ALTERNATIVE APPROACH TO CREATING A MODEL FOR PREDICTING FINANCIAL DISTRESS IN CZECH COMPANIES

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Abstract

A vast majority of financial distress prediction models are based on conventional ratio indicators. The aim of this paper is to present an alternative approach to creating a model of this kind: the approach we have taken is based on the polarities of selected indicators. To put together this new financial distress prediction model, indicators were chosen for which it is important whether their value is positive or negative. The aim of our model is to categorise companies into two groups: companies likely to experience financial distress and companies not likely to face financial distress. The model production process included logistic regression as one of the key tools, and the statistical verification was performed using -2LL statistics, Cox and Snell R^2 & Nagelkerke R^2, and the Hosmer-Lemeshow goodness-of-fit test. Indicators used to assess the quality of the model included a classification table, ROC curve and AUC. The result is a model that is is expected to indicate to Czech companies potential financial distress and a threat of bankruptcy based on clearly interpretable polarities. Besides the aforementioned statistical verification, an extensive quality assessment was performed, and both these processes have confirmed that this model is a relevant tool.

Keywords: Financial distress, bankruptcy, financial analysis, warning signals

JEL code: G33, G32

Introduction

There is a variety of financial distress prediction models in corporate practice, including, in particular, the Altman Z-Score, a bankruptcy model presented in 1968 by Edward Altman (Altman, 1968) who later modified his model several times (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2017). Research conducted in Czech companies by Mr. and Mrs. Neumaier resulted in developing what is referred to as the IN Indices, especially the last edition known as the IN05. (Neumaierová & Neumaier, 2005). Both of the models mentioned above are based on ratio indicators, and the development of each of them involved conducting a multiple discriminant analysis. Another model based on ratios was introduced by Ohlson, (1980) who states that the use of multiple discriminant analysis comes with limitations and therefore used logistic regression to develop his model. Other model developers then gradually analysed both the Altman model and the IN Indices, as well as a number of other models known today. For example, Boďa and Úradníček (2016) placed special focus on the widespread use of the Altman Z-score in Slovak corporate practice, and they recommend correcting the estimation of Z-score coefficients where the main focus is on companies in distress. Many experts believe that the predictive capacity of the IN Indices is better than that of the models compared to them. For example, Machek´s (2014) conclusion is that the best results are achieved by the IN05 and IN99 and that, conversely, the predictive capacity of the Tafler model and the Kralicek Quick Test is limited. Gavurová, Packová, Misanková and Smrčka (2017) believe that the predictive capacity of the IN05 is better than that of the models by Ohlson and Altman. Explanatory variables are an important aspect in financial distress prediction models. Kurschus, Sarapovas and Pilinkiene (2017) propose a set of qualitative and quantitative criteria for financial distress identification models used in SMEs, stating that most models based on quantitative assessment of financial ratios have limited applicability to SMEs. Pîrlog and Balint (2016) deal with the impact of key performance indicators (KPIs) on SMEs´ decision-making, where KPIs serve as early warning signals of potential financial distress, and monitoring them may improve companies´ overall performance. Another study analyses which of the key financial factors are appropriate for credit rating score measurement in family businesses. The results of this study show that family businesses achieve better results in terms of profitability, loan structure and liquidity trends (Wiener-Fererhofer, 2017).

Our alternative approach to creating a model for predicting financial distress in Czech companies is based on polarity-relevant (positive or negative) financial indicators. Different profit levels are a typical representative of this financial-indicator category. This approach thus reflects whether a profit or loss is achieved at each particular level (EBITDA, EBIT, etc.). Another typical example in this category is equity polarity. The key benefit of using polarities is their unambiguity and unambiguous interpretability. Financial distress and the potential for bankruptcy are, in many cases, mainly based on operating-level failures such as insufficient operating margins or inappropriate management and financing of working capital.

Our model puts companies into one of the two aforementioned categories, i.e. companies facing a likelihood of financial distress and heading for bankruptcy (bankrupt companies) and companies that are not likely to experience financial distress and are not threatened by bankruptcy (problem-free companies).

1 Data and methodology

Data in the form of financial statements were obtained from the Bisnode Magnusweb database. The data sample contains a total of 1,654 Czech joint-stock and limited-liability companies over 2009 – 2018, of which 827 are problem-free and 827 are bankrupt companies. The scope of the sample corresponds to the scope of data used as the basis for creating e.g. the IN05 index where the data sample contained 1,526 industrial corporations, or the IN99 index that is based on financial data of 1,698 companies. We used stratified selection to produce this (financial distress prediction) sample, i.e. we kept all bankrupt companies for which data are available in the sample and added the same number of problem-free companies, and the key criteria included company size and the line of business (Mihalovič, 2018). The data from the financial statements were then used to set relevant indicators.

The construction of the indicators reflected the specifics of this matter, i.e. the fact that the goal was to develop a model for predicting financial distress and bankruptcy threats (in contrast with credit worthiness rating). To place correct focus on the companies´ primary business activity, we used case-specific variants for the selected indicators that characterise such primary business activity - the said variants only contain components that are directly relevant to such primary operation, for example primary EBITDA which, besides revenues, only involves production costs and labour costs. Other profitability indicators were set at several levels in order to characterise the profit generation process, from the basic operating profitability (primary EBITDA) mentioned above to the overall profitability. This approach makes it possible to identify profit generation failures at companies in financial distress. Another indicator that reflects a company´s primary business activity is the balance of primary non-cash components of working capital (difference between the active and passive NCWC), including - besides stock - business receivables, business liabilities and liabilities arising from HR costs. This indicator therefore more or less corresponds to the indicator referred to above, i.e. the primary EBITDA. In addition to the aforesaid balance of primary non-cash working capital (NCWC), we also used the balance of total non-cash components (i.e. including other short-term receivables and liabilities). Another important indicator is the cash-needed polarity determined as the difference between the actual cash and the cash needed, where the cash needed was determined on the basis of a requirement to have 15% of the instantaneous (cash) liquidity.[1] The asset and capital structure are represented by the value of equity and the difference between long-term capital and fixed assets.

[1]Cash over shot-term liabilities

The above indicators that bear relevance to positivity and negativity were used as the basis for creating, in the form of dichotomous variables, polarity indicators which show whether or not their respective value is negative.

The model was designed as a scoring model based on quantitative financial analysis of companies´ historical data. The model production process included logistic regression as one of the key tools, The dependent variable is the status of the company concerned, i.e. whether the company is bankrupt or problem-free. As part of the process of developing the model using logistic regression, the dependent dichotomous variable is set to be binary: 0 for problem-free companies (no bankruptcy) and 1 for bankrupt companies (bankruptcy occurred). The explanatory variables were set in the same manner. In Step 1, all variables were put into the model, and then they were gradually eliminated using Wald statistics. Generally, the final score is then determined by the following formula

$$\pi = \frac{\exp\,(\beta_0 + \sum_{k=1}^{n} \beta_k x_k)}{1 + \exp\,(\beta_0 + \sum_{k=1}^{n} \beta_k x_k)} \tag{1}$$

where:

π = score (estimated likelihood that the company is in financial distress)

β_0 = constant

β_k = regression coefficient

x_k = value of the variable

k = the respective variable

n = number of variables

Since the dependent variable has a value of 1 for bankrupt companies, the result is an estimate of the likelihood that the company concerned is in financial distress, i.e. expresses the risk of bankruptcy.

The completed model was subjected to statistical verification and assessment of its quality in terms of classification and discriminatory capacities. Generally, the above can be seen as the answer to questions about how the model works. As stated by Řeháková (2000), we primarily need to answer the question of whether the model works well, whether there is certainty that there is a relationship between the explanatory variables and the dependent variable and how strong this relationship is. The following tools were used to verify the model. -2LL statistics (-2 log likelihood). Where this statistic is higher for a model that only contains a constant than for a model that contains explanatory variables, the explanatory variables improve the prediction of the dependent variable. Cox and Snell R^2 and Nagelkerke R^2. The interpretation in this case is analogous to the interpretation of the determination coefficient in linear regression. Another tool we used is the Hosmer-Lemeshow goodness-of-fit test,

The tools used to assess the quality of our new model included a classification table and a Receiver Operating Characteristic Curve (ROC). The classification table shows the discriminatory ability of the model, and the success of the model is assessed according to the share of correctly classified companies (of the total number). The other of the aforesaid methods used to assess the classification (discriminatory) capacity of the model was the ROC curve. If the ROC curve is shaped diagonally, the model has no discriminatory capacity and is therefore not suitable for prediction purposes. If the curve merges with the upper left corner, there is an absolute match between the actual values and the predicted ones. The model thus becomes 100% successful and therefore suitable for prediction purposes. The ROC curve is directly relevant to the AUC (*Area Under Curve*). The AUC indicator can range between 0.5 and 1, and the higher the value, the more accurate the prediction model(Valecký & Slivková, 2012). The table below shows the assessment of the model´s discriminatory capacity using the AUC.

Tab. 1: AUC-based model assessment

AUC (Area Under Curve)	**Discriminatory capacity**
0.9 - 1	Excellent
08 - 0.9	Very good
0.7 - 0.8	Good
0.6 - 0.7	Sufficient
05 - 0.6	Insufficient

Source: http://gim.unmc.edu/dxtests/roc3.htm

The asymptotic significance level of 0.05 is used to test the null hypothesis under which the AUC is 0.5 and the resulting explanatory variables therefore have no predictive capacity compared to the alternative hypothesis under which the AUC is over 0.5 and the resulting explanatory variables therefore have a predictive capacity. If the asymptotic 95% confidence interval for the AUC contains the value of 0.5, we do not dismiss the null hypothesis at the asymptotic level of 0.05 and vice versa.

The model was subsequently (and retrospectively) applied to companies that went bankrupt in 2019 and to which relevant data were available for the last year before such bankruptcy, i.e. for 2018.

2 Results

The variables used at the beginning of our financial distress prediction model (developed on the basis of data for the last year before the companies went bankrupt) were as follows:

- Equity polarity as variable x_1
- Operating EBITDA polarity as variable x_2
- EBIBTDA polarity as variable x_3
- EBIT polarity as variable x_4
- Cash-needed polarity as variable x_5
- Primary NCWC polarity[2] as variable x_6
- Polarity of the difference between long-term capital and fixed assets[3] as variable x_7
- Total NCWC balance polarity as variable x_8
- Primary EBITDA polarity as variable x_9

We gradually removed statistically insignificant variables while adding the following variables and regression coefficients to the model, using backward stepwise logistic regression.

Tab. 2: Variables added to the model

	B	S.E.	Wald	df	Sig.
Equity polarity (x_1)	1.551	0.179	75.374	1	0.000
Operating EBITDA polarity (x_2)	0.898	0.200	20.145	1	0.000
EBIT polarity (x_4)	0.760	0.200	14.412	1	0.000
Cash-needed polarity (x_5)	1.360	0.150	82.709	1	0.000
Primary NCWC balance polarity (x_6)	0.649	0.169	14.687	1	0.000
Polarity of the difference between long-term capital and fixed assets(x_7)	0.500	0.172	8.455	1	0.004
Constant	-2.558	0.134	362.185	1	0.000

Source: authors

The next step was to verify the model and assess its classification (discriminatory) ability using the methods described above. The value of -2LL in the model that only contains a constant is higher than that in the model with explanatory variables. The inclusion of explanatory variables is thus relevant and increases the model´s predictive capacity. The Cox and Snell R^2 reached 0.449, the Nagelkerke R^2 0.599. Given the Nagelkerke R^2 value, we can conclude that the model explains about 60% of the variability of the dependent variable. The contingency table for the Hosmer-Lemeshow test shows that none of the expected frequencies

[2] Non-cash working capital components
[3] Long-term fixed assets

is less than five, and the Hosmer-Lemeshow goodness-of-fit test is therefore applicable. The result of the Hosmer-Lemeshow test is this: based on the achieved level of significance, the hypothesis that the observed values and the modelled (predicted) ones do not differ cannot be dismissed at the 5% level of significance.

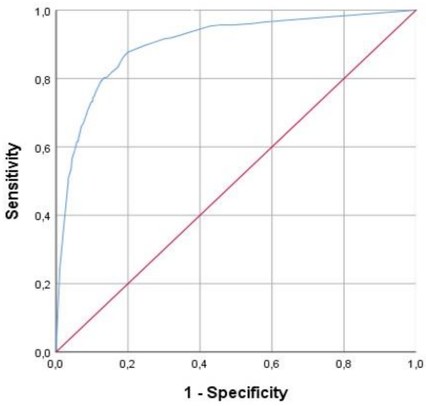
Tab. 3: Model-relevant classification table

Observed		Predicted: Company status – Problem-free companies	Predicted: Company status – Bankrupt companies	Percentage correct
Company status	Problem-free companies	705	122	85.2
	Bankrupt companies	157	670	81.0
Overall percentage				83.1

Source: authors

The classification table shows that 85.2% of the cases were correctly put into the dependent-variable category with Code 0 (problem-free companies), 81% of the cases were put into the Code 1 category (bankrupt companies) and a total of 83.1% of the cases were categorised correctly. This shows that the model has a classification (discriminatory) capacity.

Fig. 1: Model-relevant ROC curve



Source: authors

The ROC curve is near the upper left corner, which shows that the reliability of the model is high. The area under the curve reaches 0.901, and the 95% asymptotic interval is 0.886 (lower bound) and 0.916 (upper bound).

Since the 95% asymptotic confidence interval does not contain the value of 0.5, we dismiss, at the 5% level of significance, the null hypothesis of the absence of predictive capacity in the explanatory variables, i.e. the variables put into our model have a predictive capacity. The AUC indicator is 0.901, which shows, in view of Tab. 1, that the model´s discriminatory capacity is excellent.

It can therefore be concluded that our model based on the polarity of selected indicators takes, under the general equation (1), the following form.

$$\pi = \frac{\exp\,(-2{,}558 + 1{,}551x_1 + 0{,}898x_2 + 0{,}76x_4 + 1{,}36x_5 + 0{,}649x_6 + 0{,}5x_7)}{1 + \exp\,(-2{,}558 + 1{,}551x_1 + 0{,}898x_2 + 0{,}76x_4 + 1{,}36x_5 + 0{,}649x_6 + 0{,}5x_7)} \qquad (2)$$

Considering that the model was created on the basis of financial statements of Czech companies, it is suitable for Czech businesses, particularly capital companies (joint stock companies and limited liability companies). The application of the model in the form of this equation (2) to companies that went bankrupt in 2019 shows how exactly the model indicated financial distress in such companies, using data for the last accounting period before the bankruptcy declaration. A total of 91 such companies were subjected to this model exercise, and the result is shown in the following table.

Table 4: Result of applying the model to bankrupt companies

	Number of companies	Indication percentage
Financial distress indication	73	80.22%
Financial distress not indicated	18	19.78%
Total	**91**	**100.00%**

Source: authors

Applied to the bankrupt companies concerned, the model, using data from the last accounting period before bankruptcy, showed financial distress in more than 80% of the companies that subsequently went bankrupt and started insolvency proceedings.

Conclusion

The objective of this paper was to develop a financial distress prediction model using an alternative approach characterised by the use of polarity of selected indicators as explanatory variables. Unlike most of the existing models in which explanatory variables take the form of ratio indicators, the presented model is based on indicators for which it is relevant whether their value is positive or negative. The result (total score) is an estimated likelihood of financial distress and, potentially, bankruptcy.

Besides standard ratios, polarities have also been shown to be suitable explanatory variables for financial distress prediction models. In a classification table-based assessment exercise performed by the model developers the model correctly categorised more than 83% of the companies concerned, of which more than 81% in the bankrupt companies category. The reliability and discriminatory capacity of the model is also demonstrated by the shape of the ROC curve and the value of the AUC indicator. Similarly, the application of the model to data on companies that went bankrupt and started insolvency proceedings in 2019 has shown that the model is able to indicate financial distress on the basis of results achieved by such companies in the previous accounting period.

A certain disadvantage of the presented model, i.e. of the use of polarities as explanatory variables, is found in that such variables do not reflect the depth of the problem. A slight loss therefore has the same weight in the model as a significant loss, and a slight cash deficit has the same weight as a significant deficit.

We believe it will make perfect sense to apply this model to another sample of bankrupt companies in the coming months, especially companies that have gone and will go bankrupt due to the measures & restrictions adopted to fight the COVID-19 pandemic. The results of applying the model to data on such companies before the outbreak of the pandemic and during the period of restrictions against its spread will no doubt be interesting.

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