The Relevance of Trend Variables for the Prediction of Crises and Insolvencies

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Introduction/Problem Statement (1/2)

Understanding about corporate crises and insolvencies remains prominent topic in research

Past research provided several explanations and delivered many relevant factors for the explanation of both occurrences

Nevertheless, there exists no generally accepted „theory of crisis development", which is grounded on actually recognized financial theories

Additionally, insolvencies are a kind of **market imperfection**, which should be avoided due to potential costs of bankruptcy

Justification for research is given, because there are several questions left which must be answered for better understanding

Introduction/Problem Statement (2/2)

About 93 percent of analyzed variables are **accounting ratios**, so that their importance for forecasting models is given (*Du Jardin*, 2009, p. 41)

The other 7 percent are statistical variables, trend variables and non-financial variables *(Du Jardin, 2009, p. 41)*

Trend variables were also investigated in previous studies and showed quite good prediction performance *(Edmister, 1972; Blum, 1974; Lau, 1987; Bryant, 1997; Ohlson, 1980; Sen et al., 2004; Zuo et al., 2008)*

The appearance of these variables is relatively low compared to accounting ratios; consequently, there is potential for further investigation

Within this study the **potential of trend variables** (computed as the difference of accounting ratios of two consecutive years) was analyzed

Literature Review (1/2)

Almost every variable seems to have **informational content**, which could be exploited for early detection of crises and insolvencies (*Pretorius*, 2008, p. 417)

First approaches mainly used **accounting ratios** for the segregation between failed and non-failed firms (*Beaver*, 1966; *Altman*, 1968; *Edmister*, 1972; Bl*u*m 1974; *Libby*, 1975)

Such variables seem **not** to be **sufficient** to fully explain the phenomenon of crises and insolvencies

Therefore, the inclusion of **other types of variables** (e.g. market data, macroeconomic factors, trends, industry variables etc.) are necessary in order to construct more reliable and stable prediction models (*Barniv et al.*, 2002; *Grunert et al.*, 2005; *Muller et al.*, 2009; *Altman et al.*, 2010; *Madrid-Guijarro et al.*, 2011)

Literature Review (2/2)

Even if this knowledge is given, attempts to search for suitable accounting ratios remains prominent, because:

1. The **legal definitions** of bankruptcy/insolvency use „lack of liquidity" and „indebtedness" as benchmarks to assign a company to these states

2. Literature mainly assumes **semi-strong market efficiency**, so that investors can to a certain degree obtain beneficial information from reading financial statements (*Zhang*, 2006, p. 107; *Agarwal et al*., 2008, p. 461 – 463; *Varamani* et al., 2008, p. 24)

3. Accounting ratios are carrying certain information content not visible in **market prices**, so that they can be used for enterprise valuation (*Beaver et al*., 1970, p. 679; *Setiono et al*., 1998, p. 635; *Nissim et al*., 2003, p. 553; *Lambert et al*., 2007, p. 410 – 411; *Milburn*, 2008, p. 298)

4. Incorporation of accounting ratios within early warning systems is therefore arguable, as they can provide **specific warning signals** about the economic situation of a firm (*Kwon et al*., 1994, p. 346 – 347; *Piotroski*, 2000, p. 1 – 4; *Turetsky et al*., 2001, p. 339; *Chava et al*., 2004; p. 553; *Milburn*, 2008, p. 287)

Database (1/2)

Financial statements from 2,309 Austrian companies from different industries for the time period 2010 to 2012

2012 was set as the **insolvency date** and the previous periods were defined as:

- 2011: **one** year prior to insolvency
- 2010: **two** years prior to insolvency

Firms were divided into two groups: solvent and insolvent (with two subclasses)

- insolvent (1st subclass): firms declared **bankruptcy/insolvency** under Austrian law

- insolvent (2nd subclass): firms in **distress**; identified by negative earnings for two consecutive years (*DeAngelo et al.*, 1990; *Platt et al.*, 2002; *Platt et al*. 2008; *Molina et al.*, 2009)

- solvent: neither bankrupt nor distressed

Database (2/2)

No matched pairing in order to avoid **choice-based sampling** (*Zmijewski*, 1984; *Platt et al.*, 2002; *Skogsvik* et al., 2013)

Aim to replicate true proportions of reality is also **not** recommended, because insolvencies are a „rare" event (therefore, proportions based on current insolvency rate of 1.7 percent for 2012 were also not used)

Instead, a proportion was selected which was **similarly** used in several previous studies (*Ohlson*, 1980; *Zmijewski*, 1984; *Hillegeist et al.*, 2004; *Chaudhuri*, 2013)

Composition of samples

	State	Development Group	Validation Group
		full sample randomly splitted 70:30	
Group 0	Bankrupt Firms	26	11
	„Distressed" Firms	70	30
Group 1	Solvent Firms	1,520	652
	Total	**1,616**	**693**

Research Design & Methodology

Computation of **accounting ratios** from financial statements for the two years prior to the event of insolvency (22 ratios based on literature review)

Additionally, a specific **trend** was computed for each ratio defined as:

$$\text{Trend (Difference)} = \text{Ratio}_{t+1} - \text{Ratio}_{t}$$

Computation of **descriptive statstics** and test for **normal distribution**

Detection of **best discriminating variables** based on parametric (t-test, Levene Test) and non-parametric tests (U-test)

Correlation analysis and **factor analysis** for detection of multicollinearity

Calculation of different discriminant functions using <u>development group</u> (model building) and **validation** of the functions based on validation group

Evaluation of the functions using **performance measures** (Gini coefficient)

Hypothesis & Research Questions

Hypothesis:

Corporate crises and insolvencies can be much better detected when trend variables are incorporated within early warning models.

Research Questions:

1. Which accounting ratios and trends are useful for discrimination between solvent and insolvent firms and for the early detection of crises?

2. Are trend variables more suitable in forecasting potential corporate crises compared to acconting ratios?

3. Can a combination of accounting ratios and trends increase the classification performance of early warning models?

Results & Model Presentation (1/2)

Statistics revealed that data were **not normally distributed**, so that applicability of linear discriminant analysis was theoretically not given (*Hauschildt et al*., 1984; *Pacey et al*., 1990; *Barniv et al*., 1992; *Baetge et al*., 1992; *Thornhill et al*. 2003; *Chi et al*. 2006; *Yim et al*., 2007; *Pervan et al*. 2012)

Nevertheless, certain deviations can be tolerated, so that application can be justified (*Hopwood et al*., 1988; *Silva et al*., 2002)

Due to non-normality the discrimination data was analyzed using **U-test** (non-parametric approach)

Several combinations of linear discriminant functions were computed, but only those with a Gini-coefficient **above 0.5** are relevant (Anderson, 2007)

No model **only** including trend variables reached this threshold

Results & Model Presentation (2/2)

Three models remained:

$$Z_{2011} = 4.283 \cdot NI/TA + 0.001 \cdot S/TE + 0.565 \cdot TE/TA + 0.119 \cdot EBIT/S + 0.449$$

$$Z_{2010} = 2.526 \cdot NI/TA + 0.505 \cdot RE/TA + 0.073$$

$$Z_{2010(II)} = 2.338 \cdot NI/TA + 0.493 \cdot RE/TA + 0.115 \cdot \Delta CF/TD + 0.025 \cdot \Delta NI/TA + 0.104$$

	Modell Z(2011)				Modell Z(2010)				Modell Z(2010II)			
	2011		2010		2010		2011		2010		2011	
	DG	VG	DG	VG	DG	VG	DG	VG	DG	VG	DG	VG
Accuracy	0.901	0.859	0.918	0.890	0.862	0.840	0.834	0.823	0.863	0.835	0.829	0.814
Type 1. Error	0.729	0.854	0.833	0.854	0.563	0.659	0.490	0.634	0.563	0.659	0.500	0.707
Type 2. Error	0.059	0.097	0.034	0.063	0.111	0.129	0.146	0.149	0.111	0.133	0.151	0.153
AUC Single	0.777	0.719	0.766	0.794	0.774	0.796	0.778	0.742	0.771	0.802	0.755	0.735
Gini-Coeff.	0.553	0.437	0.533	0.587	0.549	0.591	0.557	0.484	0.542	0.605	0.510	0.471
AUC Grouped	0.759		0.774		0.779		0.767		0.779		0.748	
Gini-coeff.	0.518		0.549		0.558		0.533		0.557		0.495	
AUC Total	0.766				0.773				0.763			
Gini-Coeff.	0.533				0.545				0.525			

DG= Development Group; VG = Validation Group

Summary & Highlights (1/2)

Obtained variables show expected signs and can be economically interpreted:

- higher **profitability** is associated with lower probability of insolvency (*Beaver*, 1966; *Zmijewski*, 1984; *Sudarsanam et al*., 2001; *Chava et al*. 2004; *Tsai*, 2013)
- higher **retained earnings** are associated with lower probability of insolvency (*Altman*, 1968; *Coats et al*., 1993; *Neves et al*., 2006; *Altman et al*. 2010)
- higher **equity turnover** is associated with lower probability of insolvency (*Bruse*, 1978)
- higher **equity ratio** is associated with lower probability of insolvency (*Pompe et al*., 2005; *Grunert et al*., 2005)
- positive **trend** of **CF/TD** is associated with lower probability of insolvency
- positive **trend** in profitability is associated with lower probability of insolvency

The **age of the firm** was **not** correlated with retained earnings, which is in contrast to several studies (*Altman*, 1968; Charitou et al., 2004; Chi et al., 2006; *Altman et al*., 2010) but confirms results from other papers (*Thornhill et al*., 2003; *Chancharat eta al*., 2010; *Situm*, 2014a)

Summary & Highlights (2/2)

The size and the age of the firm were **not** correlated with each other, which was expected based on theory (*Jovanovic*, 1982; *Thornhill et al*., 2003)

Size can be measured by ln(TA) or ln(S), as both variables showed high correlations (*Chi et al*., 2006; *Chancharat et al.*, 2010; *Situm*, 2014a)

Correlations of accounting ratios between two consecutive years were at a relatively **low level** (not given), but much higher for insolvent firms

Information from previous year is not (sufficiently) included in the actual year therefore, the development of solvent firms rather follows a **hazard** function, whereas the movement of insolvent firms could be better explained by a **pre-determined path**

Trend variables showed much higher and more significant correlations between the two years, but it was **not possible to exploit** this aspect for improved model buidling & classification

Hypothesis Testing & Answers to Research Questions

Hypothesis:

Corporate crises and insolvencies can be much better detected when trend variables are incorporated within early warning models. **[falsification and rejection]**

Research Questions:

1. Which accounting ratios and trends are useful for discrimination between solvent and insolvent firms and for the early detection of crises?
   NI/TA, TE/TA, EBIT/S, RE/TA, Δ CF/TD and Δ NI/TA

2. Are trend variables more suitable in forecasting potential corporate crises compared to acconting ratios?
   A better oder higher suitability for trend variables was not found

3. Can a combination of accounting ratios and trends increase the classification performance of early warning models?
   A combination of both types of variables was not in the position to increase classifcation accuary and performance

Limitations

Model development with **non-normal data**, which could have influenced model building procedure and classification quality:

A theoretical pre-condition for the application of linear DA

Unequal **covariance matrices**, so that additionally model quality was affected

Another theoretical pre-condition for the application of linear DA

Even if **significances** based on Wilks-Lambda were given, there remains a great portion of **unexplained variances** between the two groups of firms:

this means that several other factors are necessary in order to optimize model quality

Definition of insolvent firms using „bankrupt" and „distressed" could affect model building:

even if both types of firms show similar behavior and patterns, their differences may be sufficient for reduction of model quality; additionally, the definition of „distress" may not be appropriate enough

Recommendations for Future Research

Computation of trend variables with **other approaches** in order to restore informational content of original values

Application of **other statstistical methods** (e. g. logistic regression) to develop models with higher accuracy, stability and performance

Optimization of the developed models according to adjustment of **cut-off value**

Correlational behavior implies the search for **more suitable methods** for the explanation of evolution of crises and insolvencies

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