Article

Models of forecasting in financial analysis of non-financial corporations

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Abstract: Corporate Diagnosis is now recognized as an important tool by decision makers to predict and correct burgeoning problems that a corporation may face. Methods based on this model stem from the use of mathematics and are increasingly being applied in the analysis of production processes. The goal of this paper is to use a logistic regression to design a scoring model for non-financial corporations in industry. Based on the data obtained from the Registry of the Slovak Republic for 738 non-financial corporations, according to SK NACE 26, SK NACE 27, the proportional financial metrics, using the logistic regression method, were calculated. By applying these methods, two logistic regression models were found to reliably estimate the probability of bankruptcy for a firm.

Keywords: logit analysis; company decline; model

1. Introduction

The prediction of future developments based on a company's financial assessment requires a broad range of mathematical and statistical methods. Many comprehensive evaluation methods of companies excel with regards to transparency but suffer due to their inaccuracy. Therefore, it is necessary for financial analysts to use various financial forecasting methods to assess the financial health of a company at the same time. For example, Kubíčková and Jindřichovská [1], Neumaierová and Neimaier [2, 3], Kameníková [4], Pilch [5], Bondareva [6], Kadarová, Turisová [7], Vochozka [8] and Kabát et al. [9] deal with the problem of forecasting of financial health of companies in their works. The first author of the bankruptcy model based on logistic regression was Ohlson [10]. The application of this model through logistic regression is mentioned by Slavíček and Kuběnka in [11] for the construction sector in the Czech Republic, Marcinkevičius and Kanapickiené [12] for the construction sector of Lithuania, Harumová, and Janisová [13] for small and medium enterprises. These analyses were based on data from enterprises studied by Presov and Kosice regions of Slovak Republic (NUTS III classification), Valecký and Slivková [14], with the scoring model for Czech enterprises, next Jakubík and Teplý [15].

There are currently many predictive models, but unfortunately few of them are applicable to Slovak companies, because they were developed in other countries, other conditions, etc. In the Czech Republic, the popular Czech model, IN95, IN99, IN01, IN05 or the Králiček index [16], is a rather popular model. A Beerman's discriminatory function is suitable for a manufacturing enterprise. According to [16], due to conditions in Slovakia the Altman's model [17] is often used as

45 a bankruptcy model, and the Goodwill Index as a good model in general. According to Kislingerová
46 and Hnilica [18], "there are countless methods and approaches to assessing a company's
47 creditworthiness and predicting the possibility of bankruptcy. Financial institutions tend to guard
48 their practices as their special and proprietary know-how. In every of these models do financial
49 indicators play a significant role. Sophisticated statistical procedures that utilize historical data to
50 calculate a company's probability of default based on certain values of financial indicators are often
51 difficult to handle.

2. Materials and Methods

53 For the purpose of determining the financial situation of non-financial enterprises, prediction
54 models are often employed: Tafflerov model Zt (1), Springate model SM according to (2), Altman's
55 model of Z-score according to (3), AGR model according to (4).

$$Zt = 0.53 \cdot \frac{EBT}{Current\ liabilities} + 0.13 \cdot \frac{OA}{Liabilities} + 0.18 \cdot \frac{Current\ liabilities}{A} + 0.16 \cdot \frac{S}{A}, \quad (1)$$

$$SM = 1.03 \cdot \frac{NPC}{A} + 3.07 \cdot \frac{EBIT}{A} + 0.66 \cdot \frac{EBT}{Current\ liabilities} + 0.44 \cdot \frac{S}{A}, \quad (2)$$

$$Z = 0.717 \cdot \frac{NWC}{A} + 0.847 \cdot \frac{EAT}{A} + 3.107 \cdot \frac{EBT}{A} + 0.42 \cdot \frac{E}{Liabilities} + 0.998 \cdot \frac{S}{A}, \quad (3)$$

$$AGR = \frac{EBITDA}{S} + \frac{EAT}{E} + \frac{EBIT}{A} + \frac{S}{A} + \frac{E}{A} + \frac{EBIT + Depreciation}{Depreciation} + $$
$$+ \frac{FA + \left(Receivables \cdot 0.7\right)}{Current\ liabilities}, \quad (4)$$

60 At present, the method based on logit analysis by Ohlson [10] and another one based on probit
61 analysis by Zmijewski [19] are still popular methods for predicting business failure. In logistic
62 regression the binomial, not the normal distribution describes the distribution of the errors [20], [21].
63 Estimates of logit model parameters were obtained using a non-linear estimate of maximum
64 likelihood in logistic regression, according to equation (5). Logistic regression models a relationship
65 between predictor variable and a categorical response variable. Independent variables can be
66 continuous, discrete or categorical. Binary logistic regression is used in case of a binary response. A
67 multiple logistic regression is modeling the probability of the variance of the dependent variable
68 depending on the variations of several independent variables. The resulting model can be used to
69 predict the variance of a dependent variable because the output of this model is a probability
70 estimate and defines the dependence between variables. Vochozka [8] (2011, p. 48) describes the
71 advantages and disadvantages of logistic regression. An important advantage of the model is that
72 the logit-score is between 0 and 1, which instantly indicates the probability of the bankruptcy of a
73 company. The weight of the determined coefficients can be interpreted separately, but only if there
74 are no multiple dependences between variables. The initial logarithmic function suggests that,
75 compared to an average healthy company, an extremely healthy company must achieve the majority
76 of improvements (worsening) of its variables proportionately to the improvement (deterioration) of
77 its financial health assessment score.
78 One disadvantage to this method is that logit models are extremely sensitive to the problem of
79 collinearity in a multiple regression. Therefore, it is necessary to prevent the inclusion of highly
80 dependent variables into model. Ratio financial indicators sometimes have the same nominator or
81 denominator, which can cause a serious problem of multiple dependences. The conditional

82 probability of occurrence of an event under the condition of occurrence of the x vector (the vector of
83 independent variables, covariates here), can be written p = P (Y = 1 | x), where Y is a binary variable
84 that acquires two possible outcomes. The logistic function expressing the relation between the
85 probability and the vector of the explanatory variables is non-linear and has the form of an
86 exponential function (5).

$$p = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}} = \frac{e^z}{1 + e^z} = \frac{1}{1 + e^{-z}}, \quad (5)$$

87 By definition, the odds for an event is *p/(1-p)* such that *p* is probability of the event and it equals
88 *e^z*. In order to use linear regression, the dependent variable is transformed into a continuous value by
89 calculating the logarithm of the odds ("logit" transformation in, order to obtain values from the
90 interval (-∞; ∞)), with odds and probabilities expressing the same information only in a different
91 form (6).

$$\text{logit}(p) = \ln\left(\frac{P(Y-1|X)}{P(Y-0|X)}\right) = \ln\left(\frac{p}{1-p}\right), \quad (6)$$

92 By logit transformation we get from non-linear to linear dependence, i.e. the relationship
93 between the logarithm of the odds and the vector of the explanatory variables has a linear character.
94 The equation of the logit model has a form according to (7).
95

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \ln\left[e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \dots \beta_k x_k, \quad (7)$$

96 **3. Results**

97 The following text contains a proposal for a predictive model for non-financial corporations in
98 the electronics industry using logistic regression.
99 When looking for an optimal model, we took into account the profitability indicators (x_2, x_3, x_9),
100 activity (x_1, x_5), debt (x_6, x_8) and liquidity (x_4). There were 8 ratios; x_1 - the time in which the firm pays
101 its trade commitments; x_2 - the return on sales measured by the ratio of the operating result before
102 interest and tax and depreciation and net turnover; x_3 - the return on total invested capital measured
103 by the ratio of the profit before tax and total assets; x_4 - ratio of current assets and short-term
104 liabilities; x_5 share of net turnover and assets; x_6 - foreign capital attributable to total capital, x_8 - total
105 assets per unit of equity; and x_9 - return on equity measured by the economic turnout for the
106 accounting period. Based on a database of 738 non-financial corporations, the parameters of the
107 estimated models are shown in Table 1. Of the original database of 748 corporations, 10 breakpoints
108 were removed during the search for the optimal model. As it turned out, it was a measure with a
109 common characteristic, i.e. they were the enterprises that originated during the analyzed period (the
110 second half of 2016).

111 **Table 1.** Estimated parameters of the proposed prediction models, their significance, goodness-of-fit
112 statistics and percentage of correctly estimated corporations. The data consists of healthy and 138
113 defaulted corporations.

	Metrik	Model 1	Model 2
	intercept	–3237.629 (7038.048)	–1.170^d (0.242)
x_1	DSZ$_{os}$	-	-
x_2	ROS	-	–0.109 (0.097)
x_3	ROI	-	–1.764^d (0.412)
x_4	L$_3$	-	–0.446^d (0.092)
x_5	OA	-	0.268^c (0.077)
x_6	CZ	3522.748 (7658.021)	-

x_8	FP	-	0.011^b (0.005)
x_9	ROE	-	-0.049^b (0.016)
	Hosmer-Lemeshow test	0.000	42.734^d
	$G^2 = -2$ log likelihood	0.009	531.838^d
	Cox & Snell R^2	0.619	0.216
	Nagelkerke R^2	1.000	0.349
	0(non d.) - 1 (default), good estimated %	100% - 100%	99% - 31.2%

114

115   The designation of parameters a, b, c and d in Table 1 expresses the significance of Wald
116 statistics at $p < 0.1$; $p < 0.05$; $p < 0.01$; $p < 0.001$; the number in brackets indicate a standard S.E. The
117 probability of bankruptcy of a company expressed by model 1 is given in equation (8) and by model
118 2 in equation (9).

119

$$p = \frac{e^{-3237.629 - 3522.748\,x_6}}{1 + e^{-3237.629 - 3522.748\,x_6}}, \tag{8}$$

120

$$p = \frac{e^{-1.170 - 0.109\,x_2 - 1.764\,x_3 - 0.446\,x_4 + 0.268\,x_5 + 0.011\,x_8 - 0.049\,x_9}}{1 + e^{-1.170 - 0.109\,x_2 - 1.764\,x_3 - 0.446\,x_4 + 0.268\,x_5 + 0.011\,x_8 - 0.049\,x_9}}, \tag{9}$$

121   Logistic regression has no limitations on the distribution of explanatory variables, but they
122 should not be highly correlated (correlation matrix is shown in Table 2). Collinearity has been
123 checked (Variance inflation factor; Condition index) and has not been demonstrated. The sample is
124 large enough for the Hosmer-Lemeshow test, (Hosmer et al., [22], cited at least 400 measurements),
125 which is suitable for testing the model for fit (fit = model fits to given data) with continuous
126 explanatory variables. These are the so-called ungrouped data for which G^2 and chi-square statistics
127 can misinform about the model's lack of fit. For the Hosmer-Lemeshow test, the values of the
128 explanatory variables are artificially distributed on the basis of estimated probabilities to
129 approximately equally large groups, and the chi-square test is applied to them. (Agresti [23]).

130   For the construction of logistic regression models, the stepwise method was used, testing the
131 significance of adding or eliminating the variable at each step. The test is based on testing the
132 significance of a change in G^2 statistics by adding or excluding a variable. Model 1 was found by a
133 stepwise procedure entering all nine predictors as covariates. The resulting model (Model 1)
134 contains only one explanatory variable x_6 - total indebtedness, where even functional dependence
135 was found. The resulting model 1 with one predictor fits perfectly, p = 1.000 for the
136 Hosmer-Lemeshow' test. The probabilities produced by the model reached only two values, 0.000
137 and 1.000. According to Bewick, Cheek, Ball [24], a small insignificant Wald statistic can be
138 generated for data that produce large coefficient estimates. Therefore the explanatory variable may
139 be incorrectly assumed to be unimportant in the model, which was the case for Model 1. (Wald's Z is
140 0.212; p = 0.646, the percentage match of estimated bankruptcies to actual is 100%). If total debt x_6
141 after deletion of deviant values is functionally dependent on the default variable, the question arises
142 as to how far default would depend on the other variables considered unless the variable x_6 is not
143 inserted into the model.

144

145   **Table 1.** Pearson correlations of of variables entering the models, N=738 corporations. The
146   designation r [a, b, c, d,] represents significance at $p<0,1$; $p<0,05$; $p<0,01$; $p<0,001$

	x_1	x_2	x_3	x_4	x_5	x_6	x_8	x_9
x_1	1	$-.572^d$	$-.031$	$-.019$	$-.095^b$	$.032$	$.038$	$.005$
x_2		1	$.105^c$	$.024$	$.065^a$	$-.078^b$	$.007$	$-.004$
x_3			1	$.042$	$.138^d$	$-.629^d$	$-.016$	$-.473^d$
x_4				1	$-.027$	$-.101^c$	$-.018$	$.014$
x_5					1	$.161^d$	$-.066^a$	$-.268^d$
x_6						1	$.014$	$-.014$
x_8							1	$-.438^d$
x_9								1

147

148   After removing the 100% fitting variable x_6, a model 2 with predictors x_2, x_3, x_4, x_5, x_8 and x_9 was
149   designed for a set of 738 non-financial corporations. The Wald test showed a significant contribution
150   of these predictors to the model, except for x2. After removing the insignificant x2 predictor, we
151   obtain the previously unpublished model, which is very similar in all characteristics to the above
152   model 2. Odds ratio (e^B) means for example, if explanatory variable x_5 is increased by one unit, the
153   odds ratio is $e^{0.268} = 1.308$ and the estimated odds of default of firm are multiplied by 1.308 for given
154   values of other explanatory variables being fixed. The Hosmer-Lemeshow test with $p<0.001$
155   indicates lack of fit of Model 2 despite the significant coefficients of the five predictors of this model.
156   The number of companies in default differs significantly from the number predicted by this model.
157   The Nagelkerke R^2 statistics (adjusted version of the Cox and Snell R^2) equals 0.349 and indicates
158   34.9% usefulness of predictors to predict default of firm. But Nagelkerke R^2 do not measure
159   goodness of fit of the model only indicate usefulness.

160   The discrimination of a model – that is, according to Bewick et al. [24], how well the model
161   distinguishes non defaulting firms from defaulting – can be judged by the area under the receiver
162   operating characteristic curve (AUROC, or ROC). The value of the ROC is the probability that a
163   defaulting firm had a higher predicted probability than did a firm which is not in default. The ROC
164   for the Model 2 gave a value of 0.857 (S.E.=0.020; p=0.000; 95% C.I.=0.818-0.895), indicating that the
165   model discriminates well. For example, Valecký and Slivková [14] report the value of AUC ROC
166   0.862 as highly reliable.

167   **Figure 1.** ROC curve for model 2; (AUC ROC = 0.857, S.E. = 0.020, p = 0.000, 95% CI = 0.818-0.895)
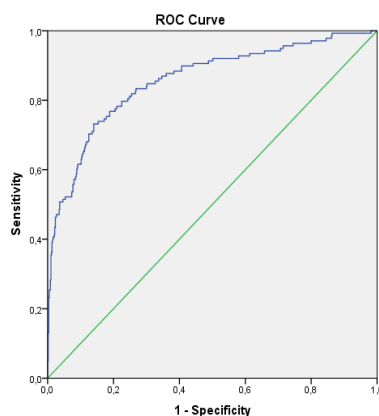
168

169

170   **4. Discussion**

171   By applying logistic regression, two logistic regression models were found to estimate the
172   company's probability of bankruptcy. The first model is a deterministic model in which it is possible

173 to estimate bankruptcy using a single explanatory variable, i.e. the indebtedness index x_6 - CZ.
174 After the omission of this predictor, a second stochastic model was developed that explains the
175 bankruptcy of the company using six predictors: profitability is defined by (x_2 - ROS, x_3 - ROI, x_9 -
176 ROE), activity (x_5 - OA) (x_4 - L3). It should be noted that by selecting from the given 8 predictors,
177 none of the resulting stochastic models lead to good fits, although AUC ROC often exhibits high
178 reliability.
179

5. Conclusions

181 For further research and modeling by logistic regression, it is necessary to take into account
182 other variables. As well as qualitative variables, other variables that should be taken into account
183 include the region or size of the business entity. The size of a business is an important factor in
184 predicting the failure of a newly established companies, because small businesses are more
185 susceptible to bankruptcy than major corporations. Large companies are predicted to have lower
186 failure rates due to their size because they can make larger transactions on more advantageous
187 terms, etc.
188

6. Patents

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