MDA FINANCIAL DISTRESS PREDICTION MODEL FOR HUNGARIAN COMPANIES

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Abstract: *Company financial distress prediction is one of the most discussed issues of economists around the world in recent decades. From the first attempts in the 1960s to the present, one of the most widely used method to create these models is Multiple Discriminant Analysis. In the paper, we present the prediction model for Hungarian companies created using this method based on real data from the financial statements obtained from database Amadeus. Our database contains data of more than 250,000 companies and 26 financial indicators used as predictors. There is possibility to predict the financial difficulties of companies one year in advance using this model.*

Keywords: *Prediction model, Multidimensional Discrimination Analysis, Financial distress, Financial ratios, Prediction ability.*

1. INTRODUCTION

Financial distress prediction has been a very interesting topic over the last decades because of its great importance for companies, interested stakeholders and even for the economy of a country. If this prediction is reliable, managers of companies can initiate remedial measures to avoid financial distress situation.

The main aim of the paper is the creation of financial distress prediction model of Hungarian companies. This model is created using Multidimensional Discriminant Analysis (MDA). The originality of the research lies in the using of a large dataset of financial indicators of more than 250,000 real Hungarian companies. The purpose of the paper is to identify potential financial risks considering Slovak economic conditions.

The rest of the paper is divided into four main parts. Literature review briefly describes of theoretical background and most important related works. The data description and principles of MDA is described in the Methodology section. Results is focused on the description of the developed model. In section Conclusion, discussion and analysis of the results is provided.

2. LITERATURE REVIEW

In this area of financial distress prediction, papers by Altman and Ohlson can be considered as groundbreaking. In 1968, Altman created the first commonly used bankruptcy model using a Multidimensional Discrimination Analysis (MDA) [1]. According to many authors, Altman's

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model still represents an effective tool to predict bankruptcy [2]. Another commonly used statistical technique for creation of prediction models is logistic regression (logit) models. In 1980, this technique of prediction model creation was used for the first time by Ohlson [3]. These two statistical methods are still commonly used in the area of financial distress prediction [4].

Among machine learning methods based on artificial intelligence, artificial neural networks and decision trees are the most commonly used techniques [5]. In 2018, Popescu and Dragotă [6] identified the financial distress predictors for five post-communist countries (Bulgaria, Croatia, the Czech Republic, Hungary and Romania) using CHAID decision tree and neural networks. In Slovakia, Gavurova [7] and Karas and Reznakova [8] developed prediction models using decision trees.

In 2001, Hajdu and Virág [9] developed the first models of financial distress prediction for the Hungarian companies. Author used a sample of 154 companies, of which half were insolvent. The models were constructed based on MDA and logistic regression approach. In 2005, Virág and Kristóf [10] developed a model based on the same data as in previous models. Also, they built another model using artificial neural networks. This model was characterised by higher efficiency compared with previous models. Again, using the same dataset, Virág and Nyitrai [11] built models using the techniques of support vector machines and rough set theory. In 2014, Ékes and Koloszár [12] estimated models predicting bankruptcy of Hungarian SMEs using MDA, logistic regression analysis, and classification trees. Models estimated by them were highly efficient, mainly, compared to other Hungarian and foreign (Altman, Ohlson, etc.) models. In 2016, based on data from 1996–2014, Bauer and Endrész [13] built a probit model for predicting the insolvency of Hungarian companies. Author included to the model some macroeconomic variables and qualitative characteristics of companies.

3. METHODOLOGY

Our database contains data more than 250,000 companies operating in Hungarian business environment. This database consists of financial indicators that was calculated from the real financial statements obtained from Amadeus - A database of comparable financial information for public and private companies across Europe. Balance sheets and profit-and-loss statements were used. Table 1 lists financial indicators used as potential predictors and the methods of their calculation. These predictors are financial ratios calculated from financial statements from the year 2016. Besides, as predictors, we use Level 1 NACE codes (according to Statistical Classification of Economic Activities in the European Community Rev. 2) and also the company size indicator (Small, Medium and Large, Very Large). These indicators have to be encoded as dummy variables.

The main aim of this research is to create a model predicting the company's financial distress one year in advance. So that the output variable *Distress* identifies the financial distress of the companies was considered in 2017. Table 2 describes the frequencies and percentages of financial-distressed and non-financial-distressed companies in our dataset.

The MDA approach was used to identify significant predictors and create financial distress prediction model. In this field, this approach is still the most frequently used statistical method [14]. The choice of significant predictors can be made based on the test of equality of means of these predictors between the group of financial-distressed companies and the group of non-financial-distressed companies. But, in this research, we use stepwise MDA approach. This approach selects only significant variables one-by-one. Moreover, it solves the problem of multi-collinearity of independent variables (predictors).

Table 1: List of financial indicators used as predictors

Predictor	*Formula*
X01	Sales/Total Assets
X02	Current Assets/Current Liabilities
X04	Net Income/Shareholders Equity
X07	Net income/Total Assets
X08	Working Capital/Total Assets
X09	EBIT/Total Assets
X10	Liabilities/Total Assets
X11	Current Assets/Total Assets
X12	Cash & Cash Equivalents/Total Assets
X15	Current Liabilities/Total Assets
X16	Current Assets/Sales
X18	Stock/Sales
X20	Net Income/Sales
X21	Non-current Liabilities/Total Assets
X22	Cash & Cash Equivalents/Current Liabilities
X24	Working Capital/Sales
X25	Current Ratio
X26	(Current Assets-Stock)/Current Liabilities
X27	ROA
X28	ROE
X30	Solvency Ratio
X35	Profit Margin
X36	Net Current Assets
X37	Working Capital

Table 2: Frequencies and percentages of financial-distressed and non-financial-distressed companies

Distress	Frequency	Per cent
No	205448	81.4
Yes	46923	18.6
Total	252371	100.0

The main result of MDA is Fisher canonical discriminant function, which is a linear function of the significant predictors. This function separates companies into the group of financial-distressed companies and the group of non-financial-distressed companies. We can calculate the discriminant score for the classification of the company into one of these two groups. Then, this score with the weighted averages of centroids (average scores in the groups of companies) can be compared [15]. If the constant in discriminant function is used, it is sufficient to compare the calculated discriminant score with zero. Analogously, based on the values of the two Fisher's linear discriminant functions, we could decide on the prediction of financial distress or non-financial distress of the company.

The quality of the MDA model can be assessed from several points of view. Statistical significance of canonical discriminant function indicates how well the model describes the data. Standardised coefficients of discriminant function and their statistical significance assess the contribution of individual predictors to explain the variability in the dataset.

The analysis of the classification table evaluates the classification or prediction ability of the developed model. This table illustrates the absolute and relative quantity of correctly and non-correctly classified companies in each group. The classification ability is usually overestimated if the ability of the model is calculated on the sample that was used to modelling. It is appropriate to divide the dataset into the sample. Training sample is used for the model creation, and the testing sample is used to calculate the classification ability of the model. We used the random division in the most frequently used ratio of 80:20. [16]

Another approach to analyse the quality of financial distress prediction model is using or Receiver Operating Characteristic (ROC) curve. The ROC curve gives an image of the behaviour of the created model. The vertical axis shows the percentage of financial-distressed companies that have been correctly classified in the financial-distressed group, called a true positive rate or also sensitivity. The horizontal axis shows the percentage of non-financial-distressed companies that have been incorrectly classified in the financial-distressed group, which we also call a false positive rate or 1-specificity.

The AUC (Area Under Curve) is a frequently used criterion for comparing financial distress prediction models or for assessing the classification ability by the created model. The maximum value of AUC is 1, i.e. 100%. Thus, if the size of the AUC is close to 1, then the created model has an excellent classification ability. If the size of the AUC is close to 0.5, the classification ability of the model is not good.

4. RESULTS

To create a prediction model, we use the stepwise MDA approach, as was mentioned already. At first, we look at the results of One-way ANOVA to identify predictors that significantly differentiate companies into a group of companies in financial distress and healthy companies. Table 4 shows these results. We can exclude variables X11, X12, X16, X18, X20, X24, X30, X36 and X37 from the next analysis because we cannot claim that their mean values for the two groups of companies are significantly different.

Table 3: Tests of Equality of Group Means

Predictor	*Wilks' Lambda*	*F*	*df1*	*df2*	*Sig.*
X01	0.999	8.006	1	10719	0.005
X02	0.999	6.881	1	10719	0.009
X04	0.990	105.279	1	10719	0.000
X07	0.989	123.248	1	10719	0.000
X08	0.999	7.325	1	10719	0.007
X09	0.988	127.341	1	10719	0.000
X10	0.977	253.259	1	10719	0.000
X11	1.000	1.339	1	10719	0.247
X12	1.000	0.989	1	10719	0.320
X15	0.982	196.736	1	10719	0.000
X16	1.000	0.038	1	10719	0.846
X18	1.000	0.012	1	10719	0.913
X20	1.000	0.003	1	10719	0.956
X21	0.998	16.773	1	10719	0.000
X22	0.999	6.388	1	10719	0.012

Predictor	***Wilks' Lambda***	***F***	***df1***	***df2***	***Sig.***
X24	1.000	0.012	1	10719	0.913
X25	0.999	6.881	1	10719	0.009
X26	0.999	6.213	1	10719	0.013
X27	0.987	138.952	1	10719	0.000
X28	0.988	126.131	1	10719	0.000
X30	1.000	0.727	1	10719	0.394
X35	0.991	100.793	1	10719	0.000
X36	1.000	2.853	1	10719	0.091
X37	1.000	0.208	1	10719	0.648
NACE=A. Agriculture, forestry and fishing	0.999	5.875	1	10719	0.015
NACE=B. Mining and quarrying	1.000	0.032	1	10719	0.857
NACE=C. Manufacturing	1.000	2.038	1	10719	0.153
NACE=D. Electricity, gas, steam and air conditioning supply	1.000	4.398	1	10719	0.036
NACE=F. Construction	1.000	0.375	1	10719	0.541
NACE=G. Wholesale and retail trade, repair of motor vehicles and motorcycles	1.000	0.112	1	10719	0.738
NACE=H. Transportation and storage	1.000	2.482	1	10719	0.115
NACE=I. Accommodation and food service activities	1.000	1.403	1	10719	0.236
NACE=J. Information and communication	1.000	0.153	1	10719	0.696
NACE=K. Financial and insurance activities	1.000	0.233	1	10719	0.630
NACE=N. Administrative and support service activities	1.000	4.907	1	10719.000	0.027
NACE=P. Education	1.000	1.418	1	10719.000	0.234
NACE=Q. Human health and social work activities	1.000	0.070	1	10719.000	0.791
company_size=Small	0.997	33.518	1	10719.000	0.000
company_size=Medium	1.000	5.146	1	10719.000	0.023
company_size=Large, Very large	0.999	11.816	1	10719.000	0.001

The canonical correlation of discriminant function is significant but is not very high (0.058 only).

Table 4: Canonical correlation

Function	***Eigenvalue***	***% of Variance***	***Cumulative %***	***Canonical Correlation***
1	100.0	100.0	0.234	.058[a]

Test of Function(s)	***Wilks' Lambda***	***Chi-square***	***df***	***Sig.***
1	0.945	603.861	11	.000

The stepwise method included variables to the model one by one. Table 5 shows the final list of relevant predictors in our model. Moreover, Table 5 describes the discrimination ability of individual variables. Variables X10 and X28 have the greatest discrimination ability.

Table 5: Standardized Canonical Discriminant Function Coefficients

Variable	*Coefficient*
X02_2015	0.326
X09_2015	-0.206
X10_2015	1.019
X11_2015	-0.142
X12_2015	0.199
X21_2015	-0.217
X22_2015	-0.201
X28_2015	-0.517
NACE=G. Wholesale and retail trade. repair of motor vehicles and motorcycles	-0.088
company_size=Small	0.278
company_size=Large, Very large	-0.159

We can calculate a discriminant score for every company using unstandardized canonical discriminant function (in Table 6). That allows to include a company into the group of companies in financial-distressed or non-financial-distressed companies.

Table 6: Canonical Discriminant Function Coefficients

Predictor	*Coefficient*
X02_2015	0.044
X09_2015	-1.330
X10_2015	3.867
X11_2015	-0.516
X12_2015	0.927
X21_2015	-1.465
X22_2015	-0.041
X28_2015	-0.596
NACE=G. Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.190
company_size=Small	0.617
company_size=Large, Very large	-0.370
(Constant)	-1.488

Analogously, we could decide on the company's inclusion based on the values of Fisher's Linear Discriminant Functions. For every company, we calculate the value of these discriminant functions. The greater value identifies inclusion to one of the companies' groups.

Table 7: Classification Function Coefficients

Predictor	*Distress*	
	No	*Yes*
X02_2015	0.143	0.220
X09_2015	4.038	1.694
X10_2015	7.193	14.008
X11_2015	7.669	6.760
X12_2015	0.924	2.558
X21_2015	5.119	2.538
X22_2015	-0.070	-0.143
X28_2015	-0.788	-1.838
NACE=G. Wholesale and retail trade, repair of motor vehicles and motorcycles	0.116	-0.219
company_size=Small	1.618	2.706
company_size=Large, Very large	1.447	0.795
(Constant)	-5.966	-10.083

For practical use of the model, the model must have sufficient discrimination ability. We evaluate this ability based on a classification table (Table 8).

Table 8: Classification Results

		Distress	*Predicted Group Membership*		*Total*
Sample			***No***	***Yes***	
Training Sample	Count	No	143120	62328	205448
		Yes	2103	44820	46923
	%	No	69.7	30.3	100.0
		Yes	4.5	95.5	100.0
Testing Sample	Count	No	144935	60513	205448
		Yes	4439	42484	46923
	%	No	70.5	29.5	100.0
		Yes	9.5	90.5	100.0

Table 8 clearly shows the better classification of financial-distressed companies. In the training sample, 95,5 % of financial-distressed companies were classified correctly. This ability is 90,5 % in the test sample. The developed model achieves a relatively high overall prediction ability. It is because 74.3 % of companies were correctly classified.

4. CONCLUSION

We have designed a model predicting the risk of financial distress of Hungarian companies one year in advance. We used the dataset of more than 250,000 Hungarian companies. Financial indicators were calculated based on the real financial statement listed in this database Amadeus. Using MDA, we identified 11 statistically signification predictors These predictors provide the best identification of financial distress.

Developed canonical discriminant function forms our prediction model. One can calculate a discriminant score for some company. Based on this score, there is possible to identify the imminent financial distress situation in this company. The overall prediction ability of our model is more than 74 %, and financial distress prediction ability is more than 90%. So, this model can be considered as relative reliable instrument to financial distress prediction. Model was designed for Hungarian companies. But there is a possibility to use this model also in other emerging market countries. In this case, we expect a lower prediction ability.

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