The Role of Apparent Signs of Financial Distress in Test Samples and Verification Samples of Bankrupt Models

Michal Kuběnka, Renáta Myšková, Josef Novotný, Vít Jedlička

[1,2,3,4] University of Pardubice
Faculty of Economics and Administration, Institute of Business Economics and Management
Studentská 84, 532 10, Czech Republic
E-mail: michal.kubenka@upce.cz; renata.myskova@upce.cz; josef.novotny@upce.cz; vit.jedlicka@student.upce.cz

Abstract: *Financial bankrupt models are characterized as quite accurate and above all very fast tools for quantitative evaluation of financial health of company. The creators report the accuracy of the predicted bankruptcy usually in the range of 70 to 90%. But the problem of bankruptcy models is the test sample on which the models were created. The sample affects the predictive power of these models. Usually indicated accuracy rate differs from the real predictive power of these models. The financial distress of certain businesses may be obvious even without the use of bankruptcy models. Apparent signs of financial distress may be insolvency, negative equity, VAT unreliability, negative economic result for several years in a row.*

Survey conducted by more than 270 companies has shown that more businesses with apparent signs of financial distress in the sample increase the reported accuracy of the bankruptcy model. The research carried out also has determined the real accuracy of selected bankruptcy models on the standard sample of Czech firms and also on a sample of companies where companies with obvious signs of financial distress were eliminated. Due to the modification of the test sample subsequently the accuracy of the selected models changed radically.

Keywords: bankrupt models, financial distress, prediction

JEL codes: G32, M10, C38

1 Introduction

The legislation on insolvency proceedings in the Czech Republic is contained in Act no. 182/2006 Coll., "On Bankruptcy and Methods of its Settlement", as amended (hereinafter the Insolvency Act). This Act entered into force on 1st January 2008 and replaced the previous regulation contained in Act no. 328/1991 Coll. The position of insolvency administrators in charge of this issue is regulated by Act no. 312/2006 Coll. on Insolvency Administrators, as amended. According to the Insolvency Act, it is possible to solve not only if financial failure has already occurred but also the imminent bankruptcy. Insolvency act (§3) defines the concept of bankruptcy with three conceptual features - plurality of creditors, the existence of repayable obligations for more than 30 days and the inability to perform financial obligations.

Table 1 Insolvency Proposals in the Czech Republic in 2010-2017

Year	Corporates	Individuals	Total
2010	5559	10559	16118
2011	6753	17600	24363
2012	8398	23830	32228
2013	6021	30888	36909
2014	3563	31577	35140
2015	3004	29349	32353
2016	2438	27067	29505
2017	1803	21343	23146

Source: CreditReform 2012, 2015, 2017

Table 1 shows that insolvency proposals are tens of thousands each year. Therefore, it is important to prevent a situation where this situation occurs in one's own business or business partner. Timely disclosure of incoming bankruptcy may cause avoidance of bankruptcy or minimize losses as a result of the bankruptcy of a business partner.

Bankruptcy models are based on the assumption that an enterprise has been showing signs of bankruptcy for years and years before it has gone bankrupt. A prediction of financial bankruptcy in advance could thus avert an imminent bankruptcy. Attempts to find a simple and yet accurate model that would be able to classify future financial decline appears in the middle of the last century. The break was 1968, when prof. Altman (Altman, 1968) created a bankruptcy model Z score using multivariate analysis. This model is based on financial data contained in account books. Therefore, the input data is easily accessible and subsequent enterprise application is possible for the general public. His model works with five financial ratios. Relatively soon it was followed by other specialists, who also used other mathematical and statistical methods. For instance, for creation of his bankruptcy model J. A. Ohlson used the logit linear probability in 1980 as the first one (Ohlson, 1980). In the year 1985 the factor analysis was used in order to get independent variables for the logit model (Zavgren, 1985). Later the progress has led to methods of artificial intelligence that mainly use the neural networks (NN) for creation of prediction models since nineties of last century. Tam and Kiang (Tam, 1991), (Tam & Kiang, 1992) belong to pioneers of NN usage. Particular methods (MDA vs. Logit vs. NN) of models creation were compared many times. The results show NN as the most suitable method as proven by (Pendharkar, 2005) (Liang, 2005) (Rafiei, Manzari and Bostanian, 2011). After the passage to the market economy (nineties 20th century) the bankrupt models also started to origin in the Czech Republic and Slovak Republic in order to predict the company bankruptcy. These models should regard the market specificity of these countries. The model (index) IN95 (Neumaierová & Neumaier, 2002) has appeared as the first one, being designed as the creditor´s model, as i tis mostly used for subjects in the creditor´s position (banks and business partners). In 1999 the same authors brought the so-called ownership´s model, named IN99. Its function consists in the prosperity prediction based on the positive economic value added (EVA). In 2001 they created the model IN01 that connected properties of both previous models, i.e. it predicts the bankruptcy as well as the prosperity. Just in the year 2005 it was updated to the version called index IN05 (Neumaierová, 2005). There is a lot of models for earnings prediction (e.g. Hou & Van Dijk & Zhang, 2012; Sheng & Thevenot, 2012; Duspiva & Novotný, 2012; Banker & Chen, 2006) but only IN05 predicts EVA. Before the economic crisis two models focused on the agriculture appeared in Slovakia. It was CH-index from 1998 (Chrastinová, 1998) and G-index from 2002 (Gurčík, 2002). After the economic crisis in 2008 only few bankruptcy models appeared at the territory of the Czech Republic and the Slovak Republic, i.e. P´model (Delina & Packová, 2013) and the bankruptcy Index of Karas and Režňáková (I_{KR}) (Karas & Režňáková, 2013). Čámská emphasizes that the application of these types of model is „user friendly as they do not require any specific mathematic and statistic knowledge of the user" (Čámská, 2013). The authors of model I_{KR} determine the model accuracy 91.71% (calculated as the weighted average of sensitivity and specificity). The authors of model P´ determine the bankruptcy prediction accuracy 21.26% and the bankruptcy prediction return at 71.84%.

Kuběnka and Slavíček (Kuběnka and Slavíček, 2014) claim that although prosperity and bankrupt models were created differently, their construction is similar, which means a combination of ratios and assigned weights of importance. Financial diagnostic and prediction models vary predominantly in their targeting. However, despite a long history of these models there are still used groups of simple ratios for economic and financial stability analysis, e.g. (International Monetary Fund; Černohorská & Linhartová, 2013).

Let´s suppose that the bankruptcy model is accurate at maximum when applied in the region (country) of its origin (due to the differences of accounting methods, market environment, etc.). Let´s also suppose that the market environment in the Czech Republic and the Slovak Republic is still very close. Thus we shall test just last two mentioned models (I_{KR} and P´model) in order to define their accuracy on sample of companies with and also without of apparent signs of financial distress. Altman´s Z score models are the most famous in the world. That is why one of them is also tested.

The goal of this survey is to answer the question whether a sampling pattern on which the accuracy of the model is validated by its structure does not affect the resulting accuracy of the model. The investigation will determine how far the specified accuracy of the models changes after eliminating the obvious bankruptcy features.

2 Tested models

The original **Altman Z-Score** of 1968 was designed for publicly traded joint stock companies. On the other hand, the Z'score (1983), which was published in 1983, was compiled for public limited companies and non-publicly traded shares. Below is a modification of the previous model where the X_4 indicator has been altered from the market value of the equity to the book value of the equity. The stated accuracy of this model is 82% (18% error of type I.). The model has the following form (Altman, 1993):

$$Z' = 0{,}717*X_1 + 0{,}847*X_2 + 3{,}107*X_3 + 0{,}420*X_4 + 0{,}998*X_5 \quad (1)$$

where:

X_1 = working capital / total assets;
X_2 = retained earnings / total assets;
X_3 = earnings before interest and tax / total assets;
X_4 = book value of equity / total assets;
X_5 = sales / total assets.

Creditworthy enterprises should have a score of more than 2.90, and on the other hand enterprises in default below 1.23. The results between boundary values (1.23; 2.90) cannot be clearly explained.

Index of Karas and Režňáková (I_{KR}) is one of the newest bankruptcy model with different structure of variables calculation. All known bankruptcy models (based on author´s knowledge) use 4 ratio indexes at minimum, whereas I_{KR} use only two of them. The first one (X_2) is the assets turnover and the second one (X_3) is the ratio of quick assets and sales. In addition, it contains the variable of absolute amount (X_1) that represent the value of total assets in EUR. The authors of index (Karas & Režňáková, 2013) created the model based on the sample of 880 financially stable and 628 bankrupted companies. Data were drawn from the accounting statements from the period 2007 to 2012. All 1508 companies belonged to the processing industry, based on their business activity, (NACE rev. 2, section C: Manufacturing).

In their text the authors (Karas & Režňáková, 2013) state that the model construction is based on the connection of linear discrimination analysis and the Box-Cox transformation variables. The model is shown as follows:

$$I_{KR} = 1.841*\frac{(X_1+16783.91)^{0.02941}-1}{0.02941} + 1.112*\frac{(X_2+1)^{-0.35627}-1}{0.35627}*13.55*\frac{(X_3+1.112)^{-2.97955}}{2.97955} - 17{,}319 \quad (2)$$

where:
X_1 = value of total assets (EUR)
X_2 = turnover of total assets
X_3 = quick assets a sales ratio

The border limit was determined by the 0 value. Then the company with achieved value IKR > 0 should be financially healthy and with IKR < 0 business goes bankrupt.

Delina and Packová (2013) proposed their own bankruptcy model using the ration indexes used in analyses models (Z-score, Creditworthiness Index, IN05) and regression analysis. The so-called **P´ model** has the following form:

$$P' \text{ model} = 2.86 - 0.0001278X_1 + 0.04851A_2 + 0.2136A_3 - 0.000071A_4 + 0.0001068B_1 - 0.0006116B_4 \quad (3)$$

where:

X_1 = (financial assets – short-term liabilities) / (operating expenses –depreciations)
A_2 = retained earnings / total assets
A_3 = profit before interests and taxes / total assets
A_4 = registred capital / (long-term + short-term liabilities)
B_1 = cash flow / total liabilities
B_4 = earnings before taxes / total operating revenue

The evaluation scale does not contain the interval of non-specified values of P′ model. The critical limit for the company classification is at the value 2,856. When P′< 2.856 the company tends to bankrupt, when P′ ≥ the company is financially healthy and the bankruptcy probability is very low.

3 Research sample description

I was found 273 companies with defined parameters. This sample was used for finding of current accuracy of selected tested model (test no. 1). The sample consist of the companies operating in the manufacturing industry, in bankruptcy, who had available financial statements both in the year of bankruptcy and in the previous year, in order to be able to monitor the possible occurring negative events even in previous years.

In general, the following may be considered as negative events: bankruptcy, execution, insolvency, claim, enforced execution, liquidation, extinction, negative equity, VAT unreliability or loss for several consecutive years. And the last one was one of the main indicators of bankruptcy, along with negative own equity and negative economic performance observed on the sample being tested.

Out of the original 273 companies, 135 companies were eliminated on the basis of the observed loss for several consecutive years, the negative equity and the negative economic result. For the rest of 138 companies selected bankruptcy models were applied, detected accuracy evaluated (test no. 2).

Table 2 Frequency of occurrence of negative events

Negative events	Absol. frequency	Relat. frequency
Loss for several consecutive years	34	25%
Negative equity & negative economic result	41	30%
Negative economic result	63	47%
Negative equity	82	61%
Total	135	100%

Source: Own

4 Results

Test no. 1 consisted of applying models to a whole sample of enterprises (273 pcs) in bankruptcy. P' model evaluated correctly as bankrupt 203 businesses, it is 74.36% of sample. This has become the most successful model in testing. Only 71.44% (28.56% type I. error) assigned creators accuracy of the bankruptcy prediction. Sample application without apparent signs reduced the model's accuracy by 6.59% to 67.77%.

Z′ score evaluated 185 companies (67.77%) in bankrupt, which is less than the creator states (82.00%). The least successful was the I_{KR} model, where the authors report accuracy of 69.91% and test no. 1 indicates accuracy 62.27%, i.e. 170 enterprises classified as bankrupt. Rank in success of prediction in test no. 1 is as follows:

- P′model (74.36%)
- Z′score (67.77%)
- I_{KR} (62.27%)

The reliability interval π for these results can be, according to Pacáková (2003), determined as follows.

$$P\left(p - z_{1-\frac{\alpha}{2}} * \sqrt{\frac{p(1-p)}{n}} < \pi < p + z_{1-\frac{\alpha}{2}} * \sqrt{\frac{p(1-p)}{n}}\right) = 1 - \alpha \quad (4)$$

where:

- p – found current accuracy of models (74.36%, 67.77%, 62.27%)

  n - the size of the base π, means number of companies in sample,
  α - determined at the level of 5%,

Table 3 states original accuracy stated by author, current accuracy checked in test no. 1, confidence interval of current accuracy and accuracy without apparent signs checked in test no. 2.

Table 3 Accuracy with and without apparent signs

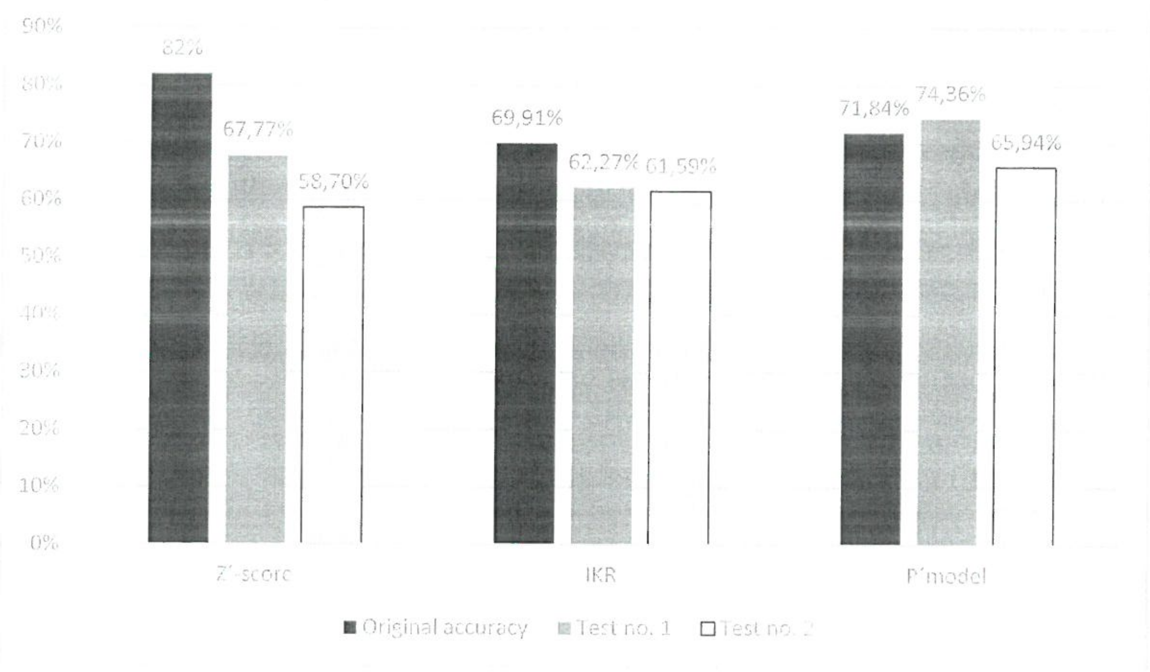
Model	Creator´s accuracy	Current accuracy	Confidence interval	Without apparent signs
Z score	82.00%	67.77%	62.23; 73.31	58.70%
I_{KR}	69.91%	62.27%	56.52; 68.02	61.59%
P´model	71.84%	74.36%	69.18; 79.54	67.77%

Source: Own

Accuracy without apparent signs was stated after reduction of research sample to 138 companies. As a result, the resulting order of accuracy will change as follows:

- P´model (67.77%)
- I_{KR} (61.59%)
- Z´score (58.70%)

Figure 1 Success of business failure prediction



Source: own

Accuracy of Z´score and P´model in test no. 2 (without apparent signs) is out of confidence interval of accuracy checked in test no. 1. It means that usage of visible features of bankruptcy leads to distortions in the stated accuracy of the models. In case of Z´score and P´model it was confirmed with statistical significance. Success of prediction of IKR has also fallen specifically from 62.27% to 61.59% but without confirmation of statistical significance.

5 Conclusion

Every day many subjects need to evaluate in fast manner the financial health of business partners, loan aplicants, debtors, etc. To this purpose there have been developed many failure prediction models. However their accuracy depends on many factors. On this basis authors have set themselves the task to answer the question whether a sampling pattern on which the accuracy of the model is validated by its structure does not affect the resulting accuracy of the model.

In order to meet this goal the classification of companies in 2009-2013 was confronted with the fact that these companies went bankrupt one year later.

I_{KR} model showed the worst prediction power in test no. 1, where was used a research sample of 273 companies. It correctly predicted a business failure in 62.27% of cases based on the data available a year earlier. Order accuracy has changed within the application to the reduced sample (without apparent signs) in test no. 2. Model moved from third to second place.

P´ model was the best in bankruptcy predicting, namely in 74.36% of cases in test no. 1. In test no. 2 the accuracy fell down to 65.94%. This change is statistically significant. This model is the most successful also in test no. 2.

Z´ score showed average accuracy in test one. This model has the worst results in test no. 2. From point of view of authors are more important the results of test no. 2 with the sample without of apparent signs.

The investigation has shown that the sample structure has a key impact on the reported accuracy of the bankruptcy model.

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