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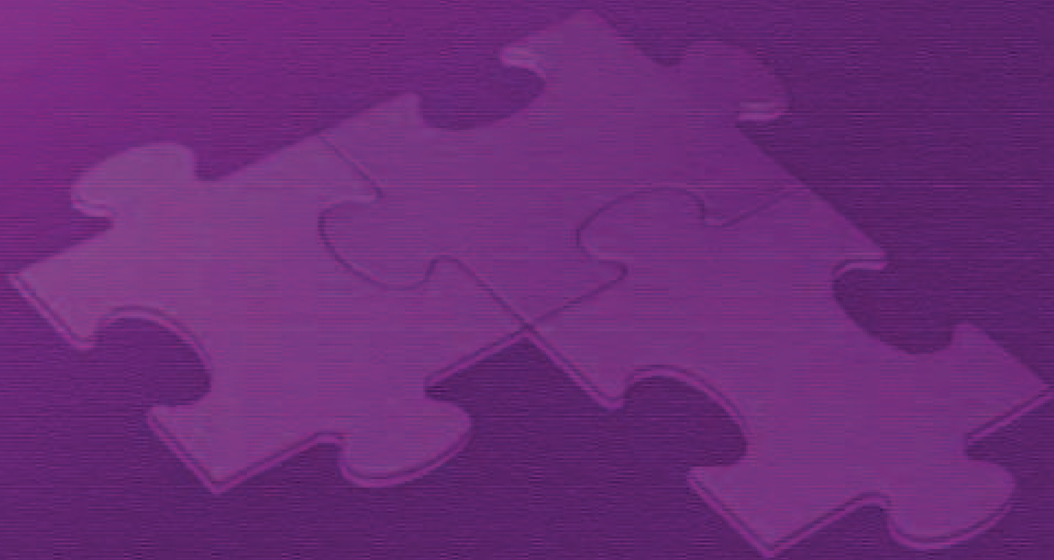

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EDITORIAL

This is the fourth issue of the second volume of *Czech Journal of Social Sciences, Business and Economics* (CJSSBE) scheduled for winter 2013.

The aim of CJSSBE is to facilitate the transmission of new scholarly discoveries in the fields of social sciences, business and economics. Thence, our journal offers a platform that supports scholars in building upon intellectual treasures and advancing our understanding about various fields of research in novel and meaningful ways. Capitalizing on this effort, we now focus on furthering our scope and consolidating our position in both conceptual developments and practical applications in the fields covered by the scope of this journal.

The research papers appearing in the fourth issue address a number of topics comprising the main three fields of the journal: social sciences, business and economics.

The papers that belong to the first section include an array of works that deal with praxeological skills of future professionals, attitutes of German authorities and society of the prisoners of war kept in the Soviet Union.

The papers that represent the business section of our journal include the research of business failure prediction model, research of occupational prestige among young people in Belarus, and psychology of corrupt behaviour and resistance to corruption amongst public servants.

The economics section of our winter issue includes the paper on the loyality programs in fast-moving consumer goods as well as the economic estimation of the effectiveness of using minerals in producing bottled drinking water.

We trust that you will enjoy reading the present issue, and we look forward to presenting you our next issue in spring 2014 that will start our Volume 3.

Wadim Strielkowski
Editor-in-Chief

Inna Čábelková
Editor

Evgeny Lisin
Editor

BUSINESS FAILURE PREDICTION MODELS BASED ON EXPERT KNOWLEDGE

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Abstract

This paper presents two business failure prediction models developed with multivariate linear discriminant analysis and multivariate logistic regression. The financial ratios as predictors for the models were selected based on results from previous empirical research. It was assumed that companies can be categorized into three classes – healthy (group 1), crisis-resistant (group 2) and insolvency endangered (group 3) – which are describing different economic conditions. Data for model building were obtained by a survey of 35 professionals from management consulting and banking industry. The results show consistency with findings of prior research. High values for equity-ratio, EBIT/total assets, operating cashflow/financial liabilities and percentage sales development are positively related to financial health. Within model building several problems occurred, which influenced classification accuracy. Non-normality of data had an impact on discriminant analysis, but also on logistic regression. Successful preliminary analyses of suitable predictors are not a guarantee that model fit including statistically significant variables will provide a superior prediction model. This indicates that model building is heavily dependent on the quality of metrics used. Logistic regression was less sensitive to outliers in terms of prediction sign within classification formula. It was also shown that crisis indicators used in practice are similar to those proposed by empirical research and literature.

Keywords: business failure prediction, discriminant analysis, logistic regression, financial ratios, early warning system, crisis indicators

JEL classification: *C00, C38, C50, G17, G33*

Introduction

Early detection of corporate crises in the wake of rapidly changing economic and environmental conditions is a topic of growing importance. The earlier a potential crisis can be detected, the more effective and better turnaround activities can be implemented. Therefore, managers need early warning systems, which assist in the detection of crises. An evaluation of companies is not only important from the perspective of banks, but is also interesting for other parties such as potential investors or shareholders.

In literature many early warning indicators had already been studied, which are based on both quantitative and qualitative factors. In counselling practice as well as in investment and

financing decisions the benefits of these results had been recognized. There are now technically sound methods (e.g. credit assessment models, rating models etc.) that assist in early detection of corporate crises. In the phase of a strategic crisis, the manifestations of the crisis symptoms are very weak, so it is especially difficult in practice to discover this early stage within a company. If detection is successful, there is little pressure to act and there is enough room to take appropriate actions out of this crisis as well as to avoid the transition into revenue crisis. The probability to detect a revenue crisis is far higher than for strategic crisis. Here the crisis is generally well advanced, but it remains sufficient time and space to avoid the risk of liquidity crisis, which is the last form of corporate crisis before insolvency occurs. It represents the most difficult phase, because there are hardly any room to handle and a high pressure of time.
Within this work a survey of 35 professionals from consulting and banking industry was conducted by questionnaire to determine crisis indicators, which are used in business practice to assess the economic situation of enterprises. Moreover an estimate of quantities for four selected financial indicators (equity ratio, EBIT/total assets, operating cash flow/total liabilities and percentage sales development) was questioned, with which a company could be divided in three categories (healthy, crisis-resistant and insolvency endangered). Based on this information multivariate linear discriminant analysis and logistic regression were estimated in order to develop business failure prediction models. The purpose is to test, whether a model built on expert knowledge is in congruence with models set up with empirical data from prior research. Additionally the potential limitations for setting up business failure prediction models are discussed.
This paper is organized as follows: Section 2 provides an overview about prior research in business failure and bankruptcy prediction, section 3 describes, how the data for model building were obtained, section 4 contains the results from statistical analyses and also the results from model building, section 5 provides a summary with implications and within section 6 a short summary of the relevant results and some implications for practioners are given.

Literature review

One of the first papers in the field of business failure prediction was published by Beaver (1966), who introduced the dichotomous classification test for the separation of failed and non-failed firms based on some chosen financial ratios. The core of his work contains the liquid-asset-flow model. He defined the firm as a reservoir of liquid assets, which is supplied by inflows and drained by outflows. This reservoir is a cushion for the firm against variations in in- and outflows. The solvency of a firm can be defined as the probability that this reservoir will be exhausted. At this point the firm will be unable to meet financial obligations and slides into bankruptcy (Beaver, 1966, p. 80- 83). The best discriminating variable was the ratio cash flow/total debt. His conclusion was that financial ratios can to a certain degree discriminate between failed and non-failed companies. The limitations can be seen in classification deficiencies concerning type I and type II errors, which were due to overlappings of distributions for the financial ratios of the different groups (Beaver, 1966, p. 101 – 102).

An extension of Beaver's work had been proposed by Altman (1968). Altman recognized that there is a potential of ratios as predictors of bankruptcy, as failing firms exhibit significantly different ratios than non-failed firms. In contrast to Beaver he decided to use a multiple linear discriminant analysis, as it can combine several measures into a meaningful predictive model (Altman, 1968, p. 589 – 593). The result brought a linear discriminant function containing five ratios (working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/book value of total debt and sales/total assets) (Altman, 1968, p. 594). Similar to Beaver (1966) this classification function was not functioning perfectly as type I and type II errors appeared. He found that these misclassifications occurred for Z-scores between 1.81 and 2.67. This area was defined as the "zone of ignorance" or "gray area" and led to the conclusion that an optimal cut-off point between failed and non-failed firms can be defined in order to control for type I and type II errors based on costs of misclassification (Altman, 1968, 602 – 607). The great contribution of this finding was that the different stages of a firm should not be categorized into dichotomous states. It is rather a continuous scale denoting different economic conditions for a firm.

After Altman (1968) several other researchers used discriminant analysis as method for prediction of firm failure (Edmister, 1972; Altman, Haldeman & Narayanan, 1977; Houghton & Woodliff, 1978; Dietrich, Arcelus & Srinivasan, 2005; Mohamad, 2005; Vuran, 2009). Alternative derivatives of discriminant analysis like quadratic discriminant analysis or non-parametric discriminant analysis had also been tried for business failure prediction models. The quadratic form did not improve classification accuracy and disappeared as a possible method for business failure prediction (Altman, Haldeman & Narayanan, 1977; Gombola, Haskins, Ketz & Williams, 1987; Pacey & Pham, 1990). The non-parametric form only showed partially better results than the linear form and therefore was not able to break through within further research (Barniv & Raveh, 1989; Barniv & McDonald, 1992).

A methodological improvement was provided by Ohlson (1980), who introduced logistic regression (logit-analysis) for business failure prediction. The big advantage was seen in the less stringent statistical assumptions in contrast to multivariate linear discriminant analysis. Additionally logit-analysis can assign probabilities that a specific company belongs to a certain group. This was the great value of this work. Ohlson was able to find some significant factors for discriminating between failed and non-failed companies. Within his work the ratio "size of the firm" appeared as very important variable, which was separating well for several years before failure (Ohlson, 1980, p. 109 – 123).

Based on Ohlson (1980) numerous empirical research using logit-regression and the related probit-regression were conducted, whereas many of the papers also developed models with discriminant analysis to compare the prediction performance between the methods (Mensah, 1984; Zmijewski, 1984; Casey & Bartzcak, 1985; Gentry, Newbold & Whitford, 1985; Gombola, Haskins, Ketz & Williams, 1987; Aziz, Emanuel & Lawson, 1988; Aziz & Lawson, 1989; Lau, 1987, Barniv & Raveh, 1989; Gilbert, Menon & Schwartz, 1990; Pacey & Pham, 1990; Barniv & McDonald, 1992).

There are several papers preferring the logit or probit analysis (Gentry, Newbold & Whitford, 1985; Lau, 1987; Aziz, Emanuel & Lawson, 1988; Barniv & McDonald, 1992; Dimitras, Slowinski, Susmaga & Zopounidis, 1999; Pervan, Pervan & Vukoja, 2011). Other researches showed better results for discriminant analysis (Poston, Harmon & Gramlich, 1994; Yim & Mitchell, 2007; Muller, Steyn-Bruwer & Hamman, 2009). The remaining results provide equal or similar performance quality of the methods (Casey & Bartczak, 1985; Gombola, Haskins, Ketz, & Williams, 1987; Boritz, Kennedy & de Miranda e Albuquerque, 1995; Doumpos & Zopounidis, 1999; Hwang, Cheng & Lee, 2007; Gepp & Kumar, 2008). Therefore it cannot be clearly argued that logit analysis is the better method for bankruptcy prediction.

With introduction of neural network applications a statistical method replicating the structure of human brain was used to set up business failure prediction models. In several studies is was concluded that this method produced better classification results compared to discriminant analysis or logit regression (Coats & Fant, 1993; Anandarajan, Lee & Anandarajan, 2001; Atiya, 2001; Charitou, Neophytou & Charalambous, 2004; Neves & Vieira, 2006; Yim & Mitchell, 2007). Nevertheless these results were not confirmed by other studies, as at least a similar performance in classification results to logit-analysis was found. In seldom cases the results of logit-analysis were superior to those of neural networks (Fanning & Cogger, 1994; Sen, Ghandforoush & Stivason, 2004; Pompe & Bilderbeek, 2005; Chen, Marshall, Zhang & Ganesh, 2006).

Researchers also applied other methods like recursive partitioning and decision trees (Marais, Patell & Wolfson, 1984; Frydman, Altman, Kao, 1985; Sung, Chang, Lee, 1999; Chen, Marshall, Zhang & Ganesh, 2006; Huang, Tsai, Yen & Cheng, 2008; Muller, Steyn-Bruwer & Hamman, 2009), Gambler´s ruin and survival models (Fanning & Cogger, 1994; Gepp & Kumar, 2008; Nam, Kim, Park & Lee, 2008), case based reasoning (Bryant, 1997; Lin, Wang, Wu & Chuang, 2009; Li & Sun, 2011), rough set theory and fuzzy set theory (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999; Ahn, Cho, & Kim, 2000; McKee, 2000; Baetge, & Heitmann, 2000; McKee, 2003; Lin, Wang, Wu & Chuang, 2009), genetic algorithm (Brabazon, & Keenan, 2004) or support vector machines (Li, Sun & Wu, 2010; Lin, Liang, & Chen, 2011; Li & Sun, 2011). Even if some of these applications showed better classification results compared to discriminant analysis and logistic regression, the last two mentioned methods remain the most favoured for model building in business failure prediction.

Data for model building and methodology

The survey was initiated by means of a questionnaire, which was given to 35 practitioners in the consulting industry covering experts from restructuring, credit risk and turnaround management. Based on a literature review the following characteristics were discussed, in which the respondents were asked to give values for three economic conditions of business based on their practical experiences (the computations of the ratios are shown in the appendix of this paper). The four ratios appeared as predictors in previous studies and were chosen to to their popularity and appearance:

- Equity-ratio and its ability to represent the financial stability of companies: The ratio appeared as relevant predictor in Barniv & Raveh (1989), Laitinen & Laitinen (1998), Laitinen & Laitinen (2000), Baetge & Heitmann (2000), Paradi, Asmild & Simak (2004) or Pompe & Bilderbeek (2005).
- EBIT/total assets as an indicator to measure profitability:
The ratio appeared as relevant predictor in Altman (1968), Houghton & Woodliff (1987), Barniv & McDonald (1992), Coats & Fant (1993), Atyia (2001), Hillegeist, Keating, Cram & Lundstedt (2004) or Chen, Marshall, Zhang & Ganesh (2006).

- Operating cashflow/total debt as a measure of the debt repayment capability:
  The ratio appeared as relevant predictor in Beaver (1966), Aziz, Emanuel & Lawson (1988), Platt, Platt & Pedersen (1994), or Beaver, McNichols and Rhie (2005), p. 101.
- Percentage sales development in comparison to previous year:
  Trends for different ratios showed contribution for improved prediction classification in Edmister (1972), Blum (1974), Lau (1987), Barniv & Raveh (1989), Abidali & Harris (1995), Sen, Ghandforoush & Stivason (2004), Muller, Steyn-Bruwer & Hamman (2009).

The three economic conditions were described as follows.

- Healthy (group 1): are companies, which are potentially in a strategy crisis and not in a revenue crisis
- Crisis-resistant (group 2): companies, which are in a revenue crisis, but are having sufficient resources for a turnaround
- Insolvency endangered (group 3): are companies, which are on the verge of a liquidity crisis and may slide into insolvency

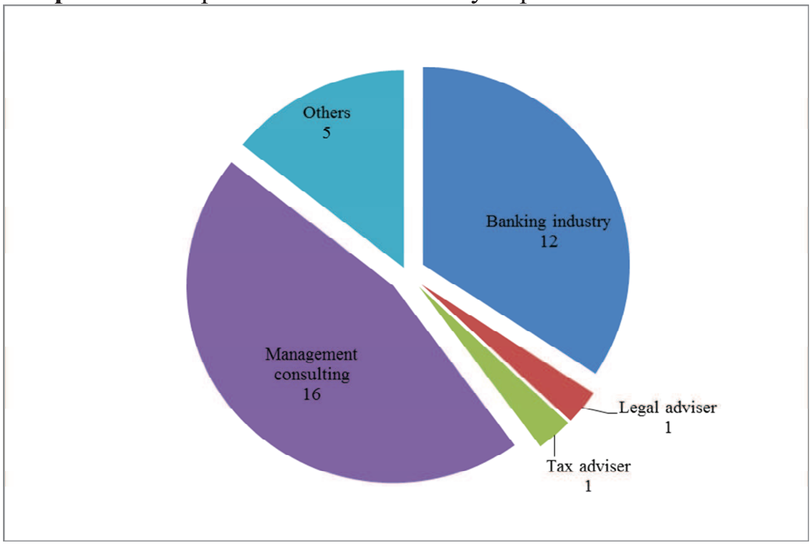
No explicit and deeper definition for the different stages was given. The three stages of crises are generally known by professionals in practice, but literature is not providing specific benchmarks, where they can be clearly divided. So the purpose was to leave some space to the respondents in order to receive potential values for the chosen ratios, which are suitable to determine the different economic conditions or crisis stages based on experiences of professionals. The developed models are replicating these experiences from a practical viewpoint, so that early warning systems could be constructed.

Statistical analyses and model building results

Descripitve statistics of surveyed professionals

The distribution of the 35 surveyed professionls is presented in graph 1. The majority of the respondents were management conultants followed by professionals from banking industry. Within the cluster „others“ people from interim management, private equity or creditor protection organizations are categorized. 86 percent of the respondents were located in Germany, whereas the rest came from Austria. This distribution provides a mix of different external partners of enterprises, which are having all different experiences and knowledge about how to assess the financial viability of a firm.

Graph 1: Descriptive statistics of surveyed professionals



Source: Own results

Statistical analyses

Based on the responses a record with a length of 105 (35 respondents multiplied by 3 groups) observations was obtained. The descriptive statistics show that the averages of groups differ fundamentally. "Healthy companies" clearly show higher values in all four variables in comparison to the other groups. The lowest values can be found for the "bad companies". Also, the standard deviations in the groups for the various indicators show differences. This would indicate that the financial ratios generally have good conditions for modelling. To analyse this more precisely, tests for normal distribution, F-tests in the course of an ANOVA and comparisons of means were conducted.

The tests for normal distribution by Kolmogorov-Smirnov and Shapiro-Wilks showed for all groups that at the significance level of 5% normality of distributions cannot be assumed. The calculated statistical significances (p-values) were all lower than 0.05, so that the risk of rejecting the null hypothesis was hardly given. Especially for discriminant analysis, a deviation from normal distribution can affect the classification results (Subhash, 1996, p. 263; Klecka, 1980, p. 61; Hopwood, McKeown & Mutchler, 1988). Even if the assumption of normality of data is not fulfilled, it is possible to reach statisfactory results. It was shown that discriminant analysis can at certain skewes of distribution provide better results than logistic regression, so that its application in research can be justified also with non-normally distributed data (Pohar, Blas & Turk, 2004, p. 159 – 160). For logistic regression this assumption is not essential and studies showed that this method is relatively robust against violations of normal distribution (Press & Wilson, 1978). However, classification accuracy can be affected to a certain degree (Hopwood, McKeown & Mutchler, 1988. p. 293). Therefore, it could be assumed on preliminary analyses that the application of logistic regression should provide better results than discriminant analysis.

Table 1: Test for normal distribution

	Group	Kolmogorov-Smirnov			Shapiro-Wilk		
		Statistic	df	Sign.	Statistic	df	Sign.
Equity-ratio	1	.213	35	.000	.930	35	.028
	2	.218	35	.000	.902	35	.005
	3	.244	35	.000	.873	35	.001
EBIT/total assets	1	.233	35	.000	.869	35	.001
	2	.200	35	.001	.821	35	.000
	3	.273	35	.000	.770	35	.000
Operating cashflow/total debt	1	.226	35	.000	.710	35	.000
	2	.281	35	.000	.529	35	.000
	3	.358	35	.000	.382	35	.000
Percentage sales development	1	.273	35	.000	.888	35	.002
	2	.201	35	.001	.895	35	.003

Percentage sales development is constant for group = 3 and was therefore not displayed

Source: Own results

Next an analysis of mean vectors was applied. The first three variables showed statistical significance of less than 0.05 (5% significance level), so that null hypothesis (equality of means between the groups) may be rejected. For the last variable "percentage sales development" the calculations were not possible as within this group all values were constant across all cases. Nevertheless it can be concluded that the variables are having good separation ability and are in principle suitable for model building. This should be particularly advantageous for the linear discriminant analysis, as this process is aiming to separate mean vectors optimally.

Table 2: Test for differences in means

		Statistic	df1	df2	Sig.
Equity-ratio	Welch-Test	105.441	2	61.940	.000
	Brown-Forsythe	80.948	2	85.614	.000
EBIT/total assets	Welch-Test	46.880	2	55.630	.000
	Brown-Forsythe	34.404	2	68.398	.000
Operating cashflow/total debt	Welch-Test	9.657	2	65.862	.000
	Brown-Forsythe	9.161	2	92.901	.000
Percentage sales development	Welch-Test	.	.	.	.
	Brown-Forsythe	.	.	.	.

Source: Own results

The variances of the individual indicators within the groups are significantly lower than the value of 0.05. This means that the alternative hypothesis is valid, and the groups are statistically different in terms of their variances at 5 % level. This is also an indication that the ratios are having a high aptitude for the modelling of a prediction tool.

Table 3: Test for differences in variances

		Square Sum	df	Mean Square	F	Sig.
Equity-ratio	Between Groups	1.043	2	.521	80.948	.000
	Within Groups	.657	102	.006		
	Overall	1.700	104			
EBIT/total assets	Between Groups	.209	2	.104	34.404	.000
	Within Groups	.309	102	.003		
	Overall	.518	104			
Operating cashflow/total debt	Between Groups	.473	2	.236	9.161	.000
	Within Groups	2.632	102	.026		
	Overall	3.104	104			
Percentage sales development	Between Groups	.054	2	.027	41.076	.000
	Within Groups	.067	102	.001		
	Overall	.121	104			

Source: Own results

Development of business failure prediction models

Multivariate linear discriminant analysis

First, a multivariate linear discriminant analysis was calculated with all variables. In addition to the criterion of normal distribution of the data covariance matrices must be the same (or similar) so that the method works well. For this purpose a box test was carried out. The significance shows a value of 0.175, so the null hypothesis (equality of the covariance matrices) can be maintained. Thus, in addition to the diversity of the group means another important criterion for the applicability of the method is given.

Table 4: Box-test – Test for equality of covariance matrices

Box-M		14.902
F	Approximation	1.395
	df1	10
	df2	22106.773
	Significance	.175

Source: Own results

A look at the canonical correlation coefficient shows a high value for the first function, so it can be assumed that it is having high separation power. Since three groups were analysed, there are two discriminant functions, which are orthogonal to each other. Essential for the quality of the model is Wilks' lambda. When the significance is less than 0.05, then a function is significantly discriminating between the groups. It is therefore sufficient to consider the first function for model building as the second function is not suitable for separation between the groups due to significance of 0.667. This was also confirmed by a check of group centroids.

Table 5: Eigenvalues und Wilks-Lambda of discriminant functions

Test of Functions	Wilks-Lambda	Chi-Square	df	Sign.
1 to 2	.300	120.928	8	.000
2	.985	1.567	3	.667

Source: Own results

Based on unstandardized canonical discriminant function the overall classification function can be set up. Due to the previous analyses it is sufficient only to consider the first function, which can be written as shown in equation 1:

$$Z = -2.665 + 8.913 \cdot X_1 + 4.549 \cdot X_2 - 0.301 \cdot X_3 + 18.518 \cdot X_4 \qquad (1)$$

X_1 : Equity-ratio
X_2 : EBIT/total assets
X_3 : Operating cashflow/total debt
X_4 : Percentage sales development
Z : Overall value

From the function one can see that the first two and the last variable contribute positively to the Z-value. This means that these ratios are having a positive association with “health”. This result is consistent with prior empirical findings. Contrary to expectations is the direction for the third ratio (cash flow/total debt), since there is a negative sign. This indicates that if a company has a high value in this ratio, it is negatively affecting Z-value. The importance of this measure within the formula is due to the very low weighting negligible. It can thus contribute to the formation of Z-value only incrementally.
The reason for this inconsistency of the sign compared to theory can only be explained from the data base. Within the third group an outlier with a value of 0.75 can be found, which distorted the results and thus caused the negative sign.
The allocation criterion is based on the calculated Z-values of the function:

- Values above 1.00: group 1
- Values between - 1.00 and 1.00: group 2
- Values below - 1.00: group 3

The obtained discriminant function assigned 78,1 % (overall classification result) of the companies into the right group. In a cross validation of the model 75.2 % were correctly classified. The model shows a quite good prediction performance, which certainly cannot be considered optimal. Nevertheless the model provides better results than a random model (AUROC: 70.63 %). The misclassifications relate primarily to the second group. There was no company from group 1, which was assigned to the third group. Also, there were no companies in group 3, which were assigned to the first group.

Table 6: Classification results for discriminant analysis including cross-validation

		Group	Prediction			Overall
			1	2	3	
Original	Amount	1	25	10	0	35
		2	7	24	4	35
		3	0	2	33	35
	%	1	71.4	28.6	.0	100.0
		2	20.0	68.6	11.4	100.0
		3	.0	5.7	94.3	100.0
Cross-Validation	Amount	1	24	11	0	35
		2	7	22	6	35
		3	0	2	33	35
	%	1	68.6	31.4	.0	100.0
		2	20.0	62.9	17.1	100.0
		3	.0	5.7	94.3	100.0

Source: Own results

Multivariate logistic regression

As second method a multivariate logistic regression was applied. From previous analyses it is expected that it should provide better results than multivariate linear discriminant analysis (lower sensitivity to non-normal distribution of ratios, discriminatory power of ratios based on ANOVA).

Table 7: Model quality of logistic regression analysis

Model	Criterion for Model-Fit	Likelihood-Ratio-Tests		
	-2 Log-Likelihood	Chi-Square	df	Sign.
Constant only	200.468			
Finally	63.705	136.763	4	.000

Source: Own results

After applying several combinations of the ratios the best model was developed with only two variables (equity-ratio and percentage sales development). To appraise the quality of the model a test for model fitting is necessary, which can be found in the following table. The Likelihood-test showed that the two ratios significantly contribute to separation between the groups.

The significance is less than 0.05, so the null hypothesis can be rejected. This means that the developed model is well suited for classification and provides significantly better results than a random assignment of objects to each group. The goodness of fit shows a significance of 0.995. This suggests that the developed model could adjust the data well.

Table 8: Goodness of fit for logistic regression analysis

	Chi-Square	df	Sign.
Pearson	48.024	76	0.995
Deviation	46.659	76	0.997

Source: Own results

The McFadden R^2 is 0.593, which is a mediocre score. The higher the value, the better the model can explain the phenomenon to be measured. This means that about 59.3 % of the variances between the figures can be explained with the measured values. Due to this, it is assumed that the model can indeed provide a good forecasting tool, but the prediction quality is partially limited.

Table 9: R^2 for explanation of the model

Pseudo-R-Quadrat

Cox und Snell	.728
Nagelkerke	.819
McFadden	.593

Source: Own results

Table 10: Parameter estimation for logistic regression

Group		B	Standard-error	Wald	df	Sign.	Exp(B)
2	constant term	3.863	1.058	13.339	1	.000	
	Equity-ratio	-10.477	3.512	8.898	1	.003	.000
	Percentage sales development	-26.173	10.296	6.462	1	.011	.000
3	constant term	9.604	1.923	24.954	1	.000	
	Equity-ratio	-42.283	11.051	14.641	1	.000	.000
	Percentage sales development	-997.589	.000	.	1	.	.000

Source: Own results

Based on parameter estimation the final logistic regression function is:

$$F = \frac{1}{1 + e^{(3.863 - 10.477X_1 - 26.173X_2)} + e^{(9.604 - 42.283X_1 - 997.589X_2)}} \quad (2)$$

X_1 : Equity-ratio

X_2 : Percentage sales development

F : Overall value

Using F-value following allocation criterion may be referred to the groups:

- Probabilities 100-50%: group 1
- Probabilities between 50% and 5%: group 2

- Probabilities less than 5%: group 3

The signs of the ratios within equation 2 are consistent with findings of previous literature. High values for both ratios are positively associated to "health". The overall classification accuracy of the model was 81.9 %, which can be seen as a slight improvement in comparison to discriminant analysis. A logistic regression model including operating cashflow/total debt showed in contrast to discriminant analysis a consistent sign with literature. This means that a high value of the ratio can be associated with "health". Such a result implies that outlier problems could be better optimized with application of logistic regression.

Table 11: Classification results for logistic regression

Observation	Prediction			
	1	2	3	Percentage correct
1	27	8	0	77.1%
2	7	26	2	74.3%
3	0	2	33	94.3%
Percentage totally	32.4%	34.3%	33.3%	81.9%

Source: Own results

Summary and implications

Within table 12 some chosen performance measures are displayed. The accuracy was better for logistic regression, but AUROC and Gini-Coefficient are much higher for discriminant analysis.

Table 12: Performance measures

Performance measure	Discriminant analysis	Logistic Regression
AUROC	70.63 %	67.99 %
Gini	0.4127	0.3599
Accuracy	80 %	81.90 %
Precision	85 %	85.5 %
Standard-Dev. Sensitivity	4.95 %	4.60 %
Standard-Dev. Specificity	6.33 %	6.33 %

Source: Own results

This indicates that discriminant analysis is the more appropriate model for business failure prediction for this case. These results were only valid for the data of model building. Therefore further research concerning validity on real enterprise data is needed in order to assess the classification accuracy and suitability for practical application of the models.

Three main reasons can be given why the developed models had no higher classification accuracy. First, the preliminary analyses showed that the data do not follow normal distribution. This is particularly problematic for discriminant analysis. As previously indicated this problem should be of minor relevance for logistic regression, but in case of this study this seemed to have a certain impact. Second, even if differences in means and variances were statistically significant, these significances were not sufficient for optimal model fit. The values for EBIT/total assets and operating cashflow/total debt showed a much

lower discriminatory power, so that their contribution for classification accuracy was limited and low. The tests are only a pre-condition for variable selection, but no guarantee that model fit including statistically significant variables will provide a superior prediction model.
Third, there was an outlier for the key figure operating cash flow/total debt, which produced an inconsistent sign within discriminant analysis. This was not in congruence with findings of prior business failure literature. This caused problems for this ratio as relevant predictor within the model, even if its contribution to Z-value is small. Interestingly this variable showed a positive sign in a logistic regression model, which is consistent to previous research. It seems therefore that logistic regression is less sensitive against outliers and extreme values in data. The results clearly show that the prediction depends largely on the quality of metrics, which are used for modelling. This means that there is the need for indicators, which are able to clearly separate between the different groups, so that misclassifications can be largely avoided. This will also be one of the important pre-conditions for establishing a currently missing theory of insolvency prediction.
The findings show that the chosen predictors obtained from expert knowledge are having a certain discriminatory power and that generally the signs of their contribution respectively their association to "health" are consistent with results from prior empirical literature. This indicates that theoretically relevant financial ratios are applied in management consulting by professionals for the evaluation of companies´ health. The developed forecasting models should be validated with respect to their applicability in practice based on a real data base. This could answer the question, whether they could be used as early warning systems in practice.

Overall conclusions

Financial ratios incorporated in multivariate models showed the ability to discriminate between the different economic situations of enterprises and are therefore suitable for prediction task to a certain degree. The application of discriminant analysis was violated due to lack of normally distributed variables, but the prediction performance was compared to logistic regression not influenced dramatically, so that a certain deviation from normality may be tolerated for model building. Nevertheless, logistic regression showed a better robustness concerning outlier problems in contrast to discriminant analysis. This was especially vacant for the ratio operating cashflow/totoal liabilities within this study. Based on the results from table 12 the models worked similarly well, so that none of both can be favoured.
For practioners the results indicate that equity-ratio and the percentage sales development are two important indicators, which should be analysed, when assessing the economic situation of a company. Consistent with prior research a high equity-ratio can be associated with health. Firms with stagnation or decline in percentage sales development are more likely to be in a crisis. The relevance of EBIT/total assets is given, but was not assigned as that important like the two previously mentioned ratios. Operating cashflow/total debt was the least important potential predictor, which only had an incremental explanatory power within discriminant analysis. A business failure prediction model is useful in practice for professionals in order to receive a single measure (Z-score or F-value), which can give an indication about the economic and financial situation of the firm based on the three pre-defined economic conditions of this work. Nevertheless, the practioner will beside of this also

have a look at other external and internal indicators, which are in many cases of qualitative nature. Prediction models are useful for setting benchmarks, but they are not the standalone solution to determine the "real" economic situation of a company.

Appendix

$$\text{Equity} - \text{ratio} = \frac{\text{Total Equity}}{\text{Total Assets}}$$

$$\text{Profitability} = \frac{\text{EBIT}}{\text{Total Assets}}$$

$$\text{Debt Repayment Capability} = \frac{\text{Operting Cashflow}}{\text{Total Debt}}$$

$$\text{Percentage Sales Development} = \frac{\text{Sales Actual Year - Sales Previous Year}}{\text{Sales Previous Year}}$$

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