5th International Scientific Conference ITEMA 2021 – Selected Papers
DOI: https://doi.org/10.31410/ITEMA.S.P.2021.65

Bankruptcy Prediction: The Case of the Czech Republic and Slovakia

Martina Sponerová[1]

Received: November 8, 2021
Accepted: November 27, 2021
Published: April 12, 2022

Keywords:
Bankruptcy prediction;
Financial distress;
SME;
Financial indicator;
Logistic regression

Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-Non-Commercial 4.0 License (https://creativecommons.org/licenses/by-nc/4.0/) which permits non-commercial use, reproduction and distribution of the work without further permission.

Abstract: *A considerable number of publications accompanies the research topic of bankruptcy prediction. This has been motivated by the massive toll on SMEs caused by the global crisis of 2007-2009, the recent COVID-19 crisis and the resulting need to update indicators of SME failure. This paper focuses on the Czech and Slovak economies, specifically at small and medium-sized enterprises (SMEs).*

This article aims to find if different factors could predict bankruptcy for Czech and Slovak companies. There were investigated 574 Czech companies and 889 Slovak companies for the period 2010 – 2018. The resulting findings confirm conclusions of the last year's literature review. It is most appropriate to construct a financial distress model for a given country or a group of countries with similar characteristics or neighbouring countries. Furthermore, it is advisable to exploit common used financial indicators with a combination of modified indicators to assess the probability of bankruptcy precisely.

1. INTRODUCTION

Predicting bankruptcy and quantifying credit risk is the subject of interest of many studies, scientific articles, and publications. Academics and practitioners have focused their research on improving the performance of existing bankruptcy models, and they are still developing new models and methods to precisely predict business failure. The abundance of bankruptcy prediction models gives rise to the idea that these models are not in compliance with the market's changing business conditions and do not meet the increasing complexity of business tasks.

This article aims to find if different factors could predict bankruptcy for Czech and Slovak companies. This paper focuses on SMEs because they are reasonably considered the most crucial economic segment in many countries. For OECD members, the percentage of SMEs out of the total number of firms is higher than 97%. Thanks to their simple structure, they can respond quickly to changing economic conditions and meet local customers' needs, sometimes growing into large and powerful corporations or failing within a short time of the firm's inception.
Considering the research objective, the following hypothesis was set: H1: Indicators used in the financial distress model for Czech companies differ from Slovak companies.

2. THEORETICAL FRAMEWORK

After performing the scientific literature analysis, it was identified that various scientists who have studied bankruptcy prediction models under different perspectives still could not indicate the most reliable model as a brief preview of the history can observe it. Many authors during the last fifty years have examined several possibilities to predict default or business failure. The seminal works in this field were Beaver in 1967 and Altman in 1968. Altman's model has been applied successfully in many studies worldwide concerning the subjects of capital structure

[1] Masaryk University, Faculty of Economics and Administration, Lipová 41a, 602 00 Brno, Czech Republic

and strategic management, investment decisions, asset and credit risk estimation and financial failure of publicly traded companies (Lifschutz and Jacobi, 2010).

For many years after that, MDA was the prevalent method applied to the default prediction models. Many authors used it; for example, very often cited in the research literature is the Taffler model developed in Great Britain in 1977 (Taffler, 1982). Inka Neumaierova and Ivan Neumaier have developed another MDA model in 1995, known as IN95. This model was constructed especially for the Czech market and was updated in the following years. (Neumaierova and Neumaier, 2005). Considering these MDAs' problems, Ohlson (1980), for the first time, applied the conditional logit model to the default prediction's study. The practical benefits of logit methodology are that they do not require the restrictive assumptions of MDA and allow working with disproportional samples. After Ohlson, most of the academic literature used logit models to predict default. Next, a very often cited model, which uses conditional probability, is a model by Mark E. Zmijewski (Zmijewski, 1984). He was the pioneer in applying probit analysis to predict default but, until now, logit analysis has given better results in this field. A probit approach is the same as the logit approach; the difference is only the distribution of random variables.

Nowadays, a prevalent topic is creating a model for a specific country or industry and selecting an appropriate method for creating the model and its comparison with other methods, whether traditional or artificial intelligence methods. The relating theme for the prediction of bankruptcy for a particular country or a particular industry, the authors aim to prove that a model developed for a given macroeconomic environment or a given industry of a specific country has better predictive power than a universal model, which has been proven in many studies. Each country has its specificities, different economic environment, and different stages of economic development, which must be taken into account when developing a model. Research on country-specific bankruptcy prediction or comparison of bankruptcy models of different countries has been published by, for example, Kovacova et al. 2019, Kliestik et al. 2020, Ninh et al. 2018. These studies have shown that it is most appropriate to construct a bankruptcy model for a given country or a group of countries with similar characteristics or neighbouring countries. It is also necessary to consider the affiliation to the specific industry in which the firms under study are located. Studies dealing with industry-specific bankruptcy models in order to build the most accurate model predicting the possibility of bankruptcy within a given industry have been published, e.g. Fedorova et al. 2016, Karas and Reznakova 2017, Alaka et al. 2015.

Another common feature of this research stream is the prediction models constructed for a given country and specifically for a particular segment - the SME segment, or separately for micro-enterprises, small enterprises, and medium-sized enterprises. According to research by Altman et al. 2020 and Gupta et al. 2018, models constructed for a specific enterprise segment increase the accuracy of bankruptcy prediction. Thus, the result of this stream of research is that models built specifically for a given industry, a given country or a given segment exhibit higher predictive power than so-called universal models. Comparisons of the predictive power of traditional bankruptcy prediction methods and so-called modern methods, or artificial intelligence methods, are among the most frequent publications on the topic of bankruptcy prediction. Many authors only compare the predictive ability of selected methods to prove that a particular selected method has a higher predictive ability than another. Traditional methods, i.e. discriminant analysis and logistic regression, are often compared with artificial intelligence (AI) methods. Most authors try to prove that AI methods have better predictive power than traditional methods. The criticism of traditional models is addressed in studies such as Alaka et al., 2018.

Overall, no method is significantly better than the other selected methods concerning the defined criteria. The study of Alaka et al. guides selecting the most appropriate method to best suit the current situation, the size of the data and the outputs expected by the modeller. (Alaka et al., 2018)

3. METHODOLOGY AND DATA

Data for the bankruptcy model creation was obtained from the Orbis database. Separately active companies were downloaded in one file and companies with status – bankruptcy, in liquidation, dissolved, dissolved – in liquidation and liquidation in the other file. For the construction of the 1-year bankruptcy model, only the statements one year before bankruptcy were left. The data has been further adjusted to contain only non-financial companies, and companies with unwanted industry codes have been sorted out. Finally, the dataset consists of 574 Czech SMEs that survived in 2010 – 2018, out of which 283 companies failed in this period and 889 Slovak SMEs that survived 2010 – 2018, out of which 436 failed in this period as shown in Table 1.

Table 1. Database sorting

	Healthy	Bankrupt	Total
Czech Republic	291	283	574
Slovakia	453	436	889

Source: Own processing

Table 2. List of financial indicators

Group	Coding	Formula
Profitability	EBIT/A	EBIT/Assets
	EAT/A	EAT/Assets
	EAT/E	EAT/Equity
	EAT/S	EAT/Sales
	EBIT/S	EBIT/Sales
Activity	S/A	Sales/Assets
	S/CA	Sales/Current Assets
	REC.TURN	Receivables*365/Sales
	PAY.TURN	Payables*365/Sales
Liquidity	CURR.A/ST.DEBT	Current Assets/Short-term Liabilities
	QUICK.R	Current Assets-Stocks/Short-term Liabilities
	CASH.R	Cash resources/Short-term Liabilities
	NCR	Working Capital-Stocks/Daily operating expenses (No Credit Interval)
	WC/A	Working Capital/Assets
	WC/S	Working Capital/Sales
	WC/E	Working Capital/Equity
Indebtedness	L/A	Liabilities/Assets
	L/E	Liabilities/Equity
	E/A	Equity/Assets
	ST.L/A	Short-term Liabilities/Assets
	LT.L/E	Long-term Liabilities/Equity
Others	CURR.A./A	Current Assets/Assets
	CASH/A	Cash resources/Assets
	EQ.R.	Registered Capital/Assets

Source: Own processing

The basis for the selection of indicators for the bankruptcy model are the classic financial indicators analysis supplemented by indicators from the study of Bellovary, Giacomino and Akers (2007). The authors have analysed more than 150 bankruptcy models; among other things, they examined the most commonly used indicators in the known bankruptcy models. Based on this study and knowledge of the financial analysis indicators, it was selected twenty-four financial indicators were divided into profitability, activity, liquidity, indebtedness, and others (see table 2).

4. MODEL SPECIFICATIONS

Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Logistic regression is used to describe data and explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables. The dependent variable should be dichotomous (e.g. in our case, bankrupt or non-bankrupt companies). There should be no outliers in the data, no high correlations (multicollinearity) among the predictors. Tabachnick et al. (2007) suggest that the assumption is met as long correlation coefficients among independent variables are less than 0.90. The variables with correlations of more than 0,60 were removed. Mathematically, logistic regression estimates a multiple linear regression function, in our case defined as:

$$\mathrm{p} = \frac{exp^{(\alpha+\ \beta_1 X_1+\ \beta_2 X_2+\ \beta_3 X_3+\cdots\ \beta_n X_n)}}{1+exp^{(\alpha+\ \beta_1 X_1+\ \beta_2 X_2+\ \beta_3 X_3+\cdots\ \beta_n X_n)}} \tag{1}$$

$$\begin{aligned}\beta =\ & \beta_1 EBIT/A+\beta_2 EAT/A+\beta_3 EAT/E+\beta_4 EAT/S+\beta_5 EBIT/S+\beta_6 S/A+\beta_7 S/CA+\beta_8 REC.TURN+\beta_9 PAY.TURN\\ & +\beta_{10} CURR.A/ST.DEBT+\beta_{11} QUICK.R+\beta_{12} CASH.R+\beta_{13} NCR+\beta_{14} WC/A+\beta_{15} WC/S+\beta_{16} WC/E+\beta_{17} L/A\\ & +\beta_{15} L/E+\beta_{19} E/A+\beta_{20} ST.L/A+\beta_{21} LT.L/E+\beta_{22} CURR.A/A+\beta_{23} CASH/A+\beta_{24} REG.C./A\end{aligned} \tag{2}$$

$$\mathrm{p} = \frac{exp^{(\alpha+\beta)}}{1+exp^{(\alpha+\beta)}} \tag{3}$$

5. RESULTS AND DISCUSSION

Data from Czech and Slovakian companies were tested separately. The dataset for the Czech Republic is named as CZ dataset, and the dataset for Slovakian companies is named the SK dataset. Variables mentioned in Table 2 entered into logistic regression with results mentioned in Table 3.

Table 3. Variables predicting the bankruptcy of manufacturing companies, commercial companies and the whole dataset

Group	Coding	CZ dataset	SK dataset
Profitability	EBIT/A	-1,557***	
	EAT/A		-4,635***
	EAT/E	0,112**	
Activity	S/A		-0,116***
	REC.TURN	0,003**	0,001*
	PAY.TURN	0,004**	0,002***
Liquidity	QUICK.R	0,013***	
	CASH.R		0,060***
	WC/E	0,125**	
Indebtedness	L/A	0,101**	
	LT.L/E	-0,212**	-0,172*
Others	CASH/A		0,731**
	EQ.R.	0,589***	1,537***
Constant		-0,783***	-0,336*
Predictability		**80,1%**	**84,4%**

Note: ***, **, * mean 1%, 5% and 10% level of significance.

Source: Own processing in IBMSPSS

The predictability of the models confirmed it through the ROC curve in the column “predictability” and is very satisfying. Based on the results, although it may seem that firms in each country show very few similar characteristics predictive of bankruptcy, the opposite is true. Looking closer at the indicators that proved to be significant, we find that they are very similar. The ROA indicator is significant for both countries in the CZ dataset is significant with EAT and in SK dataset is significant with EBIT. Liquidity is also significant in both datasets, with the only difference that QUICK.R as the quick ratio is significant in the CZ dataset and CASH. R. as cash ratio is significant in the SK dataset. The differences are in ROE, sales turnover, total indebtedness, and working capital/equity and cash/assets indicators. The significant result is that no significance shows an indicator of total indebtedness which is often used and proves his significance in many scientific studies, for example, in models of prof. Altman, in Ohlson´s model, Zmijewski model, Kováčová et al. 2019, Klieštik et al. 2020 etc., Khadelmoqorani et al. 2015. The same situation is with sales turnover, which shows no importance in the CZ dataset or SK dataset but is used in models of prof. Altman, Taffler´s model, IN 05 model and in scientific studies Fedorova et al. 2016, Kováčová et al. 2019, Klieštik et al. 2020, Khadelmoqorani et al. 2015.

Finally, it is not possible to claim that this result confirms the stated hypothesis. Used indicators are not the same but really do not differ; they are similar. This result can be seen in table 3. It could be caused by the similarity of the nations that have been one country for many years, and results achieved confirm findings of last years literature review. It is appropriate to construct a bankruptcy model for a specific country or a group of countries with similar characteristics or neighbouring countries.

6. CONCLUSION

This study analysed if there are various factors to predict bankruptcy for the Czech and Slovak SME’s. The financial data for the years from 2010 to 2018 were investigated. Each dataset was analysed separately to capture different characteristics of companies. Based on the study of Bellovary et al. 2007 and knowledge of the financial analysis indicators, twenty-four financial indicators were divided into profitability, activity, liquidity, indebtedness, and others.

The predictability of the models was confirmed through the ROC curve with 80,1% predictability for the CZ dataset and 84,4% predictability for the SK dataset. A total of thirteen variables were significant, and only five were present in only one of the datasets analysed. Based on the results, although it may seem that firms in each country show very few similar characteristics predictive of bankruptcy, the opposite is true. Looking closer at the indicators that proved to be significant, we find that they are very similar.

The comparison of all models shows the five most important indicators used often when analysing a company’s financial situation. They are ROA like indicator EAT/A and EBIT/A, receivable turnover like indicator REC.TURN, payable turnover like indicator PAY.TURN, liquidity like indicator QUICK.R and CASH.R and long-term liabilities/equity-like indicator LT.L/E. These findings can not claim that this result confirms the stated hypothesis. Used indicators are not the same but really do not differ; they are similar. It could be caused by the similarity of the nations that have been one country for many years. It is therefore not possible to confirm or reject the hypothesis. Based on the results obtained, it can be concluded that when a financial distress model is developed, it is necessary to classify companies according to similar criteria and to take into account, for example, the similarity of different nations. It is appropriate to construct a bankruptcy model for a specific country or a group of countries with similar characteristics or neighbouring countries.

ACKNOWLEDGMENT

The support of the Masaryk University internal grant MUNI/A/1219/2020 – Kryptoaktiva ve finančních výkazech obchodních společností is gratefully acknowledged.

REFERENCES

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164-184. https://doi.org/10.1016/j.eswa.2017.10.040

Altman, E. I., Esentato, M., & Sabato, G. (2020). Assessing the credit worthiness of Italian SMEs and mini-bond issuers. *Global Finance Journal*, *43*, 100450. https://doi.org/10.1016/j.gf.2018.09.003

Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education*, *33*, 1–42. http://www.jstor.org/stable/41948574

Fedorova, E. A., Dovzhenko, S. E., & Fedorov, F. Y. (2016). Bankruptcy-prediction models for Russian enterprises: Specific sector-related characteristics. *Studies on Russian Economic Development*, *27*(3), 254-261. https://doi.org/10.1134/S1075700716030060

Gupta, J., Barzotto, M., & Khorasgani, A. (2018). Does size matter in predicting SMEs failure?. *International Journal of Finance & Economics*, *23*(4), 571-605. https://doi.org/10.1002/ijfe.1638

Hafiz, A., Lukumon, O., Muhammad, B., Olugbenga, A., Hakeem, O., & Saheed, A. (2015, March). Bankruptcy prediction of construction businesses: towards a big data analytics approach. In *2015 IEEE First International Conference on Big Data Computing Service and Applications* (pp. 347-352). IEEE. https://doi.org/10.1109/BigDataService.2015.30

Karas, M., & Režňáková, M. (2017). The Potential of Dynamic Indicator in Development of the Bankruptcy Prediction Models: the Case of Construction Companies. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *65*(2), 641-652. https://doi.org/10.11118/actaun201765020641

Khademolqorani, S., Zeinal Hamadani, A., & Mokhatab Rafiei, F. (2015). A hybrid analysis approach to improve financial distress forecasting: Empirical evidence from Iran. *Mathematical Problems in Engineering*, *2015*. https://doi.org/10.1155/2015/178197

Kliestik, T., Valaskova, K., Lazaroiu, G., Kovacova, M., & Vrbka, J. (2020). Remaining Financially Healthy and Competitive: The Role of Financial Predictors. *Journal of Competitiveness*, *12*(1), 74–92. https://doi.org/10.7441/joc.2020.01.05

Kovacova, M., Kliestik, T., Valaskova, K., Durana, P., & Juhaszova, Z. (2019). Systematic review of variables applied in bankruptcy prediction models of Visegrad group countries. *Oeconomia Copernicana, 10*(4), 743-772. http://dx.doi.org/10.24136/oc.2019.034

Lifschutz, S., Jacobi, A. (2010). Predicting Bankruptcy: Evidence from Israel. *International Journal of Business and Management*, *5*(4), 133-141. https://pdfs.semanticscholar.org/9ba6/e7d44a3b6d8708b5fde7930a42d703eede2b.pdf

Neumaierová, I., & Neumaier I. (2005). Index IN05. In European financial Systems. Paper presented at 2nd International Scientific Conference EUROPEAN FINANCIAL SYSTEMS 2005, Brno Masaryk University, Brno, June 2005. pp. 143-146. ISBN 80-210-3753-9

Ninh, B. P. V., Do Thanh, T., & Hong, D. V. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. *Economic Systems*, *42*(4), 616-624. https://doi.org/10.1016/j.ecosys.2018.05.002

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131. https://doi.org/10.2307/2490395

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5, pp. 481-498). Boston, MA: Pearson.

Taffler, R. J. (1982). Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data. *Journal of the Royal Statistical Society. Series A (General)*, *145*(3), 342–358. https://doi.org/10.2307/2981867

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, *22*, 59–82. https://doi.org/10.2307/2490859