Identifying bankruptcy prediction factors in various environments: A contribution to the discussion on the transferability of bankruptcy models

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Abstract— As has been demonstrated by Beaver and subsequently Altman, financial indicators can pick up the risk of impending bankruptcy. This idea led to the construction of bankruptcy models that proved capable of identifying companies threatened with insolvency with great accuracy. A number of authors have demonstrated that the accuracy of bankruptcy models falls significantly if the given model is used in an environment other than that for which it was originally developed. The aim of this article is to identify the financial indicators that are statistically significant predictors of bankruptcy in various environments. The sample investigated is comprised of data on industrial concerns in the Visegrad Four countries for the years 2007 to 2012. A bankruptcy model based on the same set of variables was derived for each country by the method of Boosted Trees. The variables that are statistically significant in all countries and the variables that are specific for individual countries were identified by means of comparison of the significance of the variables in the models created (i.e. in different environments). Most important indicators of bankruptcy prediction can be described as indicators of company size, in our research the value of sales and total assets. Additional significant predictors are debt ratios, liquidity and profitability. However their significance for bankruptcy prediction is different, which is demonstrated by a high degree of variability of these indicators in the surveyed data sample.

Keywords— bankruptcy prediction models, financial ratios, the method of boosted trees, accuracy of bankruptcy models in various environments

I. Introduction

EXPLORING the possibility of bankruptcy prediction using financial indicators or creation of bankruptcy models has been the centre of scientists' attention since 1960s.

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Particularly work by [3] can be considered pioneering. On the basis of profile analysis he found that there are significant differences in the values of the same indicator between groups of active and bankrupt companies, namely five years prior to bankruptcy. This suggested a possibility of using financial indicators for creation of bankruptcy prediction models. The first person to follow up on his work was [1] who used a method of linear discriminant analysis to create bankruptcy prediction model. Due to clear intelligibility of this model there is a tendency to use it even today. There was a number of other works, in which the authors test the use of other indicators or explore the possibility of improving the model by application of other method, e.g. [2], [6], [11]–[14], [16], [19], [23]. In connection with the development of the models a question was raised on how effectively the models could be applied in different economic environment or different period, other than the one during which the models were created. These issues were dealt with by such authors as [8] or [22] who come with the conclusion that the accuracy of bankruptcy models significantly decreases when the models are applied in different time than in which they were created. The most important works in this context may include the research of [15] who used the logit model to research an option of bankruptcy model compilation using data from different environments.

The aim of this article is to contribute to the debate on robustness of bankruptcy models when applied in different environments by examining the information value of the indicators in different environments. Unlike with previous approaches ([8], [15], [19]) non-parametric algorithm is used for this analysis. This algorithm better corresponds to the natural characteristics of financial indicators such as outliers existence, indicator correlation, etc.

II. Sample and Methodology

The research sample is a set of 6,255 industrial businesses (NACE rev 2, mainsection: C. manufacturing) of the Visegrad Four countries (the Czech Republic, Slovakia, Poland, Hungary). Of this there are a total of 3,500 financially healthy (active) businesses and 2,755 at a risk of bankruptcy, i.e. company data acquired one year prior to the bankruptcy.

Company data were acquired between 2007 and 2012. The data was obtained from Amadeus database, which is provided by Bureau Van Dijk. The calculations used Statistica 10 program from StatSoft. The following table 1 shows the quantity of businesses sorted by country of origin and status (active or. bankrupt).

Table I Number of monitored companies

	CZ	SK	PL	HU	Total
Active	880	335	1,628	657	3,5
Bankrupt	628	407	274	1,446	2,755
Total	1,508	742	1,902	2,103	6,255

Source: Our own analysis of data from the Amadeus database

The indicator of value of total assets was used to represent businesses or properties of surveyed data. The following table 2 shows descriptive statistics of this indicator. Firstly active businesses are described, then bankrupt businesses. For the sake of result comparability the values are denominated in Euros.

Table II Descriptive statistics of active businesses

Active	valid [%]	Average	Median	Std. dev.	Skew.	Kurt.
CZ	97.39	43,855.0	17,770.8	109,212.7	8.34	84.44
SK	94.93	48,124.5	15,951.0	172,624.5	9.64	102.94
PL	98.22	42,292.9	17,871.7	88,937.2	7.49	84.09
HU	99.54	78,084.8	18612.7	434188.6	15.45	261.63

Source: Our own analysis of data from the Amadeus database

Information on active businesses is more accessible than the same data on bankrupt businesses, as seen in the percentage of valid observations in the following table. This aspect greatly complicates creation of bankruptcy models. By appropriate choice of classification algorithm it is however possible to alleviate negative impact of this phenomenon (see below).

Table III Descriptive statistics of bankrupt businesses

Bankrupt	Valid [%]	Average	Median	Std. dev.	Skew.	Kurt.
CZ	60.99	1,658.8	460.07	7,488.5	15.17	261.17
SK	44.72	2,693.6	1,100.7	4,158.7	2.97	10.38
PL	60.95	1,563.8	562.6	2,766.3	3.79	16.81
HU	83.2	1,211.4	128.8	5,523.4	12.9	222.96

Source: Our own analysis of data from the Amadeus database

The descriptive statistics show that bankrupt businesses are much smaller than active businesses. Both samples show obviously extreme values, which results in a significant difference between the average of values and median.

According to the values of skewness and kurtosis we can also conclude that the data do not show normal distribution. For this reason, non-parametric classification algorithm was used to create the model instead of a method of linear discriminant analysis.

A. Boosted Trees Method

Non-parametric classification algorithm, specifically Boosted Trees method was used to build the models and evaluate the significance of predictors. The method of Boosted Trees (BT) is a combination of the classification and regression trees method (CART), see [5], with a boosting algorithm introduced by J. Friedman [7]. Using the boosting algorithm raises the accuracy of the classification algorithm, to which it is applied by progressively reducing the error term, see [4], [7], [9]. The resultant classification rule represents a set of many "weak" learners. The boosting algorithmus most often applied to CART, but an Artificial Neural Network application may been countered as well [13]. The basis of boosting is the gradual application of the classifier G(X) to the repeatedly modified version of data and thus gradually produce other M “weak” classifiers Gm(X), m = 1, 2, …, M. It is possible to describe the method of boosting algorithms in the following schemata, see [10, p. 338].

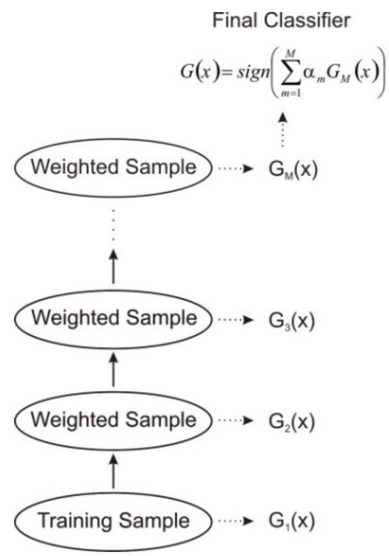

Fig. 1, AdaBoost algorithm method
Source: Own modification according to [10, p. 338]

The resulting classifier $G_{final}(X)$ is then made up of the individual partial rules $G_m(X)$, which are given the weights α_m. The output is standardized to attain a value of only *-1* or *1*, see [10, p. 338].

$$G_{final}(x)=sign\left(\sum_{m=1}^{M}\alpha_m G_M(x)\right) \tag{1}$$

The weights $\alpha_1, \alpha_2, \ldots, \alpha_M$ are calculated using a boosting algorithm, representing the partial contribution of each classifier $G_m(X)$. 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 [21]. In addition, the method allows to capture even complex (non-linear) relationships between the variables [7]. Another advantage of Boosted Trees method is that it can work effectively even with missing values. To do so, it uses the correlation obtained from complete observations of the same indicator, which compensates the loss of information. Missing values are very common at bankrupt businesses (see table 3). A useful feature of this method is that it allows the sorting out of the variables x_j according to their relative influence I_j on the variability of the approximation function $G(x)$ across the entire division of input predictors, this measurement can be described as follows, see [5].

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

To evaluate the significance of the predictors I_j rate was used as a measure.

B. Examined indicators

As a part of the research predictive ability of 14 financial indicators was tested; 4 of which were from the area of profitability and activity (asset management), 2 from the area of liquidity, indebtedness and size of business. Description of the examined indicators and their abbreviations are contained in the following table 4.

Table IV Abbreviations of examined indicators

No.	Abbrev.	Description	Area
1	AV/S	ratio of added value and sales,	Profitability
2	CF/TA	proportion of short-term financial assets and value of total assets in year t-l,	Liquidity
3	E/D	ratio of equity to total external sources,	Indebtedness
4	EBIT/TA	proportion of EBIT (operational result) to total assets,	Profitability
5	EBITDA/S	proportion of EBITDA (operational result + depreciation) to sales,	Profitability
6	NI/OR	ratio of net profit and operating revenue,	Profitability
7	S	sales,	Size
8	S/DBT.	turnover of receivables,	Activity
9	S/QA	turnover of "quickassets",	Activity
10	S/ST	turnover of inventory,	Activity
11	S/TA	turnover of total assets,	Activity
12	TA	total assets,	Size
13	TL/TA	ratio of external sources and total assets (total debt),	Indebtedness
14	WC/TA	ratio of net working capital to total assets,	Liquidity

Although the conclusions of applied BT method are not influenced by the existence of strongly correlated pairs in the sample, the existence of the said pairs represents duplicate information. To evaluate the correlation within the above-mentioned indicators Spearman's rank correlation coefficient was used especially, for its non-parametric assumptions. Although the correlation matrices are different for each environment and also for data of active and bankrupt businesses it is possible to find generally strongly correlated pairs. Such pairs of indicators, which show correlation coefficient higher than 0.9 or lower than -0.9 in more examined environments are generally considered strong pairs. Among the set of examined indicators we identified two such pairs - indicators *TL/LA* and *E/D*, and also *Sales/Quick Assets* and *Sales/Debtors.* The following table 5 shows the values of correlation coefficient approaching linearity with *Total Liability/Total Assets* and *Equity/Debt* pairs.

Table V Correlation of predictors TL/TA and E/D within the models

TL/TA vs. E/D	CZ	SK	PL	HU
Active	-0.9914	-0.9801	-0.9999	-0.9994
Bankrupt	-0.9983	-0.9453	-0.9999	-0.9860

Source: Our own analysis of data from the Amadeus database

Of these debt indicators, indicator *E/D* was given priority compared to *TL/TA* as it is more frequently applied indicator within bankruptcy models.

The values of correlation coefficient of the second pair of indicators i.e. *S/QA* and *S/DBT* are lower than the previous pair of indicators but they also indicate duplicate information. See table 6.

Table VI Correlation of predictors S/QA and S/DBT within the models

S/QA vs. S/DBT.	CZ	SK	PL	HU
Active	0.7931	0.8720	0.8088	0.8562
Bankrupt	0.9078	0.8544	0.8798	0.9442

Source: Our own analysis of data from the Amadeus database

Of this pair of indicators we gave priority to indicator S/QA compared to S/DBT because value of quick assets (QA) contains the value of receivables (DBT) plus the value of short-term financial assets. All of these correlations for both pairs of indicators are statistically significant at 5% level.

III. Results

There was a special model created using data only from businesses of the given country for each examined environment (given country of V4). The models were created using identical parameters setting of BT method and after the application of identical variables. This way we created four different non-parametric models, which we labelled CZ Model, SK Model, PL Model and HU Model. The models were created using identical parameters setting of BT method and after the application of identical variables. The data were randomly divided in 70:30 ratio, i.e. 70% of the data was used to derive the model (so called learning sample) and 30% of the data was used for testing (so called test sample). Other parameters of Boosted Trees method were set as follows: maximum number of trees was 200. Parameter defining degree of tree complexity or models, i.e. maximal number of terminal nodes was limited to 8, which is the upper limit recommended by literature [10, p. 363].

With the application of Boosted Trees method the models are derived in iterative manner, it means that the optimal number of "weak" classifiers (herein trees) is at such level when the value of error function - here deviance (see risk estimate) is minimal.

The course of model derivation can be represented graphically. For example the course of CZ model can be documented by the following graph.

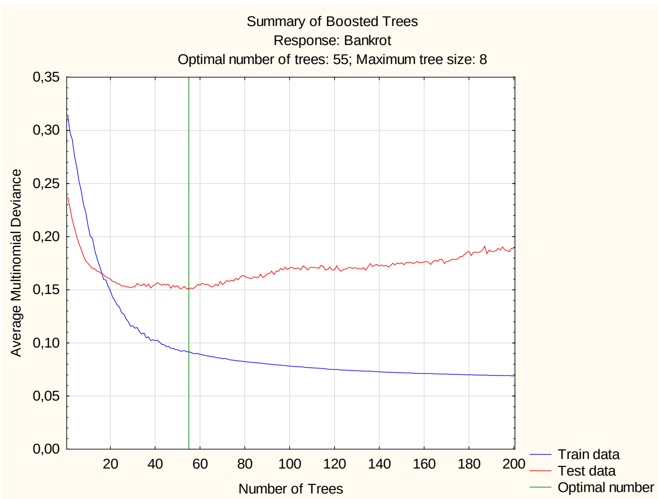

Fig. 2 Course of CZ model derivation

The optimal number of trees included in CZ model is 55. Other models included fewer trees, SK model included 13, PL model 22 and HU model 10. The achieved minimum values of error function (deviance) with optimal number of trees are shown in the following table 7. This value represents so called *goodness of fit* ratio of the given model.

Table VII Achieved minimum values of model deviance

Country	Learning sample		Test sample	
	Risk Estimate	Standard error	Risk Estimate	Standard error
CZ	0.025000	0.004434	0.048507	0.013123
SK	0.067504	0.009941	0.047619	0.020783
PL	0.028858	0.004193	0.016234	0.007201
HU	0.022599	0.003368	0.064103	0.019611

Source: Our own analysis of data from the Amadeus database

The following table shows the values of relative importance of variables for the given models. Since the aim of this paper is also to evaluate the difference in significance of predictors, the table also includes values of standard deviation and values of maximum difference of relative significance of given indicator within individual models. Predictors in this table are in ascending order by the standard deviation. See the following table 8.

Table VIII Relative significance of predictors of individual models [%]

Indicator	Area	CZ	SK	PL	HU	Mean	SD
S	S	100	100	100	100	100	0
TA	S	98.77	98.78	99.94	96.58	98.52	1.4
CF/TA	L	11.91	27.41	12.3	6.17	14.45	9.8
AV/S	P	10.56	27.12	14.73	3.89	14.8	9.78
EBITDA/S	P	26.22	33.82	17.35	10.19	21.9	10.3
S/ST	A	17.34	24.15	31.88	7.25	20.15	10.46
EBIT/TA	P	27.39	38.3	35.01	12.1	28.2	11.66
S/QA	A	19.95	20.48	38.87	6.68	21.49	13.23
S/TA	A	20.99	19.99	47.29	6.13	23.6	17.19
NI/OR	P	30.24	39.87	53.07	11.48	33.66	17.5
E/D	I	61.54	47.02	52.94	13.23	43.68	21.16
WC/TA	L	32.41	38.07	61.38	8.41	35.07	21.75

Note: S – size, L – Liquidity, P – profitability, A –activity, I – Indebtedness, SD – standard deviation. Source: Our own analysis of data from the Amadeus database

The significance of predictors in the individual countries indicates by what percentage the given indicator helps to explain the difference between prosperous businesses (active) and businesses at risk of bankruptcy. In all surveyed countries the most significant indicators are clearly indicator of size of the business, i.e. indicator of sales (S) and indicator of total assets (TA). However the indicator of size of the business (in any form) is usually absent in bankruptcy prediction models. The third most significant indicator is ratio of equity to total external sources (E/D). However in terms of its stability within environments it is the second least stable indicator. The high variability of significance of indicators in the models in different countries is affected mainly by low value of indicator of significance of indicator predicting bankruptcy in Hungary (only 13.23%). As clearly resulting from the structure of observations (number of bankrupt and active businesses, see table 1), the proportion of bankrupt businesses in relation to the total number of obtained observations during the research period was significantly higher, namely 68.76%. The fourth most significant indicator is the average ratio of net working capital to total assets (WC/TA). However its stability within environments is the lowest of all. This indicator is the most significant for bankruptcy prediction in Poland and the least significant in Hungary. On the other hand, in addition to size factors, predictors of change in the proportion of cash flow and value of total assets (CF/TA), as well as the proportion of added value or EBITDA to sales (AV/S or EBITDA/S) stand out in terms of its stability. However an average contribution of these indicators for the prediction of these indicators is low. Apart from size indicators different indicators are significant for bankruptcy prediction in terms of individual countries: In Poland it is liquidity indicator WC/TA (61.38%), profitability indicator NI/OR (53.07%), which also includes all non-operating income (e.g.: revenues from sale of assets) and debt indicator E/D (52.94 %). The same indicators are significant also for the prediction of bankruptcy in the Czech Republic, however their significance is different: the E/D indicator contributes to the explanation of bankruptcy 61.54 %, liquidity ratio WC/TA is only 32.41 % and profitability ratio 30.24 %. In case of Slovakia the liquidity ratio does not belong among five most significant indicators. In addition to the indicators referring to the size of a business, the most significant predictors are indebtedness ratios E/D (47.02 %) and profitability ratios, namely NI/OR (39.87 %) and EBIT/TA (38.30 %).The same five predictors are the five most significant bankruptcy predictors also in Hungary; however apart from the indicator of business size their importance is different.

The most significant of the indicators is a ratio between own capital and debt, i.e. E/D, namely 13.23 %. In case of profitability indicators to predict the bankruptcy the higher significance is attributed to the total profitability ratio EBIT/TA (12.10 %), the significance of NI/OR indicator for bankruptcy prediction is 11.48 %. Extremely low value of these indicators is surprising, and is the expression of total economic situation and conditions for business undertaking in Hungary, which was also reflected in the structure of our observations. Among the most frequently used indicators of predictive models are the ratios between networking capital and total assets (WC/TA), indebtedness indicators (often E/D) and operational profitability (often EBIT/TA). As indicated by our research these indicators are important for prediction of bankruptcy models in the individual countries, however their significance is different. The result is that the prediction accuracy of the model, if used in different than original environment, must be lower than originally declared model accuracy. Any use of prediction bankruptcy model in other than original environment requires at least the change of predictor weights in the model. The accuracy of the individual models for both learning and test sample is illustrated in the following table. The table also contains weighted average of accuracy on these samples, when the weights equals to the number of business in the individual samples.

Table IXI Accuracy of the individual models [%]

Sample	**Learning**		**Test**		**Total**	
Model	**Act.**	**Bank.**	**Act.**	**Bank.**	**Act.**	**Bank.**
CZ	96.29	98.94	98.54	83.87	96.82	97.45
SK	91.83	94.21	97.44	88.89	93.13	93.86
PL	96.76	98.88	99.67	**42.86**	97.30	97.45
HU	97.74	97.74	98.40	**74.19**	97.87	97.23

Source: Our own analysis of data from the Amadeus database

The generated models achieve high accuracy in learning sample, however in test sample (sample) especially in PL and HU models the accuracy is significantly lower. The total accuracy of the models, with which they can identify active business, oscillates between 93.13 and 97.87% of correctly identified businesses. Similar accuracy of bankrupt businesses oscillates between 93.86 and 97.45% of correctly identified bankrupt businesses.

IV. Discussion

Contrary to the previously published researches ([8], [15], [19]) the results presented above were obtained by application of non-parametric method that is immune against natural characteristics of financial data, such as non-normal distribution, the existence of outliers and correlation among the indicators. Another difference is that the research was focused solely on the influence of environment, not on the field of business or time period. From this perspective one can disseminate the conclusions about the robustness of certain indicators or models. Transferability of the models in different environments has already been addressed by several authors, e.g. [8], [19], [18]. According to the research conclusions of [19] the EBIT/TA and E/D predictors can be robust over the time. When examining the robustness of these predictors within the environments we have found out that their significance considerably differs. The result is that the robustness over the time does not necessarily imply the robustness among the environments. Most important indicators of bankruptcy prediction can be described as indicators of company size, in our research the value of sales and total assets. These indicators either do not occur in prediction models or they occur only in logarithmic form. In our research they are included in non-logarithmic form because the logarithmic transformation (generally transformation by means of monotonic function) does not affect the conclusions of the Boosted Trees methods [21]. Conclusions regarding the significance of size factors can represent possible explanation of limited robustness of the models that use only ratio indicators (for instance Altman's model) in different environments [8]. As the application of only ratio indicators leads to the isolation of size factor outside the model [16], [17], [20]. The most probable cause of limited robustness of the models within the environments can be either isolation of size factors outside the model and use of identical weights in case the models are used in different environments. Additional significant predictors are debt ratios (Equity/Debt), liquidity (Net Working Capital/Total Assets) and profitability (Earnings before Interest and Tax/Total Assets or Net Income/Operating Revenue). However their significance for bankruptcy prediction is different, which is demonstrated by a high degree of variability of these indicators in the surveyed data sample. The result is that to predict the bankruptcy in different environment it is possible to use the same or similar indicators; however their weights must be redefined in every respective environment.

V. CONCLUSION

As has been demonstrated by [3] and subsequently [1], financial indicators can pick up the risk of impending bankruptcy. This idea led to the construction of bankruptcy models that proved capable of identifying companies threatened with insolvency with great accuracy. A number of authors (see, for example [8], [18]) have, however, demonstrated that the accuracy of bankruptcy models falls significantly if the given model is used in an environment other than that for which it was originally developed. This study is concerned with the reasons that may influence the accuracy of prediction models in different environments. The sample investigated is comprised of data on industrial concerns in the Visegrad Four countries (the Czech Republic, Slovakia, Poland and Hungary) for the years 2007 to 2012 obtained from the financial statements of the given companies contained in the Amadeus database. A bankruptcy model based on the same set of variables was derived for each country by the method of Boosted Trees. The variables that are statistically significant in all countries and the variables that are specific for individual countries were identified by means of comparison of the significance of the variables in the models created (i.e. in different environments). Most important indicators of bankruptcy prediction can be described as indicators of company size, in our research the value of sales and total assets. Additional significant predictors are debt ratios (Equity/Debt), liquidity (Net Working Capital/Total Assets) and profitability (Earnings before Interest and Tax/Total Assets or Net Income/Operating Revenue). However their significance for bankruptcy prediction is different, which is demonstrated by a high degree of variability of these indicators in the surveyed data sample. This confirmed our assumption that the use of models in different environments leads to a fall in the accuracy of the model. This leads to the necessity of modifying or developing bankruptcy predication models separately for each environment. This conclusion should be respected both during the application of the Basel III rules in the banking sector and during the rating assessment of individual companies.

REFERENCES

[1] E. I. Altman, “Financial Ratios, “Discriminant Analysis and the Prediction of Corporate Bankruptcy”, *The Journal of Finance*, vol. 23, no.4, pp. 589-609, 1968.

[2] B. Back, T. Laitinen, and K. Sere, “Neural Networks and Genetic Algorithms for Bankruptcy Predictions,” *Expert Systems With Applications*, vol.11, no.4, pp. 407-413, 1996.

[3] W. H. Beaver, “Financial Ratios as predictors of Failure”, *Journal of Accounting Research*, vol.4, pp. 71-111, 1966.

[4] I. Braun, Ch. Mues, “An experimental comparison of classification algorithms for imbalanced credit scoring data sets”, *Expert Systems with Applications*, vol. 39, pp. 3446–3453, 2012.

[5] L. Breiman, J. H. Friedman, R. Olshen and C. Stone, *Classification and Regression Trees.* Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software, 1983.

[6] A. Cielen, L. Peeters and K. Vanhoof, “Bankruptcy prediction using a data envelopment analysis”, *European Journal of Operational Research*, vol. 154, pp. 526–532, 2004.

[7] J. H. Friedman, “Greedy Function Approximation: A Gradient Boosting Machine”, *Annals of Statistic*s, vol. 29, no 5, pp 1189-1232, 2001.

[8] J. S. Grice, R. W. Ingram, “Test of Generalizability of Altman’s Bankruptcy Prediction Model”, *Journal of Business Research*, vol. 10, pp. 53-61, 2001.

[9] L. Guelman, “Gradient boosting trees for auto insurance loss cost modelling and prediction”, *Expert Systems with Applications*, vol. 39, pp. 3659–3667, 2012.

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

[11] K. L. Henerby, “Do Cash Flows Variables Improve the Prediction Accuracy of a Cox Proportional Hazards Model for Bank Failure?” *The Quarterly Review of Economics and Finance*, vol. 36, no. 3, pp. 395-409, 1996.

[12] M. Karas, M., Režňáková, “Bankruptcy Prediction Model of Industrial Enterprises in the Czech Republic”, *International Journal of Mathematical Models and Methods in Applied Sciences*, vol. 7, no. 5, p. 519-531, 2013.

[13] M. J. Kim, D. K.. Kang, “Ensemble with neural networks for bankruptcy prediction”, *Expert Systems with Applications*, vol. 37, pp. 3373–3379, 2010.

[14] D. Martin, “Early warning of bank failure: A logit regression approach”, *Journal of Banking & Finance*, vol. 1, no. 3, pp. 249–276. 1977.

[15] M. Niemann, J. H. Schmidt, and M. Neukirchen, “Improving performance of corporate rating prediction models by reducing financial ratio heterogeneity”, *Journal of Banking & Finance*, vol.32, pp. 434-446, 2008.

[16] J. A. Ohlson, “Financial Ratios and the Probabilistic Prediction of Bankruptcy”, *Journal of Accounting Research*, vol.18, no.1, pp. 109-131, 1980.

[17] M. J. Peel, D. A. Peel, “Some further empirical evidence on predicting private company failure”, Accounting and Business Research, vol. 18, p. 57–66, 1987.

[18] D. H. Platt, M. B. Platt, “Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction”, *Journal of Business Finance & Accounting*, vol. 17, no. 1, p. 31-51, 1990.

[19] T. Shumway, “Forecasting Bankruptcy More Accurately: A Simple Hazard Model”, Journal of Business, vol.74, no.1, pp. 101-24, 1999.

[20] R. J. Taffler, “Forecasting company failure in the UK using discriminant analysis and financial ratio data”, *Journal of the Royal Statistical Society*, vol. 145, p. 342–358, 1982.

[21] B. Twala, “Multiple classifier application to credit risk assessment”, *Expert Systems with Applications*, vol. 37, pp. 3326–3336, 2010.

[22] Y. Wu, C. Gaunt and S. Gray, “A comparison of alternative bankruptcy prediction models”, *Journal of Contemporary Accounting & Economics*, vol.6, pp. 34-45, 2010.

[23] M. E. Zmijewski, “Methodological issues related to the estimation of financial distress prediction models”, *Journal of Accounting Research*, vol.22, pp. 59-82, 1984.