Alternative bankruptcy models – first results

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Abstract: The article is focused on showing first results of two newly created (alternative) bankruptcy models. The used database contains available data of Czech companies (CreditInfo database). Based on result comparison with standardized bankruptcy models (IN 05, Z-fce) the two new models are equivalent in one case and significantly better in the second case.

Keywords: discriminant function, alternative bankruptcy models, standard models

JEL codes: G17, G32, G33

1 Introduction

The exclusive position of bankruptcy models in financial analysis methods is out of question. However their accuracy is regularly being discussed.

The usual praxis of expressing successful predictions in percentages is more and more often supplemented or substituted with ROC curves (see later).

Two newly created alternative discrimination functions (CZ2 and FK) are presented in this article. Their accuracies are evaluated using ROC curves. Relative success of these functions is based on the comparison of their results with standard bankruptcy model benchmarks – Z function and IN05.

2 Aim and Methodology

The objective of this article is to provide the first objective view of the applicability of the new created alternative bankruptcy models (CZ2 and FK) in Czech Republic (hereinafter as CR).

The following shall be used to fullfil the above mentioned aim of this article:

a) proposal of new discriminant function (model) and empirical verification of theirs predicative ability in a full set of available data on businesses based in the CR
b) comparison of the predictive ability this new discriminant functions (models) with other bankruptcy models.

The used set of methodical instruments consist mainly of:

- literature review,
- comparison,
- analysis,
- historical analogy and
- synthesis.
The methodology of the construction of the new created models is out of the scope of this article. It does not allow us to neither present the process of financial ratios selection nor the process of calculating the weights of the models.

3 Data

3.1 Database of Businesses

All data used in this work come from the database Firemní monitor (Creditinfo Czech Republic 2010), formerly known as Albertina. It is a comprehensive database of all registered firms and organizations in the Czech Republic. It captures the basic data on more than 2,400,000 business and non-profit economic entities. It has the largest set of financial statements processed into a structured form. Only financial statements and industry classification CZ-NACE (Český statistický úřad 2011) was used.

The above suggests that as far as the data base, with which the proposed discriminant function operates, is concerned; it is basically about working with the base selection. All adjustments to this set described above follow only one viewpoint - to eliminate irrelevant data.

3.2 Data Export and Import

Even though the source database contains basic information on more than two million entities, at least one financial statement is available for only 149,423 entities. On average, there are three financial statements - not necessarily consecutive - available for each entity. The total amount of financial statements, which meet the verification conditions stated below, is 538,162.

During the import of the database, the data redundancy in the financial statement was used to detect and sometimes also to repair the incorrect values. The set of these functions were named verification conditions. Part of the verification conditions requires that the difference between the summands and their declared sum is insignificant. One condition is also formed by the balance equation. The value of CZK 10,000 was determined as insignificant. 2.4% of financial statements did not meet the verification conditions. This article uses data from the database Firemní monitor as of March 2010. All monetary values are in thousands of CZK, unless otherwise indicated.

3.3 Selection of the Bankrupt and the Surviving

Every financial statement, which precedes the date of bankruptcy, variably depending on the selected time horizon - in this paper 720 days (min. 2 years) - was considered a bankrupt business over time. The issue of insolvency is governed by the Insolvency Act No. 182/2006 Coll. with effect from 1st January 2008. Before this date, insolvency was governed by the Act No. 328/1991 Coll., on Bankruptcy and Settlement.

3.4 Selection of Sample and Retained Data

Each financial statement prepared for the period of 12 months is considered an individual case entering the mathematical model. A randomly selected half of all cases is always used as the sample used for the calculation of the model. The other half of the retained (validation) data serves to verify the model.
3.5 Data Profile

In terms of frequency of bankrupt firms over time, the database is of the following nature. Among all financial statements, there are 1,619 firms two years before bankruptcy, i.e. 0.3%. If we limit the information ability of the group to 3, there are 1,017 bankrupt firms, i.e. again 0.3%. If we focus on the frequency of bankruptcies declared in individual years, which is the number of businesses, the database covers 32% of all bankruptcies declared in legal entities in 2009 with a gradual decrease to 12% in 2005. The database contains a total 1,863 businesses in bankruptcy, for which at least one financial statement before the date of bankruptcy exists. In addition, the database contained a sign of bankruptcy in 1,259 businesses without a date of bankruptcy - these are ceased businesses (or in liquidation for a long time) which cannot be found in the Commercial Register or ongoing insolvency proceedings. All statements of these businesses were excluded.

An unpleasant aspect of the Czech business environment is occasional huge delays between a debt that is unpaid for 30 or 90 days and the beginning of the insolvency proceedings. Delays of four years are not an exception (Klima 2009, p. 2). The result of this situation is the fact that any bankruptcy model will see the financial data with the goal to classify it as a healthy business for a time period shorter than the mentioned delay. If it classifies it positively (as bankrupt), it will be penalized in the form of an error of second kind.

4 Results and Discussion

4.1 Resulting Models CZ2 a FK

The model CZ2 was obtained from the MDA analysis using the Fisher discriminant includes eight ratio indicators: CapitalReinvested, DaysPayableOutstanding, DaysSalesOutstanding, InventorySales, CashLiquidity, LiabilitiesHealthPension, ROA, InterestCoverageRatio.

The model FK was obtained by analysis of causalities between financial ratios. It includes only three ratios, which are listed in Table 2.

The coefficients of the CZ2 model for the horizon of two years are stated in Table 1. The coefficients of the FK model for the horizon of two years are stated in Table 2.

The definition of financial coefficients is based on standard approach. Exact definitions are not the goal of the article. Also beware of the coefficients mentioned in Table 1. They are to be used solely for economic interpretation not for direct evaluation from financial ratios.

Table 1 Linear discriminant model CZ2 with failure time horizon two years

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>CapitalReinvested</td>
<td>0.416</td>
</tr>
<tr>
<td>DaysPayableOutstanding</td>
<td>-0.160</td>
</tr>
<tr>
<td>DaysSalesOutstanding</td>
<td>-0.103</td>
</tr>
<tr>
<td>InventorySales</td>
<td>-0.047</td>
</tr>
<tr>
<td>CashLiquidity</td>
<td>0.321</td>
</tr>
<tr>
<td>LiabilitiesHealthPension</td>
<td>-0.685</td>
</tr>
<tr>
<td>ROA</td>
<td>0.317</td>
</tr>
<tr>
<td>InterestCoverageRatio</td>
<td>0.340</td>
</tr>
</tbody>
</table>

Source: Author’s construction based on data base Firemni monitor
### Table 2 Linear discriminant model FK

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>CurrentAssets/ShortLiab</td>
<td>2,0</td>
</tr>
<tr>
<td>CurrentLiquidAssets/ShortLiab</td>
<td>1,0</td>
</tr>
<tr>
<td>Inventory/ShortLiab</td>
<td>-1,0</td>
</tr>
</tbody>
</table>

Source: Author’s construction based on data base Firemni monitor

### 4.2 Models Comparison

The output of some discriminant models such as MDA or logistic regression is $x$, to which it applies that the more the value approaches infinity, the higher is the probability that the correct classification of the given case. In the field of financial risk, this value is called the score. A user of these models must determine a threshold value of the score, according to which they will classify businesses as healthy or acutely at risk of bankruptcy. Each such choice implies the size of the error of the first kind (FP or false positive) (classification of a healthy business as a business at risk of bankruptcy) and the error of the second kind (FN or false negative) (classification of a business at risk of bankruptcy as a healthy business). The function, which puts both these characteristics indirectly into a relationship, is called ROC curve and is frequently used in the newer studies on bankruptcy models (Altman, Sabato, and Wilson 2010), (Escott, Kocagil, Rapallo, and Yague 2001) and (Castro 2008).

The relation between specificity and sensitivity follows the definition in equation 1.

The accuracy of the model is defined as the area under the curve (AUC) which is related to the *Gini* coefficient $G$ given by the equation 2 where the meaning of the symbols $A$ and $B$ is shown in Figure 1. Some works (Escott, Kocagil, Rapallo, and Yague 2001), (Castro 2008) use the *Gini* coefficient instead of the AUC.

The actual accuracy of the model is not directly compared to another model, but indirectly through so-called benchmark which is one version of the Z-function by Edward I. Altman.

1. \[
    \text{specificity} = \frac{TN}{N} = \frac{N - FP}{N}
    \]

2. \[
    \frac{A}{A + B} + 1 = G + 1 = 2 \cdot \text{AUC}
    \]
4.3 Comparison of the Resulting Models

When calculating the model CZ2, the accuracy of the model on the input sample was $Gini = 0.701$ and on the holdout (validation) sample it was $Gini = 0.703$. The difference is less than half a percentage point. When calculating the model FK, the accuracy of the model was $Gini = 0.43$. There is no need to use a validation sample for model FK as the weights were not directly based on the input data.

We perform the comparison of the accuracy of the model not only against the benchmark Z-function models (as mentioned in 4.2) but also against other works (Neumaier and Neumaier 2005). For the comparison only values calculated on the validation (holdout) data were used. The comparison is divided according to data source in Figure 2.
Table 3 Model comparison using Gini and AUC values on two year time horizon

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Gini</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CZ2</td>
<td>0.703</td>
<td>0.852</td>
</tr>
<tr>
<td>IN05</td>
<td>0.500</td>
<td>0.750</td>
</tr>
<tr>
<td>Z-fce 1968</td>
<td>0.495</td>
<td>0.748</td>
</tr>
<tr>
<td>FK</td>
<td>0.434</td>
<td>0.717</td>
</tr>
</tbody>
</table>

Source: Author’s construction based on data base Firemni monitor

Conclusions
First tests of the newly created bankruptcy models provided encouraging results. Prediction horizon in this case was chosen to be two years.

The accuracy of all the tested models using the ROC curve with AUC criterion and sorted descending by accuracy is shown in table 3.

It is clear from the results that the prediction accuracy of the newly created model is fully comparable with standard models (model FK), and also clearly better (model CZ2).

The results obtained are considered as a work in progress. The final assessment will be done after a second round of tests; this time with five year accuracy.

It is appropriate to remark that the information capability of the new models is thanks to the input data base practically absolute.

References