Bankruptcy Prediction Models: Can the prediction power of the models be improved by using dynamic indicators?

Mária Režňáková, Michal Karas

*Bruni University of Technology Faculty of Business and Management, Brno 61200, Czech Republic

Abstract

The present approach to developing bankruptcy prediction models uses financial ratios related to the time of one year before bankruptcy. Some authors try to improve the prediction accuracy of the models by using averaged ratios involving several years before bankruptcy. This of course assumes that a bankruptcy can be predicted several years ahead. This idea led us to investigating the differences between the dynamics of the financial ratios developments. Here we assume that the dynamics of the values of some indicators in a group of prospering companies may be different from that of those facing bankruptcy threats. The indicators that showed a significant difference in the development dynamics were used to develop a bankruptcy prediction model. The research was carried out using data of the Czech manufacturing industries obtained from the AMADEUS database for years 2004 to 2011, with each company providing data for up to five years prior to the bankruptcy. Along with investigating the different approach to the selection of indicators for the development of a bankruptcy model, we were also concerned with the selection of a method to develop it. Researching the literature, we found that the most commonly used method is one of linear discrimination analysis, whose precision is improved if applied to normally distributed data without outliers. With financial data, however, these assumptions are difficult to meet. Therefore, a non-parametric boosted-trees method was used to select the predictors and develop the bankruptcy models.

© 2014 Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/3.0/).

Selection and/or peer-review under responsibility of the Organizing Committee of ECE 2014

Keywords: Default prediction models; Financial ratios; Non-parametric model

* Corresponding author. Tel.: +420 54114 3708
E-mail address: karas@fbm.vutbr.cz
1. Introduction

Most of the published approaches to creating bankruptcy prediction models are based on using financial ratios related to a period of one year prior the bankruptcy. These indicators may be referred to as static. Some authors try to improve the prediction accuracy of the models by using averaged ratios over a period of several years prior to the bankruptcy (see Perry et al. 1984; Niemann et al. 2008). In doing so, they assume that bankruptcy symptoms can be detected as early as several years ahead (see Beaver, 1966; Deakin, 1972; Henerby, 1996; Niemann et al. 2008). According to Niemann et al. (2008), most research projects go along the lines of finding an optimal classification algorithm while paying only little attention to the definition of the model variables.

The paper aims to analyze the potential of dynamic financial ratios for bankruptcy prediction. For the purposes of this research, by a dynamic ratio, we mean one that is calculated using data from at least two periods. To this end, two model series were built, Model 1 applying static variables and Model 2 applying dynamic variables. We also assume that the potential of dynamic variables may work in two ways, identifying new risk areas insignificant in a static form and improving the overall classification power of the model.

2. Sample and methods used

The sample used was provided by 1908 manufacturing companies (NACE rev. 2, Main section C: Manufacturing) based in the Czech Republic. These include 1500 financially viable companies and 408 companies that went bankrupt from 2004 to 2011. The data on each company describe the five recent years of its existence. They have been obtained from the Amadeus database provided by Bureau Van Dijk and processed by the Statistica 10 computer program by Statsoft. In building the models, 44 indicators were analysed used in previous studies such as Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980), Ding et al. (2008), Wang, Lee (2008), Niemann et al. (2008), Beaver et al. (2005), Tseng, Hu (2010), Psillaki, Tsolas, Margaritis (2009), Karas, Režňáková (2013b). They are listed by the below table.

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Shortcut</th>
<th>Ratio</th>
<th>Shortcut</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash flow/sales</td>
<td>CF/S</td>
<td>Log of sales</td>
<td>S</td>
</tr>
<tr>
<td>Cash flow/total asset</td>
<td>CF/TA</td>
<td>Log of total assets</td>
<td>TA</td>
</tr>
<tr>
<td>Cash flow/total liabilities</td>
<td>CF/TL</td>
<td>NI/average capital (3-year aver.)</td>
<td>NI/AC</td>
</tr>
<tr>
<td>Current liabilities/sales</td>
<td>CL/S</td>
<td>Net income/current assets</td>
<td>NI/CA</td>
</tr>
<tr>
<td>Current ratio</td>
<td>CR</td>
<td>Net income/total assets</td>
<td>NI/FA</td>
</tr>
<tr>
<td>Debt ratio (TL/EQ)</td>
<td>DER</td>
<td>Net income/operation revenue</td>
<td>NI/OR</td>
</tr>
<tr>
<td>EBIT (5- yrs volatility)</td>
<td>EBIT (5-vol)</td>
<td>Net income/total asset (= ROA)</td>
<td>NI/TA</td>
</tr>
<tr>
<td>EBIT/interest</td>
<td>EBIT/Int.</td>
<td>Ohlson’s change of NI</td>
<td>NI-change</td>
</tr>
<tr>
<td>EBIT/total asset (=ROI)</td>
<td>EBIT/TA</td>
<td>Operation cost/operation revenue</td>
<td>OC/OR</td>
</tr>
<tr>
<td>EBITDA/interest</td>
<td>EBITDA/TA</td>
<td>Operation profit (loss)/ average</td>
<td>OP/AC</td>
</tr>
<tr>
<td>EBITDA/total liabilities</td>
<td>EBITDA/TL</td>
<td>capital (3-year aver.)</td>
<td>OP/OR</td>
</tr>
<tr>
<td>Fixed assets/long-term liabilities</td>
<td>FA/LTL</td>
<td>Operation revenue/current assets</td>
<td>OR/CA</td>
</tr>
<tr>
<td>Income (loss) before tax/operation</td>
<td>EBT/OR</td>
<td>Operation revenue/current liabilities</td>
<td>OR/CL</td>
</tr>
<tr>
<td>Intangible assets/total assets</td>
<td>Int. A/Tot. A</td>
<td>Operation revenue/total liabilities</td>
<td>OR/FA</td>
</tr>
<tr>
<td>Log of equity</td>
<td>EQ</td>
<td>Operation revenue/long-term liabilities</td>
<td>OR/LTL</td>
</tr>
</tbody>
</table>
As corroborated by Beaver (1966), Deakin (1972), Henerby (1996), and Niemann et al. (2008), it may be assumed that the significance of bankruptcy predictors vary over time. This paper presents the results of building a model in which the indicators are defined in two different ways, classically as financial ratios involving one year prior to bankruptcy, that is the period \( t+1 \) where \( t \) is the time of bankruptcy and dynamically, referring mostly to year-to-year changes between the times \( t+1 \) to \( t+5 \). In addition to standard financial ratios, also company size parameters are used (usually as logarithms), indicators averaged over several periods as well as dichotomic indicators. For dichotomic indicators (such as \( TL>TA \)) and those defined for multiple times, a different method must be used of their dynamic transformation. In such dichotomic indicators, their condition was extended from one to two periods. The \( TL>TA \) indicator, for instance, assumes the value 1 if the total liabilities are greater that total assets for two consecutive years (because of the negative equity capital) and the value 0 otherwise. A similar definition was used for the dichotomic indicator \( NI<0 \) assuming 1 for a negative net income (NI) over two consecutive two periods. The indicators originally defined as multiperiodic such as \( PM \) representing the arithmetic mean of the operating margin 3 years (ratio of net profit to operating income) were, for the 5-year period prior to bankruptcy, defined for three intervals, 1 to 3 years prior to bankruptcy, 2 to 4 years prior to bankruptcy, 3 to 5 years prior to bankruptcy. The indicators used, however, are also combined such as \( NI/AC \) and \( OI/AC \) that combine the numerator values, that is, Net Income (\( NI \)), Operating Income (\( OI \)) to the denominator value representing a three-year average capital (\( AC \)). \( NI/AC \) 1324, for example, is the difference of the following two ratios, the ratio of net income (\( NI \)) at time \( t+1 \) to the average capital (\( AC \)) for the period \( t+1 \) to \( t+3 \) and the ratio of \( NI \) at the time \( t+2 \) to the average \( AC \) for the period of \( t+2 \) to \( t+4 \). The only indicator unchanged was the five-year EBIT volatility, that is, \( EBIT(5\text{-vol}) \), covering the whole five-year period in question.

2.1. Boosted Trees Method

The method of Boosted Trees (BT) combines the classification and regression trees method (CART), see Breiman et al. 1983) with a boosting algorithm introduced by Friedman (2001). Using the boosting algorithm improves the accuracy of the classification algorithm, to which it is applied by progressively reducing the error term (Braun, Mues, 2006; Breiman et al. 1983; Friedman, 2001). The resultant classification rule represents a set of many “weak” learners.

2.1.1. Classification and Regression Trees (CART)

The basic idea behind the Trees is the division of a complex problem of feature space in a set of smaller parts known as regions (\( R \)), which can be described through simpler models (for example, constants). The central problem of the method of using trees is establishing the optimal divisional boundaries \( t \) between those regions \( R \). The boundaries are established for the demarcated regions, or trees, to have a specific property defined as a node impurity and the aim of the method is its minimization. For classification purposes, with output values 1, 2, ..., \( K \), it is possible to describe node impurity as follows, see (Hastie et al. 2009, p. 306).

At node \( m \), representing region \( R_m \) with \( N_m \), the number observed is the proportion of group \( k \) in node \( m \) given as:

\[
\hat{p}_{mk} = \frac{1}{N_m} \sum_{x \in R_m} I(y_i = k)
\]

Node impurity of tree \( T \) or \( Q_m(T) \) can be defined using several standards (misclassification error, Gini index, Cross-entropy or deviance). We have used the Cross-entropy (or deviance) defined by:

\[
-\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk}
\]
2.1.2. Boosting

Boosting is a general approach by which the final decision rules are thought of as a set of several “weak” rules or classifiers. Let us consider a classification problem with a dichotomous dependent variable \( Y \), i.e. \( Y \in \{-1,1\} \), a vector of independent predictors \( X \), and a classifier \( G(X) \) that can only take the values \(-1\) and \(1\), i.e., \( G(X) \in \{-1;1\} \).

The boosting is based on applying the classifier \( G(X) \) to the repeatedly modified versions of data, thus producing another \( M \) “weak” classifiers \( G_m(X) \), \( m = 1, 2, \ldots, M \). The resulting classifier \( G_{\text{final}}(X) \) is then made up of the individual partial rules \( G_m(X) \), which are given the weights \( \alpha_m \). The output is standardized to attain a value of only \(-1\) or \(1\), see (Hastie et al. 2009, p. 338).

\[
G_{\text{final}}(x) = \text{sign} \left( \sum_{m=1}^{M} \alpha_m G_m(x) \right)
\]  

(3)

The weights \( \alpha_1, \alpha_2, \ldots, \alpha_M \) are calculated using a boosting algorithm representing the partial contribution of each classifier \( G_m(X) \). A useful feature of this method is that it allows the sorting out of the variables \( x \) according to their relative influence \( I_j \) on the variability of the approximation function \( \hat{G}(x) \) across the entire division of input predictors, this measurement can be described as follows, see (Friedman, 2001):

\[
I_j = \left( E_x \left[ \frac{\partial \hat{G}(x)}{\partial x_j} \right]^2 \cdot \text{var}_x(x_j) \right)^{1/2}
\]

(4)

Among the advantages of the BT method, aside from its nonparametric nature (the data need not be normally distributed), is its tolerance for outliers in the input variable space (Twala, 2010). In addition, the method can even capture non-linear relationships between the variables (Guelman, 2012). Since the lack of normality and the presence of outliers tend to be commonplace in financial data (Barnes, 1982, 1987; Tseng, Hu, 2010; Wu, Gant, Gray, 2010), it can be expected that a method which is immune to these aspects will deliver higher classification accuracy.

2.2. Variance Inflation Factor

Each variable included in the model should bring with it unique information. However, a situation may occur in which the information carried by a variable can be explained with a high degree of accuracy using a combination of other variables. In statistics, this is termed multicollinearity. A way of evaluating the degree (i.e. severity) of the multicolinearity problem is the Variance Inflation Factor (VIF) method as one of the tools used to diagnose the general linear regression model with the VIF value indicating how much the variance of the independent variable may be accounted for by a combination of other variables (Craney, Surles, 2002). For VIF values lower than 10 or 4, the multicolinearity can be considered insignificant (Kim, Kang, 2010).

3. Results

Both model Model 1 and Model 2 were developed in three stages, first setting up a basic model containing all the variables analysed, then disregarding less significant variables for a so-called reduced model, and, at stage three, removing redundant variables to obtain the resulting model.

The model building started by identifying strongly correlated indicator pairs to be potentially included in the set of variables. As strongly correlated were regarded those pairs for which Spearman’s correlation rank reached a value of at least 0.9. A total of 16 strongly correlated pairs were identified of a total of 17 indicators. The following 10 indicators were then excluded from the set of potential predictors: CF/TL, NI/TA, NI/CA, W/C/S, W/C/OC, NI/TA, EBT/OR, OP/OR, OR/TA a EBIT/Int. In doing so, the authors were guided by the experience from their previous research (see Karas, Režňáková, 2013b). For Model 1, the number of potential predictors used was 34 while Model
2 embraced 127 indicators. Only after testing the significance of the indicators and accounting for the model variability, the authors made further reduction.

When searching for the predictors to be used in Model 1, first, all the 34 variables were used and, subsequently, sorted by their relative significance. Seventy percent of the data were used to train the model with the remaining thirty left for testing it. Developed in much the same way, Model 2 was designed to capture the dynamics of the history of selected indicators. The number tags of variables indicate the period in which the change is analysed with the first number giving the beginning and the second the end of the period in question. For example, NI/OR 12 represents the difference between the operating income profitability in years one and two prior to bankruptcy, that is, the difference between NI/OR 1 and NI/OR 2.

In Model 1, the significance of variables ranged between 19.2 and 100 percentage points with the NI<0 a NI-change predictors being evaluated as the least significant while the sales logarithm indicator (S) ranked as the most significant. In Model 2, the significance of the variables ranged between 7.66 and 100 percentage points with the negative net income in two consecutive years (years 4 and 5 prior to bankruptcy, NI<0.45) being the least significant indicator while the EBIT(5-vol) volatility indicator (the standard deviation of earnings before interest and tax for the t+1 to t+5 period) was ranked as the most significant. For further refinement of the model, only those variables that could account for model variability with a significance greater than 60 percentage points were used. This defined a subset of potential predictors containing the bulk of information relevant for model building. The relative significance of most of the variables of Model 1, (61.76 percent or 21 out of 34) is less than 60 percentage points. In Model 2, even 88.19 percent of the variables do not reach the 60-percentage-point significance. The authors believe that excluding these variables should not reduce the prediction accuracy of the model.

3.1. Reduced Model 1 and Model 2

The reduced models are based on the same data as the original models with the same parameters set (the sample ratio and maximal number of terminal nodes). The boosted-trees method can capture a complex relationship between multiple variables. For this reason, when redefining (reducing) the number of indicators analyzed, the relative significance of the indicators changed being derived from a different subset of indicators. For example, the significance of DER 34, indicating the change in the debt-equity ratio between the third and fourth years dropped by 22 percentage points. On the other hand, the most significant positive change by 15.3 percentage points was marked in OC/OR 12, which is the change in the ratio of operation cost to operation revenue between the first and second years prior to bankruptcy. The new relative significance values reflect the relationships only between 13 significant variables of Model 1 and 15 significant variables of Model 2. The reduced models and their relative significances are listed by Table 2.

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>RI [%]</td>
</tr>
<tr>
<td>TA</td>
<td>100.00</td>
</tr>
<tr>
<td>S</td>
<td>99.26</td>
</tr>
<tr>
<td>NI/OR</td>
<td>77.00</td>
</tr>
<tr>
<td>EBIT(5-vol)</td>
<td>71.43</td>
</tr>
<tr>
<td>OR/CL</td>
<td>65.47</td>
</tr>
</tbody>
</table>

As the reduced models include different indicators providing the same information on a company such as the company size as measured by total assets and by sales, it may well be assumed that part of these indicators are redundant. In statistical terms, this is a problem of multicollinearity occurring frequently in bankruptcy models (see Shumway, 2001). A VIF method was applied to detect multicollinearity. From the set of indicators used to derive
reduced models, those indicators were reduced that showed strong multicolinearity with the VIF value higher than 4. Indicators with multicolinearity not proved are highlighted in boldface.

Table 3. Analysis of multicollinearity degree in Models 1 and 2

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>VIF</td>
</tr>
<tr>
<td>CR 1</td>
<td>4.66</td>
</tr>
<tr>
<td>DER 1</td>
<td>2.28</td>
</tr>
<tr>
<td>TL/TA 1</td>
<td>9.72</td>
</tr>
<tr>
<td>NI/OR 1</td>
<td>1.04</td>
</tr>
<tr>
<td>OR/CA 1</td>
<td>2.37</td>
</tr>
</tbody>
</table>

After a multicollinearity test, eight indicators were removed from the reduced Model 1, and five indicators from Model 2. The removal was due to their VIF value as well as with regard to the definition of indicators and the preservation of information provided.

In the case of Model 1, the highest multicollinearity was detected between the company size indicators (TA 1, EQ 1, and S 1). Assuming that large companies are more stable and have less profit volatility, company size is also reflected by the EBIT (EBIT/(5-vol)) indicator, which, in contrast to the previous indicators, does not show multicollinearity with other model indicators. This indicator was used by Niemann et al. (2008) to reduce group-level heterogeneity in financial ratios. Next the total-assets turnover-ratio (S/TA 1) indicator was discarded, which characterizes the efficiency with which the assets available are used. The fixed-assets-to-assets ratio varies over industries. As the research was carried out using the data of manufacturing companies, which may be thought of as similar in terms of the fixed assets available, the authors believe that using just an indicator of current assets and their management will be sufficient in the model. This was why S/TA 1 was disregarded while the current-assets turnover-ratio indicator (OR/CA 1) was kept.

Further indicators rated as redundant and ignored included some characterising the debt rate (TL/TA 1, OR/CL 1, OR/TL 1). The model only kept two such indicators for which no significant multicollinearity was proved, in particular, the debt-equity ratio (DER 1) and an indicator of the repayment time of the total debts from EBITDA (TL/EBITDA 1). The last indicator exceeding the multicollinearity tolerance was the current liquidity (CR 1). This indicator measures the company’s ability to repay short-term debts. Its value is strongly conditioned by the amounts of current assets and short-term debts. However, both these factors are reflected in indicators with no multicollinearity such as current-assets turnover-ratio and debt-equity ratio. Therefore, this indicator, too, was removed from the resulting model. The reduction of redundant variables entailed the necessity of reevaluation leading to the setting up of the final model.

3.2. Final Model 1 and Model 2 and their classification accuracy

From the static point of view (see Model 1), the indebtedness measured by the debt-ratio (DER 1), operating revenue profitability (NI/OR 1), operating profit/loss volatility, that is, EBIT/(5-vol), total debt repayment time from EBITDA (TL/EBITDA), and current-assets turnover-rate (OR/CA) may be thought of as the most significant bankruptcy predictors – see Table 4.
Table 4. Resulting models 1 and 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RI [%]</td>
<td></td>
</tr>
<tr>
<td>DER</td>
<td>100.00</td>
<td>EBIT(5-vol)</td>
</tr>
<tr>
<td>NI/OR</td>
<td>97.14</td>
<td>NI/OR 12</td>
</tr>
<tr>
<td>EBIT(5-vol)</td>
<td>77.23</td>
<td>OC/OR 12</td>
</tr>
<tr>
<td>TL/EBITDA</td>
<td>69.35</td>
<td>CL/S 12</td>
</tr>
<tr>
<td>OR/CA</td>
<td>61.08</td>
<td>DER 12</td>
</tr>
</tbody>
</table>

In the dynamic Model 2, the most significant bankruptcy predictors include profitability indicators, that is, EBIT (EBIT(5-vol)) volatility, change in the profitability of operation assets over the two years prior to bankruptcy (NI/OR 12), profitability change over the same period but measured by the cash-flow-total-assets ratio, change in the equity (EQ 12), which is mostly given by the profitability of equity, and change in the return on assets (EBIT/TA 23). This indicator group also includes OC/OR 12, which measures the change in the operation-cost/operation-revenue ratio between the first and second years. It follows from the above that six out of the indicators used for Model 2 belong to the profitability group. The model’s debt indicators are represented by the debt-equity ratio and total indebtedness (TL/TA 4). The debt-equity ratio occurs twice in the resulting model, as the change between the first and second periods and between the third and fourth periods (DER 12, DER 34), which points to the significance of this indicator to bankruptcy prediction. In terms of indebtedness, a major predictor between the second and third years prior to bankruptcy is the total indebtedness ratio (TL/TA 23) as DER 23 was discarded from the model in the previous step. The reason was its significance being lower than a present threshold value of 57.35 percentage points. The last indicator used was change in the current-liabilities/sales ratio between the first and second years prior to bankruptcy (CL/S 12), which characterizes the change in the behaviour of a company towards its creditors, clearly brought about by the impending bankruptcy.

When applying the boosted-trees method, the models are derived by an iterative process determining the number of “week” learners (here trees) and the weights assigned to them for the error (here risk estimate) to be minimal. The numbers of trees and the minima of the loss functions in models are listed by the below table.

Table 5. Goodness of fit of models 1 and 2

<table>
<thead>
<tr>
<th>Model 1</th>
<th>No. of trees</th>
<th>Train</th>
<th>Test</th>
<th>No. of trees</th>
<th>Train</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Risk estimate</td>
<td>Standard error</td>
<td>Risk estimate</td>
<td>Standard error</td>
<td>Risk estimate</td>
<td>Standard error</td>
</tr>
<tr>
<td>Model 1 (34 var.)</td>
<td>107</td>
<td>0.0427</td>
<td>0.0051</td>
<td>0.0158</td>
<td>0.0070</td>
<td>Model 2 (127 var.)</td>
</tr>
<tr>
<td>Model 1 (13 var.)</td>
<td>40</td>
<td>0.0589</td>
<td>0.0062</td>
<td>0.0223</td>
<td>0.0070</td>
<td>Model 2 (15 var.)</td>
</tr>
<tr>
<td>Model 1 (5 var.)</td>
<td>69</td>
<td>0.0653</td>
<td>0.0065</td>
<td>0.0363</td>
<td>0.0087</td>
<td>Model 2 (10 var.)</td>
</tr>
</tbody>
</table>

The value of the loss function indicates that, on the data set used for its derivation (train), the error rate of the final Model 2 is lower than that of Model 1. On the data set used for testing, the situation is reverse. It is clear that the error rate of a model is in direct proportion to the reduction of the variables used for its construction. It may, however, be assumed that the growing error rate is insignificant.

In testing the classification accuracy of both models (static Model 1 and dynamic Model 2) their capacity was examined to distinguish between active and bankruptcy companies. The results are listed by Table 6. The model accuracies are shown in percentage points. In addition to the classification accuracy, the table also shows the Type I error (active company evaluated as a bankrupt one) and Type II error (bankruptcy company taken for an active one).
The results clearly show that the classification accuracies of both models are very similar. As decisive may be regarded the results achieved on the basis of the testing sample. It is evident that Model 2 is encumbered by higher inaccuracy and error rates in evaluating bankruptcy companies. After reducing the number of variables, the classification accuracy dropped on the testing sample by 0.6 percentage points (Model 1) and 1.02 percentage points (Model 2), which verifies the assumption of insignificant loss of model accuracy due to a reduction in the number of model variables.

4. Discussion

The research presented aimed to determine whether the classification accuracy of a bankruptcy prediction model can be improved by using data from several consecutive periods measuring the possible role of such indicators in designing bankruptcy models. A very simple approach to this question was at hand: designing a static model and redefining its variables to represent change. In our research, we did not use this simplification on the basis that, over a long period, the significance of the indicators used may change. The research carried out verified this. A model based only on change indicators included in Model 1 could only detect bankruptcy companies with an accuracy of 14 p.p.

Both models include three indicators defined identically in the basic version: debt-equity ratio (DER), operating income profitability (N/OR), and EBIT volatility, that is, $\overline{EBIT}$ (5-vol). The meaning of these variables is then clear both from the static and the dynamic point of views: in Model 2, DER occurs both as a change of the ratio between the first and second periods and between the third and the fourth periods. This is the only indicator that takes into account the changes of indicators over four periods prior to bankruptcy. The meaning of debt rate determined one year prior to bankruptcy as a dominant factor is consistent with assumptions on bankruptcy where high debt rate is among those indicators accounting for the bankruptcy (Zavgren, 1985). Psillaki, Tsolias, Margaritis (2009) summarize the meaning of debt rate in bankruptcy models in a similar way. In addition to the above debt-equity ratio, Model 1 also places significance on another debt indicator describing the capacity to repay debts from EBITDA.

Apart from debt-rate indicators, there are other major bankruptcy prediction factors with a longer time prior to bankruptcy, change in the return on assets between the second and third years (EBIT/TA 23). The presence of the profitability factor among the most significant indicators could have been expected as these are often used by a number of models. From previous research, it is known that bankruptcy companies achieve positive EBITDA values as late as three years prior to bankruptcy, however, two years prior to bankruptcy this indicator is already positive (Karas, Režňáková, 2013a).

The $RETA$ indicator was also excluded from both models, although seen by Altman as the most important for bankruptcy prediction (Altman, 1968) and termed by him as past profitability ratio. Altman thought of past profitability as more important for bankruptcy prediction than the current profitability measured by ROA, i.e., $EBIT/TA$. The significance of the $RETA$ ratio was also emphasized by Ding et al. (2008) referring to it as
cumulative profitability. In terms of the content interpretation, this ratio seems to be better called a rate of reinvestment. Retained earnings, and their year-to-year change rate in particular, depend on how the past profit is split into a part used to pay the shareholders and a part used to finance the company assets. As long as this ratio increases, the company reinvests the profit made thus expanding or reducing its debts. In both cases, this improves the company’s viability, thus providing arguments for including the indicator in the model. However, analysing the correlation of the Altman model variables questions the significance of this indicator speaking in favour of Shumway’s criticism (see Shumway, 2001), by which up to one half of the previous models’ indicators (especially those of Altman’s) are redundant due to multicolinearity. Shumway (2001) also thought that using in a model data covering several years prior to bankruptcy decreases RETA’s significance. Even if this significance was relatively high in both Model 1 and Model 2 (by the t+3 to t+1 data, the significance ranged from 58.3 p.p. to 61.6 p.p.) with its inclusion in the models being due to the setting of the significance threshold for the variables to enter the model, we still believe that not using RETA for bankruptcy prediction models was justified because the calculations made had proved its high correlation with the debt-equity ratio.

Surprising is the finding that, except for the changes of the DER 23, TL/TA 23 debt and EBIT/TA 23 return on assets ratios, the remaining indicators relating to year-to-year changes are only significant for the last two periods prior to bankruptcy (see Table 4, Model 2). A relatively lower significance was observed in indicators relating to periods farther away from the bankruptcy, that is, those calculated as the change occurring between year three and year four or year four and year five prior to bankruptcy. Based on a multicolinearity analysis, those indicators were then removed from Model 2 calculated using data relating to the whole period analysed (that is, year on to year five prior to bankruptcy). In this connection, it is worth noting that, in the dynamic model designed only on the basis of the indicators included in the resulting Model 1, also indicators are significant relating to several previous years. In addition to DER mentioned above, TL/EBITDA, another debt ratio, appeared to be significant in all the periods observed.

On the other hand, the above simplified procedure may bring about the loss of bankruptcy-prediction-relevant information that can be found in indicators of a different type. The present method of predictor identification and the development of the final model versions (see resulting Model 1 and Model 2) are supported by the fact that, despite a major reduction of the number of variables, the model accuracy has not been significantly degraded. In other words, the procedure was successful in separating the relevant from the irrelevant pieces of information.

5. Conclusion

Although the results do not unequivocally prove a higher prediction accuracy of a model based on indicators constructed on the principle of year-to-year change, the approach presented does make it possible to identify areas in which bankruptcy symptoms can be identified a long time ahead.

The resulting Model 1 and Model 2 reached a very high accuracy on the data analysed: the accuracy of Model 1 on the testing sample was 97.99 p.p. in active companies and 60 p.p. in bankruptcy companies. For Model 2, on the same sample, the accuracy was 98.99 p.p. in active and 50 p.p. in bankruptcy companies. A lower accuracy in identifying bankruptcy companies may be due to the lower number of companies included in the testing sample. However, the potential of a dynamic approach showed mainly in identifying further risk areas in a company represented by financial ratios. It was proved unequivocally that bankruptcy symptoms change over time and a model designed on the basis of data relating to a single year cannot be modified by simply replacing the indicators by ones relating to multiple periods or by year-to-year changes.

A boosted trees method was used to design the bankruptcy model as designed by Breiman and Friedman (Breiman et al. 1983 a Friedman, 2001). The advantages of this method over the traditional methods, particularly over the discrimination analysis can be summed up by the following points:

- It does not assume normal distribution, which is rather rare in financial ratios (Barnes, 1982, 1987);
- It is immune to the existence of outliers, which are also commonplace in financial data (Shumway, 2001, Mileris, Boguslaukas, 2011) affecting the results of statistical tests (see Twala, 2010, Zimmerman, 1994, 1995, 1998);
- Thanks to the configuration of its parameters, it can capture the complex relationships between the predictors, which are very significant (see Altman, 1968, Cochran, 1964);
- It is efficient in filling in the missing values.
The use of the boosted trees method eliminates the drawbacks of the traditional methods in the development of bankruptcy models.

References

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2nd ed. Springer.