramlich, 1994; Molina & Preve, 2009; Platt & Platt, 2008)

- **Recovered** from distress was detected, when a firms show positive **net income for two consecutive years** (in accordance to a similar definition used by Jostarndt & Sautner, 2008)

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 (2008)	Negative net income (2009)	Positive net income (2010)	Positive net income (2011)

Data description and methodology
Methodology

- **Descriptive statistics** and test for **normality** as well as **winsorization** of data on the 2 percent level
- Parametric and non-parametric **tests** for **differences** for the selected variables
- Tests for multicollinearity based on **correlation analysis**
- Development of classification models based on **logistic regression** and **linear discriminant analysis**
- Tests concerning predictability via out-of-time and out-of-sample **validation**
- Evaluation of model performance using **AUC** and **Gini-coefficient**

Data description and methodology
Research hypothesis and questions

Research hypothesis:

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

*) Reliability was assumed to be the case, when the Gini-coefficient of a model was higher than 0.5 (Anderson, 2007, p. 205).

Research questions:

1. Which accounting ratios are significant in order to explain differences between recovered (successful turnaround) and insolvent firms?

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

Statistical pre-analyses

Descriptive statistics, test for normality of data and test for differences

Table 2: Results from statistical pre-analyses for best discriminating variables

		Test for Normality	Descriptive Statistics			Parametric Tests for Differences [c]		Non-Parametric [c] Tests for Differences	
Ratio	Group	KS-Test p-value [b]	Mean values	Median values	Std.-Dev. values	t-Test p-value	F-Test p-value	U-Test p-value	KS-Test 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

Models of logistic regression and linear discriminant analysis

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

		Test statistics			Model parameters		Null-model	Regression Model
Observation Period	Variables	R^2 (Nagelkerke)	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		

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

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

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

Results logistic regression

(Threshold = 0.5; for values above 0.5 a firm was assigned as recovered otherwise as insolvent)

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

[this model explained about 5 % of variances]

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

[this model explained about 17.1 % of variances]

Results discriminant analysis

(Threshold = 0; for values above 0 a firm was assigned as recovered otherwise as insolvent)

Model development and results
Validation and model performance

Table 4: Summary of classification accuracies and model performances

	Logistic Regression t(1)b				Discriminant Analysis t(1)			
	t-1		t-2		t-1		t-2	
	Initial	Valid.	Initial	Valid.	Initial	Valid.	Initial	Valid.
		OOS	OOT	OOT		OOS	OOT	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

- All Gini-coefficients were lower than 0.5, so that models are not reliable prediction instruments *(Anderson, 2007, p. 205)*
- <u>Therefore the hypothesis of this work must be **rejected**:</u>
  It was not possible to develop a prediction model, which can reliably assign firms into one of the two stages.

Model development and results

Summary of the main results

- In accordance to research question one:
  NI/S, GP/TA and EBIT/INT were the best discriminating variables one year prior to the event of insolvency.

- In accordance to research question two:
  Accounting ratios alone are not in the position to construct a well-functioning prediction model.

- Identification of three key factors for successful turnaround:
  1. Increase in **efficiency** and **profitability** (NI/S and GP/TA)
  2. Improvement of **interest coverage ratio** (EBIT/INT)
  3. Optimization in **working capital management** (CA/TA)*

*) This ratio was statistically significant two years prior to bankruptcy and higher for successful turnarounds. For the period one year prior to bankruptcy the mean and median value decreased strongly for this groups of firms, so that no statistically significant different to insolvent firms was given any more.

Model development and results

Conclusions

- Differentiation between insolvent and distressed/recovered firms is **difficult**, because they seem to haver **certain similarities** (Poston, Harmon & Gramlich, 1994; Wilson, Chong & Peel, 1994; Barniv, Agarwal & Leach, 2002)

- Models better predicted insolvent cases, but showed **weak performance** in assigning **successful turnarounds** (Jones & Hensher, 2004; Liou & Smith, 2007)

- **Accounting ratios** alone are **not sufficient** to describe the different states properly (Poston, Harmon & Gramlich, 1994; Liou & Smith, 2007)

- Also they do **not** seem to be **useful** in predicting a distressed firm's potential towards bankruptcy (contrary to the findings in Turetsky & McEwen, 2001; Jones & Hensher, 2004)

- Several **other variables** not considered in the study seem to be **relevant** to divide between the different economic and financial states

Model development and results

Limitations of the study & recommendations for future research

- **Relatively small sample** for model development and validation
- **Non-normality of data** even in case of winsorization should have a small effect on logistic regression and a much higher for discriminant analysis (Press & Wilson, 1978, p. 404; Silva, Stam & Neter, 2002, p. 404; Hayden & Porath, 2011, p. 4)
- **Definition of distress** could be a **biased** measure and maybe not linked to the „real" economic and financial situation of a company
- Need to search for more **reliable indicators** (or combinations of indicators) to assign firms into different economic and financial stages
- Expansion of model development using **non-accounting variables** and testing of the change in incremental explanatory power and model performance

Model development and results
Implications for practice

A successful turnaround needs:

- Tightening the purchase process in order to improve **gross profit**.
- Such a measure is increasing **profitability** and EBIT, so that **interest coverage ratios** can be improved.
- Introduction of a stricter **debtor** and **inventory management** in order to reduce amounts outstanding and to improve inventory turnover.
- Turnaround managers should to this **in combination**, so that the probability of a successful turnaround can be increased.

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