Analysis of Predictors in Bankruptcy Prediction Models for Slovak Companies

Lucia Svabova and Tomas Kliestik

Abstract The creation of bankruptcy prediction models is in the last years a topic, which much attention has been dedicated to. Researchers and economists in many countries have created prediction models which are useful for failure prediction of companies in that country. These prediction models used various financial ratios or other predictors to reach the best bankruptcy prediction. The effort of researchers leads to build a strongly prediction model that is able to predict a bankruptcy of companies or can, with some probability level, classify the companies into a group of prosperous or a group of non-prosperous ones. Previous works have shown that these models are then less effective in application in another country or in another time. Our work will lead to a creation of bankruptcy prediction model for Slovak companies. One of the first steps in this process is to choose an appropriate set of predictors, such as financial ratios of companies or characteristics of the environment, in which the company operates. For this purpose we do the preliminary statistical analysis of financial ratios of real Slovak companies. This analysis is made separately in different regions of Slovak Republic in order to analyze which regions are sufficiently similar in their characteristics and therefore could be analyzed together and, on the contrary, which regions are so different that we have to analyze them separately. Then, we can apply cluster analysis on basic statistical characteristics of financial ratios and get the clusters of Slovak regions that are for predicting bankruptcy appropriate to be analyzed together. This result will be very useful during the process of failure prediction model development in the future.

Keywords Bankruptcy prediction models • Financial ratios • Failure prediction • Financial distress • Default prediction • Statistical characteristics

L. Svabova (✉) • T. Kliestik
Department of Economics, Faculty of Operation and Economics of Transport and Communications, University of Zilina, Zilina, Slovakia
e-mail: lucia.svabova@fpedas.uniza.sk; tomas.kliestik@fpedas.uniza.sk

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1 Introduction

Prediction of financial distress of a company on the basis of financial analysis is nowadays an important and interesting issue. This prediction is based on estimating of whether the analyzed company is in a state of financial threats or not or whether its next development leads to bankruptcy or not. For the purpose of early detection of imminent problems of an analyzed company, prediction models are often used. Their task is to evaluate the financial health of the company on the basis of selected financial indicators or characteristics of the company and then to identify imminent bankruptcy in advance (Misankova and Kral 2015). The identification of the impending problems of the company can be important not only for company owners but also for business partners, potential or existing creditors, or employees (Bartosova et al. 2014).

In recent years many authors in different countries devote to the creation of prediction models for predicting imminent bankruptcy. Prediction of corporate financial distress and bankruptcy is an interesting topic for financial researchers. The first prediction models were constructed in the late 1960s by well-known authors, such as Beaver (1966), Altman (1968), Ohlson (1980), Springate et al. (1983), Zmijewski (1984), Fulmer et al. (1984), Shirata (1995), Dimitras et al. (1996), Shumway (2001), and others. Currently, there exist hundreds of prediction models developed at a particular time and in conditions of particular economies. Many of them are used in economic practice.

Many models were developed in different countries all over the world in recent years by the application of real data about financial ratios of companies. For example, Chung et al. (2008) have created MDA classification model for companies in the field of finance industry in New Zealand. Anandarajan et al. (2004) have used the artificial neural network for modeling bankruptcy in Germany. Altman and Sabato (2005) have developed the logit model for small companies in the USA. Lieu et al. (2008) have used logit model for companies in Taiwan. Logit model has also been used in the work of Lin and Piesse (2004) for industrial companies in the UK. Bandyopadhyay (2006) has used MDA for companies in India for bankruptcy prediction 1 year or 2 years in advance. Sun and Li (2012) have used logit and MDA too for China companies. Shams et al. in Iran (2011) have developed a logit model for securities and exchange organization. Bellovary et al. (2007) have processed the situation about existing bankruptcy prediction studies from 1930 to present.

These bankruptcy prediction models use for analysis different financial indicators of the company, the most frequently used are financial ratios, or some other characteristics of the company or environment in which it operates (Misankova et al. 2015). Our work in the future will lead to a comprehensive bankruptcy prediction model for Slovak companies, based on real data from the accounting statements of real Slovak companies. This model will be created using multivariate statistical methods, e.g., multidiscriminant analysis (MDA) or logistic regression (logit). By MDA we would like to create a prediction model that would be able to discriminate companies into a group of prosperous or into a group of

non-prosperous ones. Using logit method we would like to create a model of logistic regression, which would be able to predict a probability of company bankruptcy. Our effort will lead to create a prediction model with strong predictive ability. That means the ratio of correctly classified companies into a group of prosperous or non-prosperous ones will be as high as possible. For these reasons, it is important to do an initial statistical analysis of the variables used in the model first. In this paper we analyze the financial ratios used for prediction and their basic statistical characteristics. This analysis is made separately in eight different regions of Slovak Republic.

2 Methodology

As was mentioned above, in this paper we focus on the initial statistical analysis of predictors (financial ratios of companies) used for prediction model creation. In order to describe the basic relationships and characteristics of financial ratios of the companies, we use basic statistical methods.

To detect the basic characteristics of predictors that later will be used for failure prediction model creation, we use descriptive statistical characteristics of the financial ratios of a given set of Slovak companies. For each variable used to create a prediction model, we list the average value together with standard deviation. The average value gives us an idea of concentration of values of this financial indicator. The standard deviation gives extra information about the distraction of all the values of the indicator around the mean value. Moreover, we mention the maximum and minimum value of the financial indicator to get an idea about the range of all values. Further information gives the median value, which is the center of a set of values of the ratio indicator, that is, medianhalve the ratio values—one half of values are smaller than the median value and the second half are larger than the median.

All the statistical descriptions are made separately for every eight Slovak regions. From the basic characteristics of predictors in each region, we can get an idea of how much these financial ratios of companies are different in parts of Slovakia. We also can determine which regions of Slovakia are sufficiently similar. These results may be useful in the future in the process of model development. Based on an analysis of the basic characteristics, we can deduce which Slovak regions can be analyzed together.

By using the cluster analysis on the characteristics of financial ratios, we could obtain the information which regions of Slovakia can be merged into groups. Then we could analyze them together in the process of model development, because they are sufficiently similar. Cluster analysis is an explorative statistical method that identifies structures within the data. More specifically, it tries to identify homogenous groups of cases or observations. Cluster analysis is used to identify groups of cases if the grouping is not previously known. Its task is to identify groups of

individuals or objects that are similar to each other but different from individuals in other groups. Because it is an explorative method, it makes any distinction between dependent and independent variables. We use in our analysis the hierarchical cluster analysis, which is the most common method for clustering. It generates a series of models with cluster solutions from 1 (i.e., all cases are in one cluster) to *n* (i.e., all cases are an individual cluster). From the set of solutions, we choose the one that has such number of groups, which is for us highly usable and easily interpretable. The graphical representation of solutions with all possible models is called dendrogram.

The whole analysis is made on a dataset of 109,550 Slovak companies. We have the values of 11 financial ratios for these companies, obtained from accounting statements of companies of year 2014. The set of financial ratios uses the following notation: OM-current assets; KZ-current liabilities; CK-foreign assets; CM-total assets; VI-the equity; EBIT-earnings before interest and taxes; DT-sales⁄360; KP-accounts receivable; Z-inventory; CPK-networking capital; and NZ-retained earnings (Kocisova and Misankova 2014; Valaskova and Zvarikova 2014).

The notation of Slovak regions is the following: BA-Bratislava region; BB-Banska Bystrica region; KE-Kosice region; NT-Nitra region; PO-Presov region; TN-Trencin region; TT-Trnava region; and ZA-Zilina region.

3 Results

First we analyzed the means and standard deviations of all financial ratios that we have available. The results are in the following Table 1. The mean and standard deviation are listed for every financial ratio (in columns) and for every region of Slovakia (in rows). In the first line for every region, there is mean value, and in the second line, there is standard deviation. Using this characteristic we could compare the regions of Slovakia, how much they are different, or, on the other hand, which of them are similar in the characteristics of companies operating in the region.

In Table 2 there are the minimum and maximum values of all financial ratios that we have available for companies in all regions of Slovakia. Financial ratios are in the columns of the table; in the rows there are the regions of Slovakia. Each region has two lines of the table, in the first line there is a minimum value for the ratio, and in the second line, there is a maximum value. By comparing the values between each other, we could see the differences between them. Moreover, we could rate the similarity between some regions in order to analyze them together in our next work.

Finally, in Table 3 there are the median values of financial ratios in all regions of Slovakia. All ratios are in the columns of the table, and regions are in rows. By checking the median value, we have added information about concentration and dispersion of the values. Median value divides the set of all values into two parts. One half of all values of the given financial ratio are lower than the median value in

Table 1 Mean and standard deviation of financial ratios in all regions of Slovakia

Mean and Deviation											
Region	OM/KZ	KFM/KZ	CK/CM	CK/VI	EBIT/CM	EBIT/VI	KZ/DT	KP/DT	Z/DT	CPK/CM	NZ/CM
BA	19.77	12.99	4.86	22.37	−1.29	−1.40	53,805.97	13,913.18	4527.13	−4.08	0.75
	838.91	788.77	271.39	1743.96	70.56	137.41	3,681,301.85	1,122,308.94	671,614.46	256.28	71.15
BB	14.50	8.92	18.36	−3.06	−0.43	36.96	23,970.76	72,835.70	487.26	−19.82	0.16
	222.38	160.58	2206.40	923.08	49.27	3747.78	1,474,210.66	6,355,158.65	23,001.29	2152.92	2.14
KE	18.87	12.46	9.31	15.18	−0.97	−0.26	9109.46	5052.33	435.00	−7.94	0.15
	405.97	281.45	406.97	681.97	60.64	53.54	334,980.27	287,450.81	15,575.71	392.26	1.22
NT	6.50	4.52	7.12	17.78	−3.05	−1.08	3630.08	839.41	270.30	−5.93	−0.02
	304.81	244.74	406.11	1026.54	245.24	264.11	122,407.23	30,001.41	8867.26	403.52	14.95
PO	10.58	6.34	2.09	0.72	−0.11	−0.23	−69.95	−25,978.78	417.61	−1.12	0.12
	172.94	137.59	47.80	786.21	39.86	27.53	1,325,850.02	2,780,749.96	15,857.16	49.22	3.99
TN	9.93	6.55	3.87	11.52	−0.88	0.16	−57,350.15	−15,358.01	433.89	−2.88	0.17
	116.11	89.59	134.60	596.47	42.92	31.74	5,934,340.68	1,643,766.44	22,045.48	134.38	2.16
TT	13.22	7.11	6.45	33.69	−2.58	−2.32	3276.88	716.56	247.55	−4.79	0.42
	305.17	109.99	352.59	2792.58	230.18	194.96	73,243.74	12,080.14	4510.62	290.00	24.12
ZA	10.46	7.77	4.93	3.53	−1.06	0.21	6487.62	17,689.10	180.36	−3.76	0.08
	137.57	130.29	276.49	511.26	76.57	26.10	305,385.29	1,655,639.81	4852.25	275.36	28.45

Table 2 Minimum and maximum values of financial ratios in all regions of Slovakia

Min & Max											
Region	OM/KZ	KFM/KZ	CK/CM	CK/VI	EBIT/CM	EBIT/VI	KZ/DT	KP/DT	Z/DT	CPK/CM	NZ/CM
BA	−12,065.9	−9240.2	−16,068.4	−91,087.3	−10,303.1	−17,470.0	−31,496,058.0	−34,748,334.0	−1,274,590.1	−27,741.3	−1234.7
	144,321.8	142,185.8	28,438.2	277,883.5	631.0	2369.7	499,962,960.0	191,215,030.2	124,268,266.3	5660.8	11,827.8
BB	−1039.7	−470.0	−54,263.0	−91,946.1	−3368.1	−999.0	−13,216,680.0	−150,170.8	−10,588.0	−218,074.0	−12.4
	15,485.7	12,960.0	218,578.3	16,974.0	2151.3	382,743.5	107,679,240.0	646,618,860.0	2,175,077.0	27,355.0	127.8
KE	−2872.3	−1655.8	−55.6	−18,704.3	−4656.0	−5351.0	−1,869,877.8	−155,424.8	−2832.0	−38,316.9	−24.7
	33,200.0	26,007.0	39,924.4	51,472.0	3365.1	1565.1	29,965,320.0	24,375,600.0	1,495,269.4	56.6	65.2
NT	−29,000.8	−22,637.0	−5240.4	−24,790.3	−25,733.0	−26,802.0	−51,015.9	−1,412,245.2	−12,658.1	−39,652.2	−1637.5
	7127.5	6055.3	39,653.2	83,128.1	481.4	10,911.8	11,990,520.0	2,418,498.0	912,615.0	5180.2	31.4
PO	−8739.0	−8739.0	−1653.0	−70,341.0	−1785.4	−2074.5	−122,539,320.0	−279,612,000.0	−64,370.0	−3159.4	−383.5
	8883.5	5608.2	3163.7	25,110.2	3221.0	683.9	45,149,889.6	6,570,000.0	1,373,036.7	2103.8	74.8
TN	−205.0	−191.8	−440.0	−10,826.7	−3665.7	−2005.5	−578,625,480.0	−160,162,560.0	−16,042.2	−10,483.4	−17.5
	5845.1	4672.0	10,484.4	54,901.5	127.3	1197.2	5,350,072.8	5,431,972.8	2,004,561.6	441.0	193.1
TT	−667.6	−576.5	−16.2	−11,370.4	−22,413.0	−18,794.0	−14,479.8	−36,745.1	−475.9	−27,667.0	−9.4
	27,923.9	8945.2	33,876.3	271,726.0	902.2	308.7	6,322,434.5	572,762.6	280,478.2	16.5	2351.7
ZA	−2018.5	−2007.3	−4369.8	−22,693.2	−7538.9	−1826.0	−496,010.8	−150,446.5	−19,991.5	−28,444.9	−2720.0
	9155.0	8633.0	28,517.1	43,313.5	2401.5	1592.8	31,709,160.0	177,787,314.0	453,745.4	4370.8	1303.0

Table 3 Median value of financial ratios in all regions of Slovakia and frequencies of companies in regions

Median												
Region	OM/KZ	KFM/KZ	CK/CM	CK/VI	EBIT/CM	EBIT/VI	KZ/DT	KP/DT	Z/DT	CPK/CM	NZ/CM	Frequency
BA	1.29	0.36	0.73	0.43	0.02	0.24	123.98	54.64	0.00	0.15	0.00	34,472
BB	1.37	0.33	0.70	0.62	0.02	0.19	104.44	47.57	0.38	0.18	0.00	10,430
KE	1.31	0.29	0.72	0.56	0.02	0.19	106.16	51.20	0.00	0.17	0.00	11,889
NT	1.29	0.32	0.71	0.67	0.02	0.20	110.52	47.38	0.12	0.16	0.00	12,032
PO	1.35	0.31	0.69	0.65	0.02	0.18	101.46	55.10	0.44	0.18	0.00	10,117
TN	1.35	0.32	0.69	0.60	0.02	0.19	104.21	49.32	1.28	0.17	0.00	9509
TT	1.28	0.31	0.70	0.60	0.02	0.20	109.90	49.05	0.31	0.15	0.00	9538
ZA	1.34	0.30	0.71	0.56	0.02	0.19	104.53	54.10	0.36	0.17	0.00	11,565

the table, and the second half are higher than the median value. By comparing medians with the mean value (Table 1), we could recognize the dispersion of values of a particular ratio. Mean value is very sensitive to extreme values. If there is some extreme value, too high or too low in comparison with other values, it has strong influence on the mean value. In contrast, median value is insensitive to existence of some outliers.

By comparing median values between the regions of Slovakia, we have the information which of them are too different and, on the contrary, which are sufficiently similar. This information could be very useful in the following analyses.

In the last column of Table 3, there are the numbers of companies, which operate in the regions. These frequencies will be used during the process of cluster analysis, where we want to create segmentation of regions, which could be analyzed together in the next process of bankruptcy prediction.

3.1 Cluster Analysis

Basic statistical characteristics, which are in Tables 1, 2, and 3, can be used for creating segments of Slovak regions, groups of regions that are so similar that can be analyzed together. We are checking for regions that are as similar in their characteristics as possible and different with regions in other groups. We have performed the hierarchical clustering that gives us all possible solutions. It starts from eight groups, where every region is in its own cluster and stops with one cluster with all regions in it. In the next dendrogram, we can see the models (Fig. 1).

The model with three or four groups of regions is most suitable for us. So we specify these two possibilities. In the model with three clusters, the following regions of Slovakia are in the clusters:

1. Group: Bratislava region
2. Group: Banska Bystrica region
3. Group: other regions—Trnava region, Nitra region, Trencin region, Presov region, Zilina region, and Kosice region

As in this case, both first and second groups are only one region, and all the other regions are in the last group; the possibility with four groups is better usable and more helpful. The model with four groups consists of the following:

1. Group: Bratislava region
2. Group: Banska Bystrica region
3. Group: Trnava region and Nitra region
4. Group: Trencin region, Presov region, Zilina region, and Kosice region

Again, first and second clusters are one region alone, but it means that there regions which are really different from the other regions in other groups and between each other too. In fact, especially Bratislava region is really different

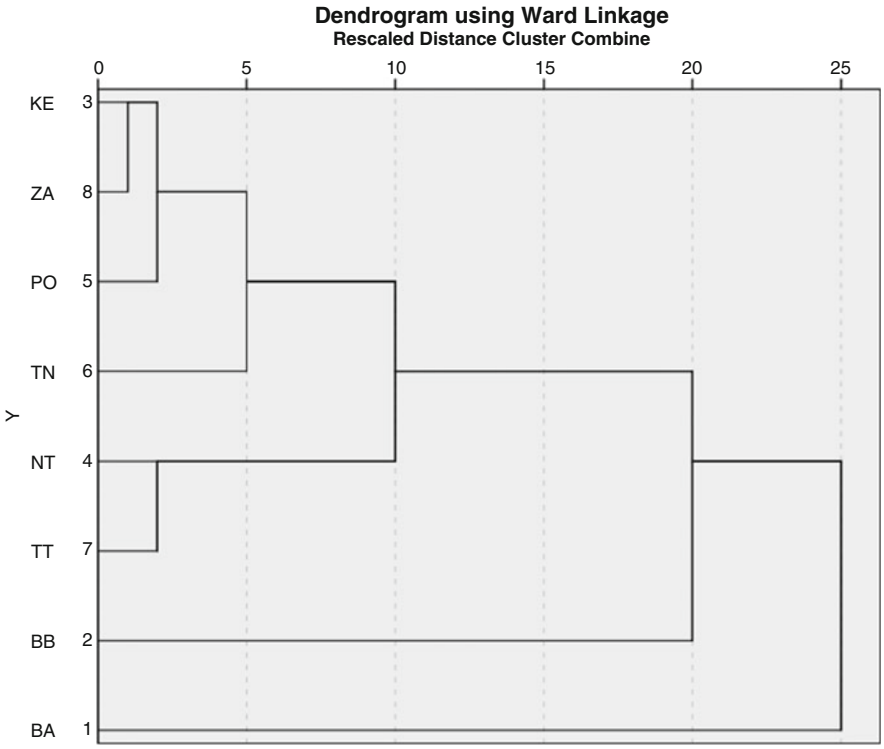

Fig. 1 Dendrogram of hierarchical cluster analysis for regions of Slovakia

from other parts of Slovakia, and the companies there really have different values of financial characteristics. In the third group, there are two regions, Trnava and Nitra. These two regions are both close to Bratislava region of the capital city, and companies in both could be affected by the capital city. Other four regions, namely, Trencin, Zilina, Presov, and Kosice, are together in one group of regions. That means that companies in these regions are similar in characteristics of their financial ratios. Consequently we could analyze these regions together.

4 Conclusion

The essence of our work lies in the analysis of financial ratios of companies in different regions of Slovakia. These ratios are often used in the process of creating the bankruptcy prediction model for companies. Prediction model is able either to predict the probability level, at which the next life of the company will lead into a financial distress, or to classify the company into a group of prosperous or a group of non-prosperous ones. Our next work in the future will be dedicated to derivation

of such prediction model for companies in Slovakia. The first step of the process for us is the basic statistical analysis of the predictors, used in this prediction model. Thus we have introduced the descriptive characteristics and then used them in hierarchical cluster analysis. We get the model with four groups of regions. Similar analysis could be done with the sectors of national economy, in which the companies in our dataset cooperate. The number of these sectors is quite high, so that it will be helpful and usable to find the model with smaller number of groups of these sectors. Then in the next process, the cluster membership of sectors of national economy could be included in the prediction model. Similarly it could be the membership in the group of regions that has been derived in this analysis.

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References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), 589–609.

Altman, E. I., & Sabato, G. (2005). Modeling credit risk for SMEs: Evidence from the US market. *Abacus, 43*(3), 332–356.

Anandarajan, M., Lee, P., & Anandarajan, A. (2004). *Bankruptcy prediction using neural network, business intelligence techniques: A perspective from accounting and finance*. Heidelberg: Springer-Verlag.

Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds – logistic and Z-score model approaches. *The Journal of Risk Finance, 7*(3), 255–272.

Bartosova, V., Hraskova, D., & Paliderova, M. (2014). Basic rules and methodological framework of the financial analysis of the group of companies in the Slovak Republic. *Advances in Education Research, 61*, 86–91.

Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71–102.

Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education, 33*, 1–43.

Chung, K. C., Tan, S. S., & Holdsworth, D. K. (2008). Insolvency prediction model using multivariate discriminant analysis and artificial neural network for the finance industry in New Zealand. *International Journal of Business and Management, 3*(1), 19–28.

Dimitras, A., Zanakis, S. H., & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research, 90*(3), 487–513.

Fulmer, J. G., Jr., Moon, J. E., Gavin, T. A., & Erwin, M. J. (1984). A bankruptcy classification model for small firms. *Journal of Commercial Bank Lending*, 25–37.

Kocisova, K., & Misankova, M. (2014). Prediction of default by the use of Merton's model and black and cox model. *Advances in Education Research, 51*, 563–568.

Lieu, P., Lin, C., & Yu, H. (2008). Financial early-warning models on cross-holding groups. *Journal of Industrial Management & Data Systems, 108*(8), 1060–1080.

Lin, L., & Piesse, J. (2004). Identification of corporate distress in UK industrials – a conditional probability analysis approach. *Journal of Applied Financial Economics, 14*(2), 73–82.

Misankova, M., & Kral, P. (2015). *Application of CreditRisk+ for the calculation of credit risk. Proceedings of 10th International Scientific Conference Financial management of Firms and Financial Institutions* (pp. 807–814). Ostrava: Czech Republic.

Misankova, M., Spuchlakova, E., & Frajtova-Michalikova, K. (2015). Determination of default probability by loss given default. *Procedia Economics and Finance, 26*, 411–417.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*, 109–131.

Shams, M. F., Sheikhi, M., & Sheikhi, Z. (2011). Financial distress prediction: Comparisons of logit models using receiver operating characteristic (ROC) curve analysis. *African Journal of Business Management, 5*(30), 12164–12173.

Shirata, C. Y. (1995). Read the sign of business failure. *Journal of Risk and Management, 23*, 117–138.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business, 74*(1), 101–124.

Springate, G., Sands, E., & Var, T. (1983). Predicting business failures. *CGA Magazine, 17*, 24–27.

Sun, J., & Li, H. (2012). Financial distress prediction using support vector machines: Ensemble vs. individual. *Applied Soft Computing, 12*(8), 2254–2265.

Valaskova, K., & Zvarikova, K. (2014). Prediction of credit risk by selected theoretical rating models. *Advances in Social and Behavioral Sciences, 5*, 160–166.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research, 22*, 59–86.