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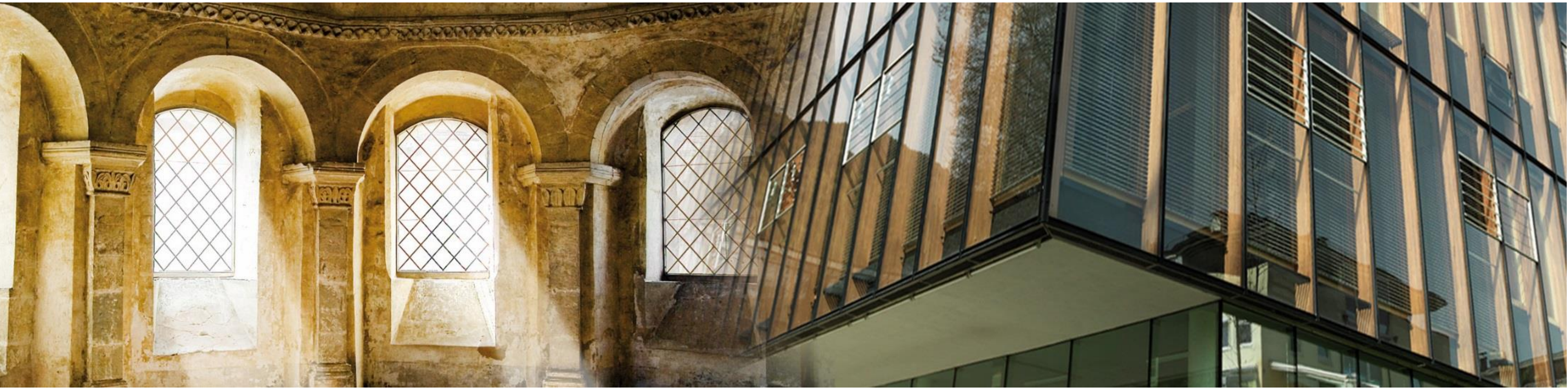

The divergence between corporate success and crisis: The separability of recovered and healthy companies

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Introduction and problem statement

- Economic and financial stage of a firm cannot be captured by **dichotomous** thinking (bankrupt & non-bankrupt)

- This was recognized relatively early in research (Altman, 1968; Edmister, 1972)

- Degree of corporate health can instead be explained by a **continuum** between the extremes bankrupt and healthy, where a company moves steadily in-between both states (Cestari, Risaliti & Pierotti, 2013; Haber, 2005; Keasey & Watson, 1991; Ward, 1999)

- Despite of several years in research this continuum and the evolution of corporate crisis as well as the occurrence of different stages of corporate health are **not** clearly **measureable nor** have been **understood** (Platt & Platt, 2008, p. 132; Pretorius, 2009)

Relevance and aim of the study

<u>Several motivations for the study supporting the relevance:</u>

1. Potential of a company to go into bankruptcy is a kind of **market imperfection**, affecting valuation properties in theoretical and empirical sense (Altman, 1969, p. 888)
2. Insolvency rate of a state reflects **development** and **robustness** of the economy (McKee, 2000, p. 159)
3. Early prediction of corporate crises could lead to better **allocation** of **resources** and **liquidity** provided by the market (McKee, 2003, p. 573-576; McKee, 1995, p. 30)
4. Early prediction of corporate crises and potential insolvency would be helpful for investors, providing liquidity to **distressed companies** in order to achieve future returns (Altman & Hotchkiss, 2006, p. 46; Moyer, 2005, p. 8)

<u>Aim of the study:</u>

- Division of companies into **three states of corporate health** (healthy, successfully and unsuccessfully recovered)
- **Detect** and **explain differences** between these types of firms using accounting ratios, industry-related accounting ratios and a proxy for insolvency rate of the industry

Methodology and research design

Selection of potential discriminating variables based on literature review
(Accounting ratios, age of the firm, industry-related accounting ratios & GDP_{growth} of industry as proxy for insolvency rate of industry [Altman et al. 2008, p. 229]; selected ratios of profitability were adjusted for yearly inflation)

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Winsorization of data
(proposed by Löffler & Posch, 2006, p. 15-19 in order to increase model quality and to eliminate extreme deviations from normality)

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Descriptive statistics and tests for differences
(using mean, median and standard deviation; test for differences to identify the most important risk drivers as proposed by Porath, 2011, p. 32 using U-test, t-test, ANOVA and H-test)

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Principal component analysis
(check for redundancy of data and to avoid multicollinearity in accordance with Afifi, May & Clark, 2003, p. 274; Chan, 2006, p. 56 and Klecka, 1980, p. 11)

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Computation of linear discriminant functions
(in order to differentiate between the different types of companies and to detect the risk drivers)

Literature review (1/3)

- **Different methods** used in research to construct insolvency prediction models (e.g. linear discriminant analysis, logistic regression neural networks, recursive partitioning etc.)

- Many studies used failure, bankruptcy, distress and insolvency were set equal to **legal description of insolvency** (e.g. Altman, 1968; Beaver, 1966; Mensah, 1984; Zmijewski, 1984; Shumway, 2001; Pang & Kogel, 2013; etc.)

- Mostly studies therefore focused on the **dichotomous thinking** (bankrupt vs. non-bankrupt; distressed vs. non-distressed; insolvent vs. solvent)

- Several studies can be found, where the behaviour **in-between** the dichotomous thinking were conducted in order to observe and explain different degrees of corporate health (e.g. Barniv, Agarwal & Leach, 2002; Gilbert, Menon & Schwartz, 1990; Lau, 1987; Moulton & Thomas, 1993; Tsai, 2013; Wilson, Chong & Peel, 1995; Whitaker, 1999 etc.)

Literature review (2/3)

- The studies show that it is in most cases **difficult** to distinguish reliably between the different types of corporate health
- Authors used different definitions of “distress” etc., so that a comparison between the studies is almost **impossible** and this indicates that our actual knowledge and understanding about the crisis evolution process is **limited** and **relatively low**
- There is **lack of knowledge** as to how the different stages of corporate health can be reliably defined and economically explained (Pretorius, 2009)
- There is **no** single, accepted definition in research and practice of the stages of (financial) distress and recovery (Platt & Platt, 2008, p. 132; Pretorius, 2009)
- The findings emphasize **the need** for additional research in order to better understand the crisis evolution process

Literature review (3/3)

Definitions concerning corporate stages	Main results	Reference
Introduction of five states [financially stable firms = stage 0; firms omitting or reducing dividend payment = state 1; firms in technical default and in default on loan payments = state 2; protection under Chapter X or XI = state 3; and bankrupt or liquidated firms = state 4]	Certain states can be predicted well, whereas others are quite difficult to predict	Lau (1987)
Comparison of bankrupt and non-bankrupt as well as bankrupt and distressed firms; distress was defined as the occurrence of negative cumulative earnings over any consecutive three year period between 1972 and 1983	Different indicators were relevant to distinguish between the different types of firms; a separation between bankrupt and distressed is more difficult than a segregation between bankrupt and non-bankrupt companies	Gilbert, Menon & Schwartz (1990)
Non-failed firms, failed and distressed-acquired firms	Their model provided an accuracy of 98.2 percent for the three states; the differentiation between failed and distressed acquired was very difficult and indicates that both types of firms have common characteristics	Wilson, Chong & Peel (19995)
Non-acquired distressed, acquired distressed and non-distressed companies; distress was defined as the situation where a firm exhibited at least one of the following characteristics: debt default, debt renegotiation attempts and/or an inability to meet fixed payment obligations on debt	Different predictors were relevant to divide between the different types of firms; the distinction between distressed acquired and distressed non-acquired remained difficult	Theodossiou et al. (1996)
Distressed and recovered firms; financial distress was seen to be pre-existing, when the cash flow was less than the current maturity of long-term debt; recovery was defined as the situation where a firm´s cash flow is greater than the current maturity of long term debt	Management actions are a significant factor for an improvement in industry-adjusted market value; management actions are not relevant, when distress is caused by a general decline of economic conditions in the industry	Whitaker (1999)
Investigation of failure process, using the change of operational cash flow from positive to negative	Higher financial leverage is positively associated with default; default has a significant association with business failure; certain states are closely associated to each other	Turetsky & McEwen (2001)
Application of Taffler´s Z-score (1983, 1984) to assign firms as recovered and non-recovered; recovery was defined as the situation where a firm exhibited two consecutive years of positive Z-scores	Both types of firms can be relatively well distinguished by using profitability ratios; recovered firms showed significantly better values in these ratios when compared to non-recovered firms	Sudarsanam & Lai (2001)

Hypotheses and research questions

Hypotheses:

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

[in some studies the consideration of inflation as explanatory variables for insolvencies increased prediction accuracy of models – e.g. Bartley & Boardman, 1990; Butera & Faff, 2006; Gudmundsson, 2002; Liou & Smith, 2007; Tirapat & Nittayagasetwat, 1999; however, no study was found where inflation-adjusted ratios were applied to the stages of distress and recovery, so that a new design was tried within this study]

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

[based on Edmister, 1972 and Lau, 1987 the accounting ratios for the firms were set into relation to the median value of the respective accounting ratio of their industry; the used approach was not tested for firms in distress and recovery before]

Research questions:

- Which variables are most suitable to explain the differences between the three types of companies?
- How relevant are industry-related accounting variables in the prediction of the two types of recovery?
- Can the implicit consideration of the industry insolvency rate (here replicated by the variable GDP_{growth}) help to increase the prediction accuracy and performance of models?

Definitions and sample description

Distress = two consecutive years of negative NITA adjusted for yearly inflation [in accordance to Krueger & Willard, 1991; figures without inflation provide distorted information (Bartley & Boardman, 1990, p. 68; Bulow & Shoven, 1982, p. 234; Dearden, 1981, p. 8), so that correction for inflation seems appropriate to determine the „real“ economic and financial situation of the firm]

Recovery = two consecutive years of positive NITA adjusted for yearly inflation [similar to the concept of Jostarndt & Sautner, 2008; their distress and recovery indicator was interest coverage based on EBIT]

Adjustment for inflation based on Coulthurst, 1986, p. 33; Solnik & McLeavey, 2009, p. 43:

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

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

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

Main results (Part I)

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

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

- **no higher accuracy** and **performance**, when inflation-adjusted variables are used (similar to Norton & Smith, 1979)
- a division between the two types of recovered firms is **easier** than to divide between unsuccessfully recovered and healthy firms
- The prediction accuracy **two years after** detection of **distress** is much higher than the first year after distress
- Healthy and successfully recovered firms are having a **higher profitability** and **equity base** compared to unsuccessfully recovered firms

Main results (Part II)

	Application of accounting ratios & industry-related ratios		Application of inflation adjusted accounting ratios & industry-related ratios	
Part A: Measures	0 vs. 1	0 vs. 2	0 vs. 1	0 vs. 2
Explained Variance (in %)	43.226	40.192	43.225	39.908
Wilks Lambda (Sign.)	0.000**	0.000**	0.000**	0.000**
Box´s M (Sign.)	0.000**	0.000**	0.000**	0.000**
Part B: Application on two years after distress (t+2)				
Accuracy (in %)	92.793	88.372	92.793	87.209
Type I error (in %)	2.128	2.128	2.128	4.255
Type II error (in %)	10.938	23.077	10.938	23.077
Part D: Performance measures				
$AUC_{(t+2)}$	0.977**	0.932**	0.977**	0.930**
$Gini\text{-}Coefficient_{(t+2)}$	0.955	0.865	0.955	0.860
$AUC_{(t+1)}$	0.476	0.498	0.509	0.540
$Gini\text{-}Coefficient_{(t+1)}$	-0.049	-0.005	0.019	0.080
Part E: Explanatory variable				
NIS	1.780	1.989	-	-
NISinfl.	-	-	1.812	2.012
EBITTA	18.039	1.921	-	-
EBITTAinfl.	-	-	18.375	1.537
TETA	1.012	1.419	1.013	1.379
EBITSind.	0.083	-	-	-
EBITTAind.	-	0.854	-	-
EBITSind. infl.	-	-	0.086	-
EBITTAind. Infl.			-	0.909
Constant	-1.131	-1.021	- 0.725	- 0.714

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

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- Inclusion of industry-related variables is **beneficial** to increase explained variance, accuracy and performance (Butera & Faff, 2006; Chava & Jarrow, 2004; Thornhill & Amit, 2003)
- a comparison of **profitability** to industry median of profitability seems helpful for higher explained variance

Final conclusions and answers to research questions

- Firms with higher **profitability** are more likely to be assigned as healthy and/or successfully recovered (Begley, Ming & Watts, 1996; Doumpos & Zopounidis, 1998; Situm, 2015a; Sudarsanam & Lai, 2001)

- Firms exhibiting a higher **equity ratio** are more likely to be assigned as healthy and/or successfully recovered (Bartual et al., 2012; Grunert, Norden & Weber, 2005; Pompe & Bilderbeek, 2005)

- Firms exhibiting higher **profitability in comparison to industry mean** are more likely to be assigned as healthy and or/successfully recovered (Edmister, 1972; Chava & Jarrow, 2004; Hoshi, Kashyap & Scharfstein, 1990; Thornhill & Amit, 2003)

- GDP_{growth} (replicating insolvency rate of the industry as proposed by Altman et al. 2008, p. 229) was **not statistically significant** at all

Hypotheses testing

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

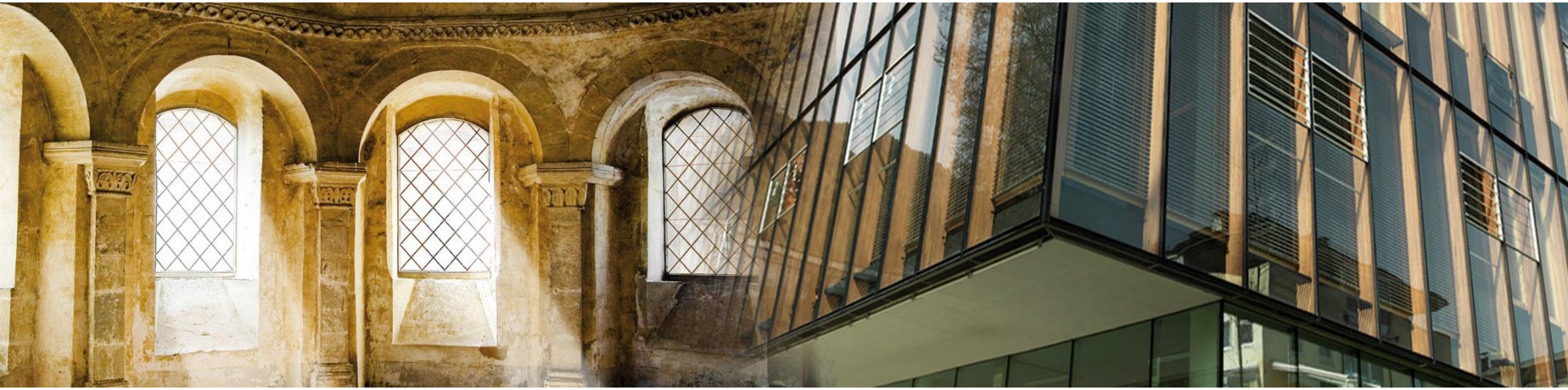
Limitations of the study

- Variance(covariance) matrixes of the groups were **not equal**, so that a theoretical pre-condition for proper application of linear discriminant analysis was violated (Afifi, May & Clark, 2003, p. 274; Atkinson, Riani & Cerioli, 2004, p. 300); however, this should be of **minor relevance** if amount of discriminators and the differences in group sizes are low (Klecka, 1980, p. 61)

- Even of data was winsorized **non-normality of data** was not a given, which is another theoretical pre-condition for proper application of linear discriminant analysis (Klecka, 1980, p. 61; Subhash, 1996, p. 263); nevertheless, a small deviation form normally can be accepted as this does not influcence classification accuracy of forecasting models (Hopwood, McKeown & Mutchler, 1988; Feldesman, 2002; Silva, Stam & Neter, 2002)

- Within this study a relatively **small sample size** is a given, which may have influenced model quality and explanatory power of the models

Contact data



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