Journal of Business and Economics, ISSN 2155-7950, USA
February 2019, Volume 10, No. 2, pp. 117-125
DOI: 10.15341/jbe(2155-7950)/02.10.2019/003

http://www.academicstar.us

Bankruptcy Model Construction and its Limitation in Input Data Quality

Dana Kubíčková[1], Vladimír Nulíček[2]

(1. Department of Finance, Faculty of Economic Science, University of Finance and Administration, Czech Republic; 2. Department of Computer Science and Mathematics, Faculty of Economic Science, University of Finance and Administration, Czech Republic)

Abstract: The aim of the research project solved at the University of Finance and administration is to construct a new bankruptcy model. The intention is to use data of the firms that have to cease their activities due to bankruptcy. The most common method for bankruptcy model construction is multivariate discriminant analyses (MDA). It allows to derive the indicators most sensitive to the future companies' failure as a parts of the bankruptcy model. One of the assumptions for using the MDA method and reassuring the reliable results is the normal distribution and independence of the input data. The results of verification of this assumption as the third stage of the project are presented in this article. We have revealed that this assumption is met only in a few selected indicators. Better results were achieved in the indicators in the set of prosperous companies and one year prior the failure. The selected indicators intended for the bankruptcy model construction thus cannot be considered as suitable for using the MDA method.

Key words: bankruptcy models; prediction ability; financial indicators; normal distribution

JEL codes: M21, G33

1. Introduction

The prediction of the future development of a company and the early detection of the possible failure is still a very important information for all stakeholders and their decision-making. The attention is aimed on existing models and their reliability and also on the construction of new models based on the actual time and local condition. The research revealed that the prediction ability and accuracy of the bankruptcy models decrease being used in different environment and different time than they were originally compiled for. It has become an incentive for research projects to be focused on developing new models with defined time and environment in which they have to be used.

The aim of the research project supported of internal grant agency on VSFS Prague is to construct a new prediction model for the Czech SMEs. The base is the set of accounting data of 50 companies which real went to the bankruptcy in the year of 2013 and of 50 companies from the same period which were in stable good financial condition. We suppose to use multivariate discriminant analyses (MDA), which is a part of the SPSS software.

Dana Kubickova, Ph.D., Assistant Professor, Department of Finance, Faculty of Economic Science, University of Finance and Administration; research areas/interests: financial reporting, assesment of firm's financial performance and its prediction, accounting and reporting ability of financial statements, impact of IFRS, cultural and national factors in the IFRS implementation. E-mail: dana.kubickova@centrum.cz.

Vladimír Nulíček, Ph.D., Assistant Professor, Department of Computer Science and Mathematics, Faculty of Economic Science, University of Finance and Administration; research areas/interests: design of database systems, algorithms of statistical analysis in economic research, web design. E-mail: vnulicek@gmail.com.

In the first stage we have specified the indicators which could be sensitive to the future financial failure. Based on the comparison of the indicators included in the bankruptcy models constructed for the conditions of the CEE countries we set out 39 indicators for the next testing. The results of this stage were presented in the HED conference last year (Kubíčková, Nulíček, 2015).

In the next stage we intend to define the indicators in which the two sets of companies (failure and prosperous) differed in the greatest extent. Application of the MDA used for this purpose is conditioned by several assumptions which determine the sensitivity and the reliability of the resulting model. Thus the first step in using the MDA method became to verify these assumptions. The results of the verification whether or not the suggested indicators met the main assumptions of MDA, are presented in this paper.

The structure of the paper is as follows: in the next chapter the MDA method and its assumptions are characterised. In the third part the two sets of firms and data are characterised. In the fourth part we present an overview of the indicators, the distribution and mutual relation we have verified. In the fifth part we present the result of the verification with the commentary. In the last part the conclusions are presented and the questions and suggestions for the next stage and further research are formulated.

2. Literature Review

In response to the experience with the elder models and their lower reliability when applied in conditions and time different from those in which they were developed, the researches aimed to construct new versions of the older models (Altman, 2000) as well as the new models based on the wider scale of variables (Altman et al., 2010). Special models were created for a specific location, branch or type of companies: the Altman model has been adapted for conditions of the UK SMEs (Altman et al., 2010), specific model for the Polish, Slovak, Lithuanian and Czech environment has been created (Chrastinová, 1998; Prušak, 2004; Neumaier & Neumaierová, 2005; Gurčík, 2002; Hálek, 2013; Andrzejewski & Maślanka, 2015). Ohlson´s model has been transformed for the conditions of Iran or China (Zhang et al., 2010). Special model for bankruptcy prediction for Russian trade companies has been created (Davydová, Belikov, 2013), Altman model was adapted for the trade and non-production companies etc.

The experience in models construction turned attention of researchers both to the accounting data quality and reliability (Altman et al., 2010; Režňáková, Karas, 2014) as well as to the method used to identify the indicators sufficiently sensitive to future financial distress. In this context, the researchers attention turned to the method used to derive the indicators, i.e., mainly MDA method, and its assumptions. The impact of the methodology used for model building on its predicting accuracy has been discussed (Režňáková, Karas, 2013, 2014, Sánchez-Lasheras et al., 2012 and others).

3. Data and Method

The data sets used in our research project were obtained from the annual reports and financial statements of companies presented in the insolvency register and the business register. The examined sample includes 100 companies operating in the Czech Republic. 50 of these companies have actually ceased operations due to financial difficulties and insolvency, the other 50 companies are viable and prosperous, in good financial condition. The year of failure of all the 50 companies was 2013. The structure of both subsets was similar concerning size, legal form and sector. The data were collected from the period of five years before the 2013, i.e., 2009-2013, both for the failed and the prosperous companies. Only for the last year prior to insolvency we have obtained data only of 35 failed companies.

In the previous stage of research 39 indicators were defined for the verification in the next stage. As a base for this definition we used the list of signs of future failure in the literature (Schönfeld, 2011) and the comparison of the indicators included in the bankruptcy models created mainly in the CEE countries. Based on this analyses 39 indicators describing various aspects of the company's financial situation were specified (Kubíčková, Nulíček, 2015). For this stage of the model building 15 indicators have been selected (Table 1).

Table 1 The Indicators in the Examination

No	Indicator	Abbrev.	Area
1.	Assets/Liabilities;	A/L	Indebtedness - Modified financial leverage
2.	EBIT/Interests	EBIT/I	Indebtedness - Interests coverage
3.	EBIT/Assets	EBIT/A	Profitability - ROA
4.	Revenues/Assets	R/A	Activity - Turnover rate of assets
5.	Current assets/ST liabilities	CA/STL	Liquidity - Current liquidity
6.	Inventories/Assets	INV/A	Activity - Share of inventory in assets
7.	ST Liabilities/Sales	STL/S	Activity - Turnover of current (short-term) liabilities
8.	Receivables/Revenues	C/R	Activity - Turnover of the receivables
9.	Receivables/Current Assets	C/CA	Activity - Share of receivables on current assets
10.	ST Liabilities/Assets	STL/A	Indebtedness - Debt ratio
11.	EBT/Sales	EBT/S	Profitability - ROS
12.	EAT/Equity	EAT/E	Profitability - ROE
13.	Retained Earnings/Assets	RE/A	Profitability - long term ROA
14.	Equity /Liabilities	E/L	Indebtedness -Debt coverage of equity
15.	Cash flow/Liabilities	CF/L	Indebtedness - Debt coverage of CF

Note: Sales = sales of goods and own products; Revenues = sales + all other incomes; Retained earnings = funds from profits + earning of the previous years + profit of the current period; Cash flow = EBT + depreciation and amortization.

As the signs of the financial failure the financial ratios were used. A set of indicators includes only those that are computed as a ratio of items from the financial statements. No other indicators, absolute or dichotomous, were included. The indicators were calculated based on the financial statements data one and two years prior to the year of bankruptcy, i.e., the period t-2 and t-3.

For the creation of a bankruptcy model the MDA method is intended to be used. This method allows to identify those indicators whose values in both groups of companies, i.e., failed and prosperous, are the most different. MDA is a method based on linear regression, which assumes certain characteristics of the input data. The assumption of the MDA method are summarised in the next chapter.

The verification of the assumptions, namely the one of the normal distribution of input data (selected indicators) is the aim of this paper.

4. Assumptions for MDA

Multivariate discriminant analysis (MDA) is a statistical method determining which variables discriminate between two or more naturally occurring groups. This method was described in more details in our previous research paper (Kubíčková, Nulíček, 2016).

Multivariate discriminant function analysis is computationally very similar to MANOVA. To use this method, there are several assumptions to be fulfilled. In general, one can say, that all assumptions for MANOVA apply also for MDA. A wide range of diagnostics and statistical tests of assumption are available to examine whether or not the data are suitable for the discriminant analysis.

4.1 Normal Distribution

It is assumed that the data for the variables represent a sample from a multivariate normal distribution. It is preferable that normality be assessed both visually using histograms of frequency distribution, and through some normality tests. There is a wide range of normality tests available, e.g., Shapiro-Wilk test, Kolmogorov-Smirnov test, Anderson-Darling test, D'Agostino skewness test, Cramer-von Mises test and many others. Some researchers recommended the Shapiro-Wilk test as a most powerful tool for normality testing (Razali, 2011). This test is implemented in the SPSS software (Pallant, 2007).

When the normality assumption is violated, interpretation and inferences may not be reliable or fully valid. But some researchers claim, that small violations of the normality assumption are usually not fatal, the resultant significance tests etc. are still trustworthy (Hebák, 2015).

4.2 Homogeneity of Variances/Covariances

The other assumption for using MDA is that the variance/covariance matrices of variables are homogeneous across groups. As above, minor deviations from this assumption are not that important, especially, when the sample sizes in all the considered groups are equal. However, before accepting final conclusions for an important study, it is a good idea to review the within-groups variances and correlation matrices. For this purpose a scatterplot matrix can be produced. One may also use the numerous tests available whether or not this assumption is violated in the data which are subject to your research. One of the suitable tests is the Box's test, which is an extension of the Barlett's test. This test is also implemented in SPSS (Pallant, 2007).

4.3 Correlations Between Means and Variances

The validity of significance tests is most threatened when the means for variables across groups are correlated with the variances (or standard deviations). If there is a large variability in a group with particularly high means on some variables, then those high means are not reliable. The overall significance tests are based on the average variance across all groups. Thus, the significance tests of the relatively larger means (with the large variances) would be based on the relatively smaller pooled variances, resulting erroneously in statistical significance. This pattern occurs if one group in the study contains a few extreme outliers. These extremes impact the means significantly, and also increase the variability. To explore this correlation between the means and variances or standard deviations, one must use some methods of the descriptive statistics (Zhang, 2007).

4.4 Redundancy of the Variables

Another strong assumption of MDA is that the variables used to discriminate between groups are not completely redundant. To check up this redundancy, invert the variance/covariance matrix of the variables in the model. If any one of the variables is completely redundant with the other variables then the variance/covariance matrix is "ill-conditioned", and it cannot be inverted.

To guard against matrix ill-conditioning, it is suitable to constantly check the *tolerance value* for each variable. In multiple regression, tolerance is used as an indicator of multicollinearity. The tolerance is estimated by $1 - R^2$, where R^2 is calculated by regressing the independent variable of interest onto the remaining independent variables included in the multiple regression analysis (Tabachnick, 2001). The test of the tolerance value is available in SPSS, as well.

When a variable is almost completely redundant and the matrix ill-conditioning problem is likely to occur, the tolerance value for that variable will approach zero.

4.5 Shapiro-Wilk test

To test the normal distribution of the defined indicators values we used Shapiro-Wilk test (Shapiro, Wilk, 1965). The Shapiro–Wilk test utilizes the null hypothesis principle to check whether a sample $x_1, \dots x_n$ came from a normally distributed population. The test statistic is

$$\mathrm{W} = \frac{\left(\sum_{i=1}^{n} a_i x_i\right)^2}{\sum_{i=1}^{n} (x_i - \overline{x})^2}$$

where x_i = the i-th order statistic, i.e., the i-the smallest number in the sample,

$\overline{x}$ = mean of the sample

a_i = constant, which is given by:

$$(a_1, \dots\dots, a_n) = \frac{m^T V^{-1}}{\left(m^T V^{-1} V^{-1} \dot{m}\right)^{1/2}}$$

where $m = (m_1, \dots\dots, m_n)^T$ are the expected values of the order statistic of independent and identically distributed random variables sampled from the standard normal distribution, V = is the covariance matrix of those order statistics.

4.6 Interpretation of the Resulting Values

If the p-value is less than the chosen alpha level, there is evidence that the data tested are not from a normally distributed population (the null hypothesis is rejected); in other words, the data are not normal distributed. On the contrary, if the p-value is greater than the chosen alpha level, then the data came from a normally distributed population (the null hypothesis cannot be rejected). However, since the test is biased by sample size, the test may be statistically significant from a normal distribution in any large samples. Thus a Q-Q plot is required for verification in addition to the test.

The Q-Q plot is a graphical method to compare if two variables have approximately the same distribution of probability. If we construct a Q-Q plot for theoretical normal distribution on one axis and for the compared variable on the other axis, we can decide from the shape of the plot, if the compared variable is (approximately) normally distributed or not. When the variable is close to the normal distribution the points in their Q-Q plot are close to the line with 45 degrees slope. If the variables are not close to the normal distribution, the slope of line will differ. *In that case the slope of the line, and spacing values around it reveal the influence of extreme values.*

In first step we have tested the normal distribution in case of 15 selected indicators presented in the Table 1. The results of the Shapiro-Wilk test of the normal distribution are presented in the next chapter.

5. Results and Discussion

The results of the Shapiro-Wilk test of the normal distribution in the set of 15 selected indicators are presented in Table 2 and Table 3 (in the Table 2 the W-values for the time t-2, in the Table 3 the W-values for the time t-3). For the set of n = 50 elements the limit W-value on the level p = 0.01 is 0.93, on the level p = 0.05 is 0.947. If the W-value of the indicator is lower than these limit values, the analysed indicator is not normally distributed. In the set of 15 selected indicators only a few indicators reached the limit of the W-values confirming the normal distribution.

Table 2 Results of the Normal Distribution Test in the Year t-2

Ind.	Failed Companies					Prosperous Companies				
	Average	Median	Variance	Skewness	W	Average	Median	Variance	Skewness	W
1	1,058	1,037	0,164	1,064	0.930	2,849	2,474	3,493	2,386	0.777
2	-8,102	0.120	243077,0	-2,871	0.383	2143,4	13,208	125671048,5	6,531	0.209
3	-0.045	0.002	0.051	-0.261	0.880	0.075	0.065	0.005	0.615	0.933
4	2,420	1,613	7,709	4,437	0.571	1,854	1,723	1,071	1.028	0.933
5	1,286	0.809	10,190	6,884	0.240	3,358	1,551	64,863	6,708	0.270
6	0.181	0.134	0.032	1,003	0.871	0.157	0.104	0.019	0.808	0.890
7	0.715	0.556	0.365	2,383	0.754	0.237	0.171	0.029	1,836	0.830
8	0.301	0.220	0.070	1,397	0.882	0.315	0.148	0.889	6,890	0.237
9	-0.045	0.664	24,855	-7,007	0.197	0.493	0.480	0.052	-0.055	0.954
10	1,016	0.872	0.437	2,433	0.800	0.344	0.286	0.042	0.723	0.942
11	-0.080	-0.005	0.144	-3,557	0.522	0.060	0.036	0.015	5,404	0.477
12	-0.215	0.105	10,151	-4,019	0.531	0.177	0.095	0.100	3,587	0.618
13	-0.242	-0.021	0.417	-2,646	0.740	0.440	0.409	0.053	0.090	0.959
14	0.058	0.037	0.164	1,064	0.930	1,849	1,474	3,493	2,386	0.777
15	-0.015	0.010	0.023	-0.266	0.961	0.291	0.197	0.096	2,283	0.769

In the year t-2 in sum 8 indicators reached or exceeded the level p = 0.01 of the limit value: three indicators in the set of failed companies (A/L, RA/A, CF/L) and five indicators (EBIT/A, R/A, P/CA, STL/A, E/L) in the set of prosperous companies. On the level p = 0.05 there were three indicators (CF/L, P/CA, E/L) that proved the normal distribution, from which only one was in the set of failed companies. None of the indicators was confirmed as normally distributed both in the set of failed and prosperous companies. Thanks to these facts we concluded that no indicator in the 15 analysed indicators is suitable for the MDA method application.

The W-values reached in the 15 analysed indicators in the year t-2 in comparison of the value limits are presented in Figure 1.

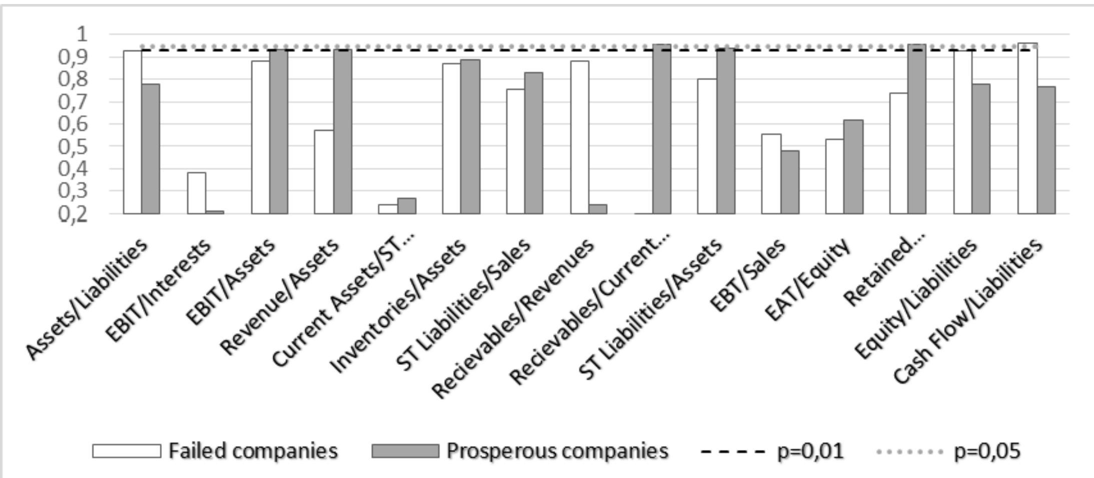

Figure 1 Results of Normal Distribution Testing in the Year t-2

In the year t-3, i.e., two years before the bankruptcy of companies (see Table 3), in sum only six out of fifteen indicators has reached the limit level: three in the set of failed companies (P/CA, A/L, RE/A — the last two were slightly below the limit) and three in the set of prosperous companies (P/CA, E/L, STL/A — the last one was slightly below the limit). In case of p = 0.05 there was not detected any indicator with the normal distribution of its value. In this year one indicator (P/CA) with proved normal distribution of both in the set of failed companies and at the same time in the set of prosperous companies was identified.

The values of descriptive statistics (Table 2, Table 3) illustrate the uneven distribution of the indicators values in both sets of companies and in both years. They also indicate the influence of extreme values. The new calculation of the W-values with the exclusion of extreme values as well as using the other methods for testing will be the aim of the next stage of verification.

Table 3 Results of the Normal Distribution Test in the Year t-3

Ind.	Failed Companies					Prosperous Companies				
	Average	Median	Variance	Skewness	W	Average	Median	Variance	Skewness	W
1	1,137	1,090	0.174	1,095	0.928	3,429	2,375	20,014	5,624	0.438
2	15,482	1,208	1019368.6	3,865	0.330	2535,5	15,930	112597563,2	5,281	0.277
3	-0.094	0.011	0.090	-2?187	0.777	0.096	0.065	0.015	1,256	0.867
4	2,451	1,910	4,985	3,786	0.640	1,995	1,711	1,651	1,673	0.873
5	1,143	0,860	2,574	6,092	0.383	2,214	1,759	2,133	1,826	0.755
6	0.178	0.143	0.027	0,896	0.884	0.168	0.103	0.030	2,436	0.786
7	1,480	1,163	1,265	2,246	0.725	0.303	0.190	0.190	4,545	0.467
8	0.272	0.219	0.044	1,508	0.873	0.212	0.141	0.046	3,492	0.673
9	0.672	0.701	0.100	0,709	0.942	0.512	0.563	0.060	-0,156	0.937
10	0.904	0.860	0.239	1,422	0.889	0.371	0.319	0.045	0,582	0.924
11	-0.143	0.002	0.182	-3,916	0.484	0.063	0.038	0.010	2,658	0.751
12	0.047	0.054	8,032	-0,126	0.718	0.164	0.098	0.063	2,300	0.807
13	-0.146	0.002	0.243	-1,737	0.826	0.454	0.424	0.079	1,013	0.941
14	0.137	0.090	0.174	1,095	0.928	2,429	1,375	20,014	5,624	0.438
15	-0.055	0.006	0.092	-2,156	0.799	0.419	0.207	0.299	1,878	0.771

The influence of the extreme values was confirmed in the Q-Q test. The test and the figure were run for each of 15 indicators — the one of CF/L indicators (Cash-flow/Liabilities) is presented on Figure 2. In the year t-3 in the set of prosperous companies the result of the Shapiro-Wilk test for this indicator reached 0.771 and thus the normally distribution was not confirmed. The shape of the plot in the Q-Q test confirmed this conclusion: the values are not on the line with 45% degree slope and are considerably scattered from the regress line of its distribution ($y = 0.8758x\text{-}1E^{-16}$). By using the Q-Q test we proved the influence of extreme values especially for five indicators: EBIT/I, R/A, CA/STL, C/CA, EAT/E. These findings indicate a need of recalculation of this test excluding the outliers. That will be focused on in the next stage of our research.

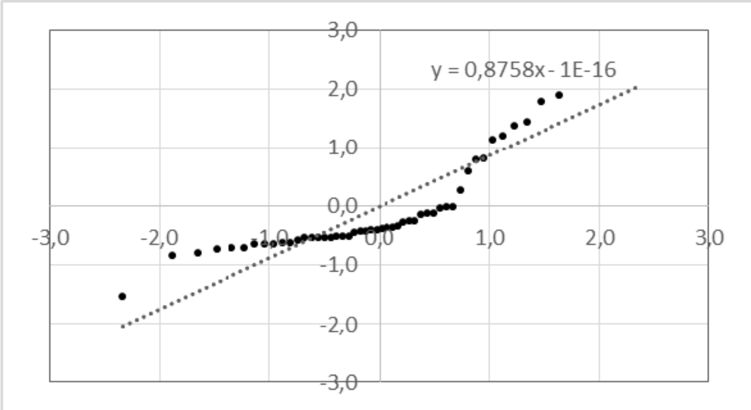

Figure 2 Q-Q Test of the CF/L Indicator Value in the Set of Prosperous Firms in the Year t-3 (W-value is 0.771)

Note: The line in the plot is a regression line for the values – the equation of it is in the figure.

6. Conclusions and Questions for the Further Research

The reliability of the results obtained by using the MDA method in bankruptcy model construction depends, among other things, on certain characteristics of the input data. One of them is the normal distribution of the values. The verification of the normal distribution of the selected indicators, as a base for constructing a new bankruptcy model, brought some useful findings. For verification 15 indicators from the 39 indicators, which we have proposed as potential indicators of bankruptcy in previous phases, were selected. They have been selected so that each of the areas signalling the future failure was represented by at least one indicator. We were verifying if the values of these indicators are normally distributed. For testing the Shaphiro-Wilk test and then the Q-Q test was used.

The normal distribution was confirmed only for a small number of indicators. More indicators of normal distribution were found in the period t-2 compared to the period t-3. The number of indicators with the normal distribution differed in the set of failed and prosperous companies. Normally distributed indicators were identified as normal only in one of the sets of companies, not in both at the same time. The only exception was the indicator C/CA in the year t-3.

Based on these result it can be concluded, that none of the selected 15 indicators is fully suitable for the MDA method and consequently for the creation of a bankruptcy model. These findings also confirmed that it is very important to pay attention to the quality of input data.

Based on these findings and experiences, two main directions of our next research can be formulated. The first one is focused on verification whether or at what extent the results, that we have achieved, are affected by the extreme values. The second one is focused on verification whether or not the other indicators in the set fulfil the assumption of the normal distribution. Only on the basis of this verification, further assumptions for using MDA method can be examined.

Acknowledgement

This article has been supported by the Institutional support for long-term strategic development of the research organization University of Finance and Administration, as a result of Research project IGA [No 7429].

References

Altman E. I. (2000). "Predicting financial distress of companies: Revisiting the Z-score and Zeta Model", available online at: http://www.pages.stern.nyu.edu/~ealtman/.

Altman E. I., Sabato G. and Wilson N. (2010). "The value of non-financial information in small and medium-sized enterprise risk management", *The Journal of credit Risk*, Vol. 6, No. 2, pp. 1-33.

Andrzejewski M. and Maślanka T. (2015). "Procedures of an audit in the prospective verification of the going-concern principle", in: *Proceedings of the Conference IFRS — Global Rules and Local Use 2015*, Anglo-American University, Prague, October 2015, pp. 49-59, available online at: http://car.aauni.edu/conferences/ifrs-2015.conference.

Čamska D. (2012). "National view of bankruptcy models", in: *Proceedings of the 6th International Days of Statistics and Economics*, (MSED), Praha, 13-15 September 2012, pp. 268-278, Prague, University of Economics, available online at: http://msed.vse.cz /msed_ 2012/en/index.

Davydova H. and Belikov A. (2005). *Methods of Quantitative Risk Assessment of Business Risk* (3rd ed.), Irkutsk: State Economy Academie in Irkutsk, available online at: http://masters.donntu.edu.ua/2005/kita/sroka/library/art9.htm.

Gurčik Ľ. (2002). "G-index – metóda predikcie finančného stavu poľnohospodárskych podnikov", *Agricultural Cconomics*, pp. 373-378.

Hálek V. (2013). *Predikce finanční tísně podniku na základně vlastního bankrotního modelu CCB*, Hradec Králové: Gaudeamus, p. 275.

Hebak P. (2015). *Statistické myšlení a nástroje analýzy dat./Statistical Thinking and Data Analysis Tools* (2nd ed.), Praha: Informatorium.

Chrastinová Z. (1998). *Metódy hodnotenia ekonomickej bonit a predikcie finančnej situácie poĺnohospodárskych podnikov*, Bratislava: VÚEPP.

Karas M. and Reznakova M. (2013). "The impact of methodology on the effectivenens of bankruptcy modelling", in: *Proceedings of the International Conference on Economics and Business Administration (EBA 2013)*, pp. 99-102.

Karas M. and Reznakova M. (2014). "To what degree is the accuracy of a bankruptcy prediction model affected by the environment? The case of the Baltic States and the Czech Republic", in: *Procedia-Social and Behavioural Sciences*, Vol. 156, pp. 564-568.

Kubickova D. and Nulicek V. (2016). "Predictors of financial distress and bankruptcy model construction", *Journal of Management Science and Business Administration*, Vol. 2, No. 6, pp. 34-42, doi: 10.18775/ijmsba.1849-5664-5419.2014.26.1003, available online at: http://researchleap.com/ predictors-of-financial distress-and-bankruptcy-model-construction.

Neumaier I. and Neumaierova I. (2005). "Index IN05", in: *Proceedings of the conference Evropské finanční systémy*, Brno, Masaryk University, pp. 143-148.

Pallant J. (2007). *SPSS survival manual, a step by step guide to data analysis using SPSS for Windows* (3 ed.), Sydney: McGraw Hill, pp. 179-200.

Razali N. and Wah Y. B. (2011). "Power comparisons of Shapiro–Wilk, Kolmogorov–Smirnov, Lilliefors and Anderson–Darling tests", *Journal of Statistical Modelling and Analytics*, No. 2, pp. 21-33, available online at: https://web.archive.org/web/ 20150630110326/http://instatmy.org.my/downloads/e-jurnal%202/3.pdf .

Reznakova M. and Karas M. (2014). "Bankruptcy Prediction Models: Cant the Prediction power of the models be improved by using dynamic indicators?", in: *Proceedings of the Conference "Enterprise and Competitive environment 2014"*, 6-7 March 2014, *Brno: Procedia Economics and Finance*, No. 12, pp. 565-574.

Sanchez-Lasheras F., De Andrés J., Lorca A. P. and De Cos Juez F. C. (2012). "A hybrid device for the solution of sampling bias problems in the forecasting of firms' bankruptcy", *Expert Systems with Applications*, Vol. 39, pp. 7512-7523.

Shapiro S. S. and Wilk M. B. (1965). "An analysis of variance test for normality (complete samples)", *Biometrika*, Vol. 52, No. 3-4, pp. 591-611, doi: 10.1093/biomet/52.3-4.591.JSTOR2333709.MR205384.

Schönfeld J. (2011). *Moderní pohled na oceňování pohledávek*, Praha: C. H. Beck, p. 192.

Tabachnick B. G. and Fidell L. S. (2001). *Using Multivariate Statistics* (4th ed.), Boston, MA: Allyn and Bacon.

Zdeněk R. (2013). "Využití diskriminační analýzy a logistické regrese ve finanční analýze", in: *Proceedings of the International Conference INPROFORUM 2013*, České Budějovice, University of South Bohemia, pp. 381-387.

Zhang L., Altman E. I., and Yen J. (2010). "Corporate financial distress diagnosis model and application in credit rating for listing firms in China", *Front Comput. Sci.*, Vol. 4, No. 2, pp. 220-236.

Zhang L. (2007). "Sample mean and sample variance: Their covariance and their (in)dependence", *American Statistician*, Vol. 61, pp. 159-160.