FINANCIAL DISTRESS PREDICTION FOR MANUFACTURING AND COMMERCIAL COMPANIES

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ABSTRACT

A large number of studies on bankruptcy prediction are published every year. The topic of SME failure prediction has evolved over the past decades into a relevant research area that has grown exponentially across many disciplines, including finance and management, for obvious reasons. 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. Many authors during the last fifty years have examined several possibilities to predict business failure. They have studied bankruptcy prediction models under different perspectives but still could not indicate the most reliable model. This paper focuses on the Czech economy, specifically at small and medium-sized enterprises (SMEs).

This article aims to find if there exist different factors that could predict bankruptcy for manufacturing and commercial companies. Considering the research objective, the following hypotheses were set: H1: Indicators used in the financial distress model for manufacturing companies differ from commercial companies.; H2: Applying a model based on different segmentation criteria improves the reliability of bankruptcy prediction.

It is the ongoing research about the value of several popular bankruptcy models that are often applied, namely the Altman Z-score, the Ohlson O-score, the Zmijewski's model, the Taffler's model, and the IN05 model. The logistic regression has been used to investigate around 1800 companies, of which 308 failed during 2010 – 2017.

Reached results confirm both hypotheses and some suggestions arise from it. When we develop a bankruptcy model, it is necessary to sort companies according to different criteria. It also confirms findings of the last years literature review the closer the similarity of businesses, the greater accuracy of bankruptcy models. Further, it is required to exploit common used financial indicators with a combination of modified indicators to assess the probability of bankruptcy precisely.

Keywords: *bankruptcy prediction, financial distress, SME, financial indicator, logistic regression*

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 there exist different factors that could predict bankruptcy for manufacturing and commercial companies. Considering the research objective, the following hypotheses were set: H1: Indicators used in the financial distress model for manufacturing companies differ from commercial companies.; H2: Applying a model based on different segmentation criteria improves the reliability of bankruptcy prediction.

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.

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. The researcher William Beaver was the first to apply several ratios, which could discriminate between failed and non-failed companies five years before the bankruptcy. Altman improved Beaver's method and assessed the complete financial profile of firms. Altman examines 22 potentially helpful financial ratios and selects five that provide, when combined, the best overall prediction of corporate bankruptcy. He is the first to develop a multiple discriminate analysis (MDA) prediction model with a 95.0% accuracy rate; he is considered the pioneer of insolvency predictors. Altman's model has been applied successfully in many studies worldwide concerning the subjects of capital structure and strategic management, investment decisions, asset and credit risk estimation and financial failure of publicly traded companies [1].

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 [2]. 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. [3].

Considering these MDAs' problems, Ohlson [4], 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 [5]. 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, [6], [7], [8]. 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. As with country specifics, industries have specificities such as seasonality, different asset and liability structures on the balance sheet, and different activity costs. Therefore these facts must also be taken into account. 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. [9], [10], [11].

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 [12], [13], 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. As has been already mentioned, there are many studies published on bankruptcy prediction, so only a few examples and results of this research stream will be presented. 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 [14].

Overall, no method was significantly better than the other selected methods concerning the defined criteria. The study guides selecting the most appropriate method to best suit the current situation, the size of the data and the outputs expected by the modeller. [14]

METHODOLOGY AND DATA

The dataset consists of 1800 SMEs that survived in 2010 – 2017, out of which 308 companies failed in this period. This data was exclusively gained from a bank database by a random selection of SMEs that survived and all SMEs that failed.

The database was split into two groups – manufacturing companies and commercial companies.

Table 1. *Database sorting*

Size	Healthy	Bankrupt	Total
Manufacturing companies	646	115	761
Commercial companies	856	193	1049
Total dataset	1502	308	1810

Source: own processing

Sixteen financial indicators were used see Table 2. The variables were taken from the models used in Altman's Z-score, Ohlson's O-score, Zmijewski's model, Taffler's model, and the IN05 model as their prediction power was compared in the previous research. They measure most of all leverage and profitability. Most of these indicators are not often used in financial analysis; they have been used in known bankruptcy models, which we have examined in our previous research.

Table 2. *List of financial indicators*

Coding		Formula
Leverage	C/DEBT	capital/liabilities
	ST DEBT/A	short-term liabilities/total assets
	A/DEBT	total assets/liabilities
	DEBT/C	liabilities/capital
	DEBT/A	liabilities/total assets
	C/LT A	capital/long-term assets
	LT SOURCES/A	capital + reserves + long-term liabilities/long-term assets
Liquidity	WC/A	working capital/total assets
	CURR.A/ DEBT	current assets/liabilities
	ST DEBT /CURR.A	short-term liabilities/current assets
	CURR.A/ST DEBT	current assets/short-term liabilities
Profitability	RET.EARN/A	retained earnings/total assets
	EBT/ST DEBT	EBT/short-term liabilities
	EBIT/INT. COST	EBIT/interest cost
	EAT/A	EAT/total assets
Activity	SALES/A	sales/total assets

Source: own processing

MODEL SPECIFICATIONS

Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, logistic regression is a predictive analysis. 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. [15] suggest that as long correlation coefficients among independent variables are less than 0.90, the assumption is met. 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:

$$p = \frac{\exp^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \beta_n x_n)}}{1+\exp^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \beta_n x_n)}} \quad (1)$$

p =⟦exp⟧^((α+β_1C/DEBT + β_2 STDEBT/A + β_3A/DEBT + β_4DEBT/C + β_5DEBT/A + β_6C/LT A + β_7LT SOURCES/A + β_8WC/A + β_9CURR.A/DEBT + β_10ST DEBT/CURR.A + β_11CURR.A/ST DEBT + β_12RET.EARN/A + β_13EBT/ST DEBT + β_14EBIT/INT.COST + β_15EAT/A + β_16SALES/A))/⟦1+exp⟧^((α+β_1C/DEBT + β_2 STDEBT/A + β_3A/DEBT + β_4DEBT/C + β_5DEBT/A + β_6C/LT A + β_7LT SOURCES/A + β_8WC/A + β_9CURR.A/DEBT + β_10ST DEBT/CURR.A + β_11CURR.A/ST DEBT + β_12RET.EARN/A + β_13EBT/ST DEBT + β_14EBIT/INT.COST + β_15EAT/A + β_16SALES/A)) (2)

RESULTS AND DISCUSSION

Each group – manufacturing, commercial companies and all the datasets were tested separately. The results are mentioned in Tables 3. Variables mentioned in Table 2 entered into logistic regression with the below-mentioned result.

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

Coding	Manufacturing companies	Commercial companies	Whole dataset
Constant	-1,767	-3,801***	-1,859**
C/DEBT	-1,783	-,852	-,729
ST DEBT/A	,754	-,766	-,272
A/DEBT	1,234	,066	,175
DEBT/C	,000	,000	,000
DEBT/A	,007	,037***	,017**
C/LT A	,123	,023	,026
LT SOURCES/A	-,040	-,013	,026
WC/A	-,314	-,208	-1,207
CURR.A/ DEBT	,173	1,142***	,599**
ST DEBT /CURR.A	-,269	,009	-,309
CURR.A/ST DEBT	-,115	-,467*	-,090
RET.EARN/A	-3,034***	-,736	-1,898***
EBT/ST DEBT	-,164	,730**	,056
EBIT/INT. COST	-,001	,000	-,001
EAT/A	-6,328***	-2,706	-,309**
SALES/A	-,079	,043***	,041***
Predictability	81%	79,9%	78,2%

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

Source: own processing

The comprehensive comparison shows that when we segment the dataset, each segment shows a different result. The comparison of all models shows the five most important indicators used very often when analysed a company's financial situation. They are indebtedness like indicator DEBT/A, liquidity modification like indicator CURR.A/DEBT used in Taffler´s model, ROA like indicator EAT/A, minor ROA modification like indicator RET.EARN/A is used in Altman´s model and assets turnover like indicator SALES/A. We can see that the result of the overall model is a mix of models broken down by sector of activity. The model for manufacturing companies shows that it is necessary to pay attention to profit indicators. In contrast, the model for commercial companies shows that it is necessary to pay attention to debt indicators and sales turnover.

Finally, we can say that this result confirms both hypotheses. H1 - indicators used in the financial distress model for manufacturing companies differ from commercial companies. This result can be seen in table 3. Hypothesis H2 says that applying a model based on different segmentation criteria improves the reliability of bankruptcy prediction. The predictability of the models confirmed it through the ROC curve.

CONCLUSION

This study analysed if there are various factors to predict bankruptcy for different characteristics of Czech SME´s. The financial data for the years from 2010 to 2017 were investigated. The whole dataset was divided into two groups – manufacturing and commercial companies. The analyses were done separately for each group and for the whole dataset to capture different characteristics of companies. The variables used in Altman´s Z-score, Ohlson´s O-score, Zmijewski's model, Taffler's model, and the IN05 model were used as their prediction power was compared in my previous research.

It was found that when we segment the dataset, each segment shows a different result. The model for manufacturing companies shows that it is necessary to pay attention to profit indicators. In contrast, the model for commercial companies shows that it is necessary to pay attention to debt indicators and sales turnover. The comparison of all models shows the five most important indicators used very often when analysed a company's financial situation. They are indebtedness like indicator DEBT/A, liquidity modification like indicator CURR.A/DEBT used in Taffler´s model, ROA like indicator EAT/A, slight ROA modification like indicator RET.EARN/A is used in Altman´s model and assets turnover like indicator SALES/A.

These findings confirm both hypotheses – H1 and H2 and some suggestions arise from it. When we develop a bankruptcy model, it is necessary to sort companies according to different criteria. It also confirms last year´s literature review; the closer the similarity of businesses, the greater accuracy of bankruptcy models. Further, it is required to exploit common used financial indicators with a combination of modified indicators to precisely assess the probability of bankruptcy.

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