Gavurova, Beata; Janke, Frantisek; Packova, Miroslava et al.

Article

Analysis of impact of using the trend variables on bankruptcy prediction models performance

Reference: Gavurova, Beata/Janke, Frantisek et. al. (2017). Analysis of impact of using the trend variables on bankruptcy prediction models performance. In: Ekonomický časopis 65 (4), S. 370 - 383.

Analysis of Impact of Using the Trend Variables on Bankruptcy Prediction Models Performance[1]

Beáta GAVUROVÁ – František JANKE* – Miroslava PACKOVÁ* – Mojmír PRÍDAVOK***

Abstract

The main objective of this paper is to analyse the impact of trend variables on the predictive ability of the models constructed using two methods: discriminant analysis and decision tree technique. The second objective is to develop a new model with prediction accuracy higher by at least 10% in comparison with other models being currently used in the Slovak business environment (Altman model, Index IN05). After analysing and comparing these methods, we came to the conclusion that the most suitable method for developing the model was the decision tree technique. Using this technique we were able to extract classification rules for bankruptcy prediction and achieve predictive ability of about 85% which, in comparison with other models, showed higher predictive performance by about 10%. Moreover, we confirmed that by applying the dynamic approach predictive ability of the decision tree increased; however we did not derive the same result using the discriminant analysis method.

Keywords: *bankruptcy prediction models, failure, discriminant analysis, decision tree*

JEL Classification*:* G33, C81, C36

Introduction

It has been years since companies, managers and researchers started looking for answers to the questions: Can business failure be predicted? Can we recognize symptoms of an upcoming failure? Up to now there have been published many studies devoted to this issue. A summary of the findings of over 190 studies

* Beáta GAVUROVÁ – František JANKE – Miroslava PACKOVÁ, Technical University of Košice, Faculty of Economics, Department of Banking and Investment, B. Němcovej 32, 040 01 Košice, Slovak Republic; e-mail: beata.gavurova@tuke.sk; frantisek.janke@tuke.sk; miroslava.packova@tuke.sk

** Mojmír PRÍDAVOK, Technical University of Košice, Faculty of Economics, Department of Finance, B. Němcovej 32, 040 01 Košice, Slovak Republic; e-mail: mojmir.pridavok@tuke.sk

[1] This paper is supported by VEGA č. 1/0978/16 *Financial health of companies and its importance in the context of supplier-customer relations.*

can be found in the publication of Du Jardin (2009) who divided the symptoms of failure into three types of variables. The first includes both financial variables and variables that represent the major characteristics of the company itself. The second deals with the market or sector-driven variables, and the third with the financial markets. As proved in Du Jardin (2009), the first category is the most commonly used when predicting a company failure. For other evidence we can see the overview of bankruptcy prediction models in Bellovary, Giacomino and Akers (2007), Balcaen and Ooghe (2006) or Altman and Narayanan (1977).

In spite of the fact that since the first Altman's model (1968) many other models have been created, Altman's model is still one of the most used models not only in research but also in "real life". The model is the first based on the discriminant analysis (DA) with 95% accuracy one year and 72% two years before the bankruptcy. As the model was developed for the companies listed on the stock exchange, in 1983 it was revised to also include non-listed companies (Altman, 1984). Many later studies were aimed at validating the Altman's model (Soon et al., 2013; Sulub, 2014; Lifschutz and Jacobi, 2010; etc.) or its revision (Anoop, Banerjee and Francis, 2007; Karas et al., 2013; etc.). The discriminant analysis was also used in the studies conducted by Gurčík (2002), Neumaierová and Neumaier (2005), Alaminos, Castillo and Fernández (2016), etc.

Despite the popularity of DA, this method as one of the parametric statistical methods has to deal with assumptions such as normality or equal variance-covariance matrix of independent variables. Moreover, the assumption of normality is often not met which may lead to bias of results. Hence, in 1980 Ohlson, for the first time, applied the logit analysis (Ohlson, 1980). The Ohlson's model outperformed the previous models based on the DA method, and, as proved later in Lennox (1999), Kordlar a Nikbakth (2011), Charitou, Neophytou and Charalambous (2004), the logit models were superior to the DA models. However, should be mentioned that even the logit analysis has its assumptions. The issue of assumption was solved in 1990, when Odom and Sharda (1990) applied the technique of artificial intelligence – Neural Network (NN) which required no assumption. Since then, the methods such as NN, hybrid NN, or data mining techniques especially in the form of decision trees have been very popular in literature (e.g. in Atiya, 2001; Chen and Du, 2009; Chen, 2011; etc.) and become superior to traditional statistical methods (proved in Zhang et al., 1999; Charitou, Neophytou and Charalambous, 2004)

Static vs. Dynamic Approach

Despite the wide range of models available, most of them are based on static variables – static financial ratios. According to Du Jardin (2009), only 14% of

190 analysed studies include at least one trend variable (mostly from year to year changes in a ratio or financial variable).

It is a very small percentage considering the proved positive impact of using trend variables on the performance of bankruptcy prediction models (e.g. Chava and Jarrow, 2004; Campbell, Hilscher and Szilagyi, 2008).

Dynamic (trend) variables can be seen in the model by Ohlson (1980), where the income trend was observed. The relevance of this variable was proved in Low, Nor and Yatim (2001) as well. Trend variables were also included in the model by Kahya and Theodossiou (1999), Huang et al. (2008), Situm (2015) and others.

Based on the previous research, we can summarize the reasons for including trend variables in the analysis:

- Trend variables embody the dynamic character of a failure as it is not a sudden or unexpected event but may take some time (Shumway, 2001). While static models examine a company's failure as a discrete event without paying attention to the dynamics of the process, dynamic models based on trend variables can reveal a deteriorating trend of the financial health of a company. It should be mentioned that trend and static variables are complementary. In other words, dynamic models cannot be created using only trend variables, but both trend and static variables need to be included. As pointed out in Du Jardin (2009), static variables can detect imbalance, while trend variables can define a direction.
- As stated by Lev (1969), failed companies have a greater degree of instability in their financial statements in comparison with non-failed companies and therefore the change in their financial ratios will be greater. So, a model including a trend variable is more sensitive to financial instability and can better distinguish between a failed and non-failed company.

Taking into consideration all these aspects, it seemed useful to examine the impact of including trend variables into the analysis of the predictive ability of the created model. Moreover, there is little evidence of this in literature, in the Slovak conditions hardly any.

1. Methodology

1.1. Objectives and Hypothesis

Due to the above-mentioned advantages of trend variables, one of our objectives was to find out whether the implementation of the dynamic approach (understanding the involvement of trend variables) within the Slovak business environment would lead to an increase in the performance ability of bankruptcy prediction models based on two selected methods: Discriminant analysis as a traditional one and Decision tree as an artificial intelligence technique. In doing so we met our second objective, i.e. creation of a new model that would perform better than currently used models – Altman's model and Index IN05.

To meet the objectives, we worked with three hypotheses:

Working hypothesis No. 1: *Using the dynamic approach will increase the accuracy of static DA model*

Working hypothesis No. 2: *Using the dynamic approach will increase the accuracy of static Decision tree model*

Working hypothesis No. 3: *We created a model with the accuracy higher by at least 10% in comparison with the models most commonly used in the Slovak environment (Altman's model, Index IN 05)*

1.2. Sample

The analysed sample consisted of the financial data of 1 182 Slovak non--listed companies: 277 bankrupted and 905 non-bankrupted businesses. For each company we had financial statements at our disposal covering the period of at least four years in a row, i.e. for the analysed years from 2009 – 2014. By analysing four financial statements in a row we eliminated start-ups and companies trading on the market for a very short time from the sample, because this group of companies have different failure paths compared with the established companies (Ooghe and De Prijcker, 2008).

In order to meet the objectives of the paper, we divided our sample into two parts: in-sample set of 720 companies (including 140 bankrupted) for model estimation and out-of-sample set of 482 companies (including 137 bankrupted) for model verification using a random approach.

1.3. Variables

A set of variables is one of the key tools for performing the analysis. The way the variables are chosen will influence the input and finally the output data as well. In literature, we can find authors who do not explain their choice of a method (e.g. Ohlson, 1980; Yap, Yong and Poon, 2010), while others use methods such as correlation analysis (e.g. Shirata, 1998), descriptive statistics (e.g. Šarlija and Jeger, 2011), factor analysis (e.g. Chen, 2011) or previous studies (Chen and Du, 2009), etc. In our analysis, we started with a basic set of 51 variables most commonly considered and studied in literature:

a) Altman's model (Altman, 1984) – Variables of this model are most frequently used in the bankruptcy literature. Even models based on NN using these variables proved to have high accuracy (Odom and Sharda, 1990).

b) Index IN05 (Neumaierová and Neumaier, 2005) – Index IN05 was created based on a sample of Czech companies. As proved in Packová (2015), Index

IN05 has performed very well even in the Slovak conditions (see the description in Belás et al., 2015a; Belás et al., 2015b; Majková, Solík and Sipko, 2014) and has over performed models such as Altman (1984) or Ohlson (1980). Taking into account these results, we assume high statistical significance of IN05 variables in our sample as well.

c) Analysis of Chen and Du (2009) – The study is focused on using neural networks and data mining techniques in the prediction of company failure. According to authors, the choice of this study was based on the fact that variables had already been found as significant in the studies conducted by Kirkos et al. (2007), Spathis (2002), Spathis, Doumpos, and Zopounidis (2002), Fanning and Cogger (1998), Persons (1995), Stice (1991), Feroz, Park, and Pastena (1991), Loebbecke, Eining, and Willingham (1989) and Kinney and McDaniel (1989). From all the financial (33) and non-financial (4) variables used in their study, we selected financial ratios suitable for non-listed companies (Chen and Du, 2009).

For the purpose of the analysis we worked with two kinds of sets:

1. To create static models, we worked with 51 static financial ratios used in the publications of the authors mentioned above

2. To create dynamic models, we worked with 51 static financial ratios used to create static models as well and, moreover, we added 51 trend ratios derived from static financial ratios using the following formula: $(X_1 – X_0)/X_0$.

1.4. Techniques

To develop the new models, two methods were used: DA and decision trees. Using these methods, we identified the most significant variables from the basic sets in terms of prediction bankruptcy/non bankruptcy of companies within the Slovak business environment.

Discriminant Analysis

Discriminant Analysis is a classificatory discriminant analysis used to classify a dependent variable into two or more groups based on independent variables. To meet the assumption of equal variance-covariance matrix, the discriminant function takes two forms: linear (if assumption met) or quadratic (if assumption not met). When the dependent variable is dichotomous, the linear function performs well (Lachenbruch, 1975). As failure/ non-failure is a dichotomous variable, most of the bankruptcy prediction models are linear functions (see overview in Bellovary, Giacomino and Akers, 2007; Balcaen and Ooghe, 2006; Altman and Narayanan, 1997). Thus, in our analysis the linear discriminant function is of the following form:

$$Y = v_1X_1 + v_2X_2 + v_3X_3 + ... + v_nX_n \tag{1}$$

where Y is a dependent variable, X_i is a value of independent variable i, and v_i is a vector of independent variable which helps to separate the considered groups in such a way that the intra – group variability is minimized while the inter – group variability is maximized (Kočišová and Mišanková, 2014).

To select the most significant variables from our basic set, Wilk's Lambda test was used. By applying this test it was possible to compare the statistical significance of the average of variables between two groups: the group of bankrupted companies and the group of non-bankrupted companies. In the following step, statistically significant variables were tested for the presence of correlation, and redundant variables were not included in the model.

Decision Tree

Decision trees are simple classifiers that consist of three types of decision nodes represented in the form of a tree (Wu et al., 2016):

- Nodes with no incoming edges (root node) – the splitting variable of the highest classification ability
- Nodes with outgoing edges (test node) – splitting of variables with high classification ability which starts decreasing as the node moves off the root until the decision node is reached
- Decision nodes (leaves) – final splitting of variables of the tree branches, whereby each leaf is assigned to one target attribute or indicates the probability of the target attribute having a certain value (Rokach and Maimon, 2007)

Decision trees are used to classify an object (e.g. company) to a predefined set of classes (e.g. failed/non-failed) based on their attributes (e.g. financial variables).

The process of building decision trees involves splitting the data set into homogenous subsets with respect to the target variable (Rokach and Maimon, 2007). In each splitting step, the explanatory variable splits the set achieving two aims simultaneously, i.e. to minimize the intra-subsets' variability and maximize the inter-subsets' variability.

There are several algorithms used for constructing decision trees such as classification and regression trees (CART), C 4.5, C 5.0, chi squared automatic interaction detection (CHAID), QUEST, etc. When making a decision, which algorithm to use for the analysis we put emphasis on the previous research. Our first choice was CART and CHAID algorithms, because these are the most valuable for classification (Azar et al., 2010). Both CART and CHAID algorithms can be applied to analyse classification problems with good results as was also proved by Shiri et al. (2012) in their study. In making a decision which algorithm to use, either CART or CHAID, we relied on the comparison of their benefits.

A major difference found by the analysis was the number of outgoing edges. While CART algorithm splits only by one variable, CHAID algorithm has no limitations and the tree is branchier. Therefore, CHAID seems to be more suitable as there is no limitation to the number of outgoing edges. When taking their advantages into account, both algorithms can deal with categorical and numerical variables, outliers or missing values (Lakshmi, Indumathi and Nandivi, 2015). Hence, CHAID algorithm was chosen for the purpose of our analysis.

2. Results

First, we present the results obtained by applying the DA method to the created static and dynamic DA model. Then, the results of the Decision tree technique are compared with the results of the DA method. Finally, we use an out-of-sample test to validate all the models mentioned in this paper and compare their results with the results of the existing models: Altman (1984) and Index IN05, which are most commonly used in the Slovak environment, both in science and practice.

2.1. Results of DA Method

As mentioned above, the variables were selected using Wilk's Lambda test which were identified as significant (at the 95% confidence level) in both static and dynamic DA models. After performing the correlation test, the following static and dynamic models were developed:

Table 1

Function of Static DA Model and Dynamic DA Model

STATIC DA MODEL	Function
	1
Capital/Loan Capital	–.209
Inventory/Assets	1.810
Current Liabilities/Current Assets	.071
Loan Capital/Assets	.273
Earnings After Taxes/Costs	–1.636
Bank Loan/Assets	.998
(Loan Capital – Current Financial Assets)/CF	.001
Long-term Assets/Assets	1.305
Liabilities/Assets	3.175
Assets/Equity	.001
(Constant)	–2.281

DYNAMIC DA MODEL	Function
	1
Liabilities/Assets	1.161
Current Assets/(Current Liabilities + Bank Loan)	–.122
Current Liabilities/Assets	.453
EAT/Costs	–2.586
Turnover/Equity	.003
EAT/Long-term Assets	–.106
(Turnover$_1$/Assets – T_0/A_0)/($T_0 – A_0$)	.187
(Cur. Liabilites$_1$/Cur. Assets$_1$ – CL_0/CA_0)/(CL_0/CA_0)	.042
(Financial Costs$_1$/Liabilities$_1$ – F_0C_0/L_0)/(F_0C_0/L_0)	.231
(Inventory$_1$/Turnover$_1$*360 – I_0/T_0*360)/(I_0/T_0*360)	.004
(Long-term Assets$_1$/Long-term Liabilities$_1$ – LtA_0/LtL_0)/(LtA_0/LtL_0)	.021
(Liabilities$_1$/Assets$_1$ – L_0/A_0)/(L_0/A_0)	.009
(Turnover$_1$/Inventory$_1$ – T_0/I_0)/(T_0/I_0)	.023
(Turnover$_1$ – Costs$_1$)/Turnover – ($T_0 – C_0$)/T_0)/($T_0 – C_0$)/T_0)	.005
(Constant)	–.611

Source: Own elaboration in SPSS Statistics Programme.

In both cases we set the cut off value at 0.23. Thus, when M is higher than 0.23, a failure is more likely to happen when compared with M value less than 0.23. Using the model on the in-sample set we got the following performance:

T a b l e 2

Accuracy of DA Model in Two Predicted Periods

Predicted period	**Overall accuracy**	**Failure accuracy**		**Ist type error**		**Non-failure accuracy**		**IInd type error**	
	%	No.	%	No.	%	No.	%	No.	%
1 year (static/dynamic)	75.00 76.71	111 112	79.27 80.00	29 28	23.57 20.00	414 425	73.93 75.89	146 135	26.07 24.11
2 years (static/dynamic)	**74.71** **73.71**	104 95	74.29 67.86	36 45	29.29 32.14	419 421	74.82 75.18	141 139	25.18 24.82

Source: Own elaboration in MS Excel.

The results given in the table show that using the dynamic approach in the analysis we were able to increase the predictive ability of the static model in three of four cases. In terms of non-failure accuracy, the dynamic approach had a slightly positive impact, whereas in terms of failure accuracy we had to differentiate between one and two years before bankruptcy. The dynamic approach showed improvement in prediction accuracy one year before bankruptcy, however, two years before bankruptcy the accuracy decreased. The decrease was so significant that it influenced the overall accuracy in a negative way and as a result the accuracy of the model predicted for the period of two years was worse in comparison with the static model.

Based on the above, we *couldn't confirm* our *Working hypothesis No.* 1 as our assumption worked only for one-year predicted period.

In general, the performance of both models could not be considered sufficient as the predictive ability of the models for both periods was less than 75%. These results might be the consequence of breaking the assumptions of the DA method. The Shapiro-Wilk and Kolmogorov-Smirnov test showed that not satisfying the assumption of normal distribution could lead to bias results and decrease in the total quality of the model. Based on these facts we assumed a higher predictive ability by applying the decision tree method which makes no assumptions.

2.2. Results of Decision Tree Technique

The results of the DA models were not sufficient enough as the total accuracy of prediction one and two years ahead was only about 75%. This could be caused by breaking the assumptions of the applied method that could lead to bias results. On the other hand, the decision tree technique did not require any statistical assumption and showed quite a high level of predictive ability proven in numerous research studies.

In our analysis we used CHAID algorithm, and from the decision tree we extracted the following rules indicating if the company would fail:

T a b l e 3

Classification Rules Extracted from Decision Trees

RULES Static DT
0.7011298 > Loan Capital/Assets <= 0.89107156 and Cash Flow/Loan Capital <= 0.0018514878
0.89107156 > Loan Capital/Assets <= 1.4669329 and Cash Flow/Loan Capital <= 0.024816984
Loan Capital/Assets > 1.4669329
RULES Dynamic DT
Assets/Equity <= –1.6861705 and Bank Loans/Assets > 0
Assets/Equity <= –1.6861705, Bank Loans/Assets < 0 and Cash Flow/Loan Capital <= 0.024961582
–1.6861705 > Assets/Equity <= 0.03737541
Assets/Equity > 3.422917 and Cash Flow/Loan Capital <= 0.0006137677
Assets/Equity > 3.422917, 0.0006137677 > Cash Flow/Loan Capital <= 0.024961852 and Financial Assets/Current Liabilities <= 0.20828587

Source: Own elaboration in MS Excel.

When looking at these rules, it is obvious that after applying the dynamic approach the rules changed, however, there were no trend variables present in the rules. It means that by using algorithm CHAID we did not find any significant trend variables, but by adding trend variables we changed the relative significance of explanatory variables.

The great advantage of these rules is that, in comparison with the DA models, they are much easier to use as the only calculation that needs to be performed is to verify if the financial ratios of a company fit any of the rules. By applying these rules to a training sample we obtained the following results:

T a b l e 4

Accuracy of Classification Rules Extracted from Decision Trees

Predicted period	**Overall accuracy**	**Failure accuracy**		**Ist type error**		**Non-failure accuracy**		**IInd type error**	
	%	No.	%	No.	%	No.	%	No.	%
1 year (static/dynamic)	**85.86** **86.71**	113 115	80.71 82.14	27 25	19.29 17.86	488 492	87.14 87.86	72 68	12.86 12.14
2 years (static/dynamic)	**84.29** **86.14**	103 100	73.57 71.43	37 40	26.43 28.57	487 503	86.96 89.82	73 57	13.04 10.18

Source: Own elaboration in MS Excel.

With the decision tree model we obtained overall accuracy of around 85% on average where the accuracy of DA models was higher by about 10% in comparison with the previous results. When looking at the accuracy for failed and non-failed companies, it is obvious that our models performed better for non--failed companies in both predicted periods. The failure prediction accuracy of the models two years before the bankruptcy decreased in comparison with one year before the bankruptcy which was the same as with DA models. Based on that we could conclude that failure prediction accuracy of the models was highly influenced by the predicted time period, and the models best predicted a failure only one year ahead. The decrease in failure prediction accuracy goes hand-in-hand with stagnating or increasing the accuracy in non-failure prediction, thus, the overall accuracy was only slightly influenced.

The analysis of the overall accuracy showed that the use of the dynamic approach improved the accuracy in both predicted time periods. Thus, based on the results we can *confirm Working hypothesis No.* 2 as we proved that the dynamic decision tree showed a better performance than the static one.

Moreover, we proved higher predictive ability of the dynamic decision tree model in comparison with the dynamic DA model on the one hand and higher predictive ability of the static decision tree model in comparison with the static DA model on the other.

Based on the results we can state that we created a model that fits the Slovak business environment very well as the total accuracy was at the level of about 85%. To compare the results of this model with the models used in Slovakia we used out-of-sample validation.

2.3. Validation

As mentioned above in 2.2, we divided the sample into in-sample and out-of--sample so that we could validate all the models on a new sample that was not used to develop the models. Validation revealed the real predictive ability of the models as we used a sample different from the original since they had different characteristics.

In general, validation results appeared to be worse than those obtained previously. It could result from the fact that the models are trained on a training sample to fit this sample as best as possible and when using another sample their predictive ability usually decreases. Thus, the more the model is over-trained on the training sample, the higher the probability of getting worse results on another sample is.

The results of the models created by us are given in the table below. Moreover, we chose two existing models to compare them with our models. For the purpose of comparison, we chose the Altman's model (1983), which is the most commonly used model in literature and Index IN05 that is most often used in the Slovak and Czech environment.

T a b l e 5

Validation of Models

Predicted period: 1 year/2 years	Overall accuracy		Failure accuracy		Ist type error		Non-failure accuracy		IInd type error	
	No.	%	No.	%	No.	%	No.	%	No.	%
ALTMAN	293 286	60.79 59.34	99 86	72.26 62.77	38 51	27.74 37.23	194 200	56.23 57.97	151 145	43.77 42.03
IN05	280 283	58.09 58.71	102 100	74.45 72.99	35 37	25.55 27.01	178 183	51.59 53.04	167 162	48.41 46.96
DA static model	284 275	58.92 57.05	62 48	45.26 35.04	75 89	54.74 64.96	222 227	64.35 65.80	123 118	35.65 34.20
DA dynamic model	303 309	62.86 64.11	99 104	72.26 75.91	38 34	27.74 24.82	204 205	59.13 59.42	141 140	40.87 40.58
Static DT	365 356	75.73 73.86	109 98	79.56 71.53	28 39	20.44 28.47	256 258	74.20 74.78	89 87	25.80 25.22
Dynamic DT	387 374	**80.29** **77.59**	114 111	83.21 81.02	23 26	16.79 18.98	273 263	79.13 76.23	72 82	20.87 23.77

Source: Own elaboration in MS Excel.

As stated above, validation results are generally worse than the results obtained initially, and this was also our case. All newly created models showed lower accuracy on the validation sample. The DA model performed worse by about 10 – 17%, while the decision tree model by about 6 – 10%. In both cases, the decrease in accuracy was higher when using the static models.

As the table shows, the best results were obtained by using the dynamic decision tree model followed by the static decision tree model ranked the second and from among the DA models the dynamic model proved to be superior to the static one. Taking into account the ranking within out-of-sample there was no change when compared to the ranking within in-sample.

However, when we compared the results of our models with the Altman's model and Index IN05 we could see that our DA static model performed worse compared with both existing models. This means that application of the DA method and static approach did not lead to a model that could be superior to the established models. In general, the DA method did not provide sufficiently reliable results even after applying the dynamic approach. On the other hand, the decision tree model showed a very good predictive ability in comparison with the newly created DA models as well as the selected existing models (Altman, 1983, IN05). Based on these results we proved that our dynamic *decision tree model was superior* to the other models including also the validating sample. In other words, we *confirmed Working hypothesis No.* 3 as we developed a model that over performed the already existing models on the one hand as well as other models created by us on the other. Moreover, we even exceeded our expectations as the dynamic decision tree reached the accuracy at the level of approx. 80% which, in comparison with the Altman's model and Index IN05, was higher by about 20%.

A summary of all the results used to confirm our working hypothesis on both training and validating samples is given in the Table 6.

T a b l e 6

Summary of Confirmation of Working Hypothesis

Working hypothesis	Training sample	Validating sample
Using the dynamic approach will increase the accuracy of static DA model	✗	✗
Using the dynamic approach will increase the accuracy of static Decision tree model.	✓	✓
We create a model that will be superior to the Altman model, index IN 05	–	✓

Source: Own elaboration.

From the summary it is obvious that with regards to the working hypothesis there was no difference between the training and validation sample, however, as mentioned above, there was a change in the predictive ability.

Conclusion

The main objective of this paper was to explore the impact of using trend variables in model creation on the predictive ability of the developed model and consequently to create a model superior to the models that are already being used in the Slovak business environment. To meet the objectives, we developed four new models based on two methods: discriminant analysis and decision tree technique by applying two approaches: static and dynamic. From the analysis of the results it is obvious that the dynamic approach, i.e. using trend variables, increased the predictive ability of the model only in the case of the decision tree technique. Moreover, by applying the decision tree technique and the dynamic approach we were able to extract classification rules that proved the best performance with other analysed models as they reached the accuracy of about 80% in the validation sample. Based on all the results obtained in the Slovak business environment we can conclude that our objective to create a model superior to the other models analysed in this paper was achieved.

References

ALAMINOS, D. – CASTILLO, A. – FERNÁNDEZ, M. A. (2016): A Global Model for Bankruptcy Prediction. PLoS One, *11*, No. 11. Available at: <http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166693>.

ALTMAN, E. I. – NARAYANAN, P. (1997): An International Survey of Business Failure Classification Models. Financial Markets, Institutions & Instruments, *6*, No. 2, pp. 1 – 57.

ALTMAN, E. I. (1984): The Success of Business Failure Prediction Models. Journal of Banking and Finance, *8*, No. 2, pp. 171 – 198.

ANOOP, J. – BANERJEE, P. – FRANCIS, V. (2007): Modelling and Empirical Validation of Revised Altman's Credit Risk Model for Indian Banks. Social Science Electronic Publishing. Available at: <http://ssrn.com/abstract=960213>.

ATIYA, A. F. (2001): Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and new Results. IEEE Transactions on Neural Networks, *12*, No. 4, pp. 929 – 935.

AZAR, A. – PARVIZ, A. – MOHAMMAD, V. (2010): The Design of Human Resources Selection Model with Data Mining Approach. IT Management Journal, *2*, No. 4, pp. 3 – 22.

BELÁS, J. – DEMJAN, V. – HABÁNIK, J. – HUDÁKOVÁ, M. – SIPKO, J. (2015a): The Business Environment of Small and Medium-sized Enterprises in Selected Regions of the Czech Republic and Slovakia. E&M Economics and Management, *18*, No. 1, pp. 95 – 110.

BELÁS, J. – BILAN, Y. – DEMJAN, V. – SIPKO, J. (2015b): Entrepreneurship in SME Segment: Case Study from the Czech Republic and Slovakia. Amfiteatru Economic, *17*, No. 38, pp. 308 – 326.

BELLOVARY, J. L. – GIACOMINO, D. – AKERS, M. (2007): A Review of Bankruptcy Prediction Studies: 1930 to Present. Journal of Financial Education, *33*, Winter 2007, pp. 1 – 42.

BALCAEN, S. – OOGHE, H. (2006): 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and their Related Problems. The British Accounting Review, *38*, No. 1, pp. 63 – 93.

CAMPBELL, J. Y. – HILSCHER, J. – SZILAGYI, J. (2008): In Search of Distress Risk. Journal of Finance, *63*, No. 6, pp. 2899 – 2939.

Du JARDIN, P. (2009): Bankruptcy Prediction Models: How to Choose the Most Relevant Variables? Bankers, Markets & Investors, *98*, No. 1, pp. 39 – 46.

GURČÍK, Ľ. (2002): G-index – metóda predikcie finančného stavu poľnohospodárskych podnikov. Agricultural Economics, *48*, No. 8, pp. 373 – 378.

HUANG, S. M. – TSAI, C. F. – YEN, D. C. – CHENG, Y. L. (2008): A Hybrid Financial Analysis Model for Business Failure Prediction. Expert Systems with Application, *35*, No. 3, pp. 1034 – 1040.

CHARITOU, A. – NEOPHYTOU, E. – CHARALAMBOUS, C. (2004): Predicting Corporate Failure: Empirical Evidence for the UK. European Accounting Review, *13*, No. 3, pp. 465 – 497.

CHAVA, S. – JARROW, R. (2004): Bankruptcy Prediction with Industry Effects. Review of Finance, *8*, No. 4, pp. 537 – 569.

CHEN, M. Y. – DU, Y. K. (2009): Using Neural Networks and Data Mining Techniques for the Financial Distress Prediction Model. Expert Systems with Applications, *36*, No. 2, pp. 4075 – 4086.

CHEN, M. Y. (2011): Bankruptcy Prediction in Firms with Statistical and Intelligent Techniques and a Comparison of Evolutionary Computation Approaches. Computers and Mathematics with Applications, *62*, No. 12, pp. 4514 – 4524.

KAHYA, E. – THEODOSSIOU, P. (1999): Predicting Corporate Financial Distress: A Time-Series CUSUM Methodology. Review of Quantitative Finance and Accounting, *13*, No. 4, pp. 323 – 345.

KARAS, M. – REZNAKOVA, M. – BARTOS, V. – ZINECKER, M. (2013): Possibilities for the Application of the Altman Model within the Czech Republic. Recent Researches in Law Science and Finances, pp. 203 – 207. Available at:
<http://www.wseas.us/e-library/conferences/2013/Chania/ICFA/ICFA-30.pdf>.

KOČIŠOVÁ, K. – MIŠANKOVÁ, M. (2014): Discriminant Analysis as a Tool for Forecasting Company´s Financial Health. Social and Behavioral Sciences, *110*, pp. 1148 – 1157. Available at: <http://www.sciencedirect.com/science/article/pii/S1877042813056012>.

KORDLAR, A. E. – NIKBAKHT, N. (2011): Comparing Bankruptcy Prediction Models in Iran. Business Intelligence Journal, *4*, No. 2, pp. 341 – 348.

LACHENBRUCH, P. A. (1975): Discriminant Analysis. New York: Hafner Publishing.

LAKSHMI, B. N. – INDUMATHI, T. S. – NANDIVI, R. (2015): An Empherical Study on Decision Tree Classification Algorithms. International Journal of Science, Engineering and Technology Research (IJSETR), *4*, No. 11, pp. 3705 – 3709.

LENNOX, C. (1999): Identifying Failing Companies: A Revaluation of the Logit, Probit and DA Approaches. Journal of Economics and Business, *51*, No. 4, pp. 347 – 364.

LEV, B. (1969): Information, Entropy and the Aggregation Problem in Financial Statements. Accounting and Information Theory, Studies in Accounting Research, Chapter 2. Miami, FL: American Accounting Association.

LIFSCHUTZ, S. – JACOBI, A. (2010): Predicting Bankruptcy: Evidence from Israel. International Journal of Business and Management, *5*, No. 4, pp. 133 – 141.

LOW, S.-W. – NOR, F. M. – YATIM, P. (2001): Predicting Corporate Financial Distress Using the Logit Model: The Case of Malaysia. Asian Academy of Management Journal, *6*, No. 1, pp. 49 – 61.

MAJKOVÁ, M. S. – SOLÍK, J. – SIPKO, J. (2014): The Analysis of Chosen Business Obstacles and Problems with the Financing of Young Entrepreneurs in Slovakia. Economics & Sociology, *7*, No. 3, pp. 90 – 103.

NEUMAIEROVÁ, I. – NEUMAIER, I. (2005): Index IN05. In: Evropské finanční systémy: sborník příspěvků z mezinárodní vědecké konference. [Proceedings.] Brno: Masarykova univerzita v Brne, pp. 143 – 148.

ODOM, M. C. – SHARDA, R. (1990): A Neural Network Model for Bankruptcy Prediction. In: IEEE International Joint Conference on Neural Networks. [Proceedings.] San Diego, CA: IEEE, pp. 163 – 168.

OHLSON, J. (1980): Financial Ratios, & the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, *18*, No. 1, pp. 109 – 131.

OOGHE, H. – DE PRIJCKER, S. (2008): Failure Processes and Causes of Company Bankruptcy: a Typology. Management Decision, *46*, No. 2, pp. 223 – 242.

PACKOVÁ, M. (2015): Bankrotové predikčné modely. [Dissertation Thesis.] Košice: Technická univerzita v Košiciach.

ROKACH, M. – MAIMON, O. (2007): Data Mining with Decision Trees: Theory and Applications. Singapore: World Scientific Publishing Co. Pte. Ltd., 264 p. ISBN: 978-981-277-171-1.

SHIRATA, C. Y. (1998): Financial Ratios as Predictors of Bankruptcy in Japan: An Empirical Research. Available at: <http://www.apira2013.org/past/apira1998/archives/pdfs/31.pdf>.

SHIRI, M. M. – AHANGARI, M. – VAGHFI, S. H. – KHOLOUSI, A. (2012): Corporate Bankruptcy Prediction Using Data Mining Techniques: Evidence from Iran. African Journal of Scientific Research, *8*, No. 1, pp. 404 – 426. Available at: <http://www.journalsbank.com/ajsr_8_3.pdf>.

SITUM, M. (2015): The Relevance of Trend Variables for the Prediction of Corporate Crises and Insolvencies. Zagreb International Review of Economics & Business, *18*, No. 1, pp. 17 – 49.

SHUMWAY, T. (2001): Forecasting Bankruptcy more Accurately: A Simple Hazard Model. Journal of Business, *74*, No. 1, pp. 101 – 124.

SOON, N. K. – MOHAMMED, A. A. E. – AHMAD, A. R. – TAT, H. H. (2013): Applicability of Altman's Revised Model in Predicting Financial Distress: A Case of PN17 Companies Quoted in Malaysian Stock Exchange. Entrepreneurship Vision 2020: Innovation, Development Sustainability, and Economic Growth, pp. 349 – 358. Available at: <http://eprints.uthm.edu.my/4119/1/paper_35.pdf>.

SULUB, S. A. (2014): Testing the Predictive Power of Altman's Revised Z' Model: The Case of 10 Multinational Companies. Research Journal of Finance and Accounting, *5*, No. 21, pp. 174 – 184.

ŠARLIJA, N. – JEGER, M. (2011): Comparing Financial Distress Prediction Models Before and During Recession. Croatian Operational Research Review (CRORR), *2*, No. 1, pp. 133 – 142.

WU, D. J. – FENG, T. – NAEHRIG, M. – LAUTER, K. (2016): Privately Evaluating Decision Trees and Random Forests. Proceedings on Privacy Enhancing Technologies, Vol. 2016, No. 4, pp. 335 – 355.

YAP, B. – YONG, D. G. Y. – POON, W. C. (2010): How Well Do Financial Ratios and Multiple Discriminant Analysis Predict Company Failures in Malaysia. International Research Journal of Finance and Economics, *54*, No. 13, pp. 166 – 175.

ZHANG, G. – HU, M. – PATUWO, B. – INDRO, D. (1999): Artificial Neural Networks in Bankruptcy Prediction: General Framework and Cross-validation Analysis. European Journal of Operational Research, *116*, No. 1, pp. 16 – 32.