MDA FINANCIAL DISTRESS PREDICTION MODEL FOR SELECTED BALKAN COUNTRIES

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Abstract: *The issue of company financial distress and the early prediction of potential bankruptcy is one of the most discussed issues of economists around the world in recent decades. The most widely used method to create these models is Multidimensional Discrimination Analysis from the first attempts in the 1960s to the present. In the paper we present prediction model for some emerging market countries in Balkan region created using a Multidimensional Discriminant Analysis method based on real data from the financial statements obtained from Amadeus - A database of comparable financial information for public and private companies across Europe. Our database contains data more than 200 000 companies and about 25 predictors. Using this model, it is possible to predict the financial difficulties of companies one year in advance.*

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

JEL Classifications C52 · C53 · G33

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1. INTRODUCTION

Bankruptcy of the company brings huge economic losses for the investors and other stakeholders. Its existence calls for an analysis of the bankruptcy causes and early identification of signs of approaching bankruptcy. These signs can be reflected in the company financial statements. For this reason, accounting data are a common source of information for assessing the financial situation of an enterprise (Siekelova et al, 2017).

Many authors are trying to create a model for early identification and prevention of financial distress or bankruptcy. Such model is significant contribution to the efficiency of company management. In this area, papers by Altman and Ohlson can be considered as groundbreaking (Kliestikova, Misankova and Kliestik, 2017). Altman (1968) created the first commonly used bankruptcy model using a Multidimensional Discrimination Analysis (MDA). According to many authors, Altman's model still represents an effective tool to predict bankruptcy (Li, Ragozar, 2012). Another commonly used 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 (1980).

Currently, there exists many prediction models developed at a particular time and in conditions of particular economies. Many of them have been created for companies in a particular sector of national economy. For example, in New Zealand Chung, Tan and Holdsworth (2008) have created classification model for companies in the field of finance industry. Sun and Li (2012) have applied the Logit method and also MDA method for creation of company distress prediction model in China. In Iran, Shams, Sheikhi and Sheikhi (2011) have developed a Logit bankruptcy prediction model. Bellovary, Giacomino and Akers (2007) have described the situation about existing models for predicting bankruptcy from 1930 to 2007. In 2017, Altman et al. (2016) use the original Z-Score model developed by Altman in 1983 for non-financial companies across all industrial sectors, from 31 European and three non-European countries using different modifications of the original model.

Of course, even authors in the western part of the Balkan region are concerned with the issue of bankruptcy prediction models. For example, Jovanovic, Todorovic, Grbic (2017) and Simic, Kovacevic, Simic (2012), but also Obradovic et al. (2018) have created prediction models for Serbian companies. The topic of identifying financial problems is also discussed for Croatian companies (Kundid, Ercegovac; 2011; Sarlija, Jeger, 2011; Pervan, Pavic, Pervan, 2014; Zikovic, 2018). Further, for Slovene companies several prediction models have been created (Bonca, Ponikvar, Pusnik and Tajnikar, 2015; Zidek, 2016).

2. SAMPLE AND METHODOLOGY

Our database contains data more than 200 000 companies from Croatia, Serbia, Slovenia, Macedonia and Montenegro. Table 1 lists the frequencies of these companies according to these countries. The most numerous is the group of Croatian companies and, on the other hand, the least of Montenegrin.

Table 1: Company frequencies

Country	***Frequency***	***Percent***
Croatia	64076	31,5
Macedonia	44973	22,1
Montenegro	6730	3,3
Serbia	42017	20,6
Slovenia	45804	22,5
Total	203600	100,0

Real data in our database was calculated from the financial statements obtained from Amadeus - A database of comparable financial information for public and private companies across Europe. Table 2 lists potential predictors and the methods of their calculation. Two of these predictors are indicators: country-specificity and size of the companies (Small, Medium and Large)). These indicators have to be encoded as dummy variables. The remaining predictors are financial ratios calculated from financial statements from the year 2015.

Table 2: List of 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
Country	Croatia, Macedonia, Montenegro, Serbia or Slovenia
Size	Small, Medium or Large

Our aim is to create a model predicting the company's financial distress one year in advance. Therefore, the output variable *Distress* identifies the financial distress of the companies in 2016. Table 3 describes the frequencies and percentages of companies in selected countries.

Table 3: Frequencies of companies

Country	*Distress*	*Frequency*	*Percent*
Croatia	No	46103	72,0
	Yes	17973	28,0
	Total	64076	100,0
Macedonia	No	36317	80,8
	Yes	8656	19,2
	Total	44973	100,0
Montenegro	No	3987	59,2
	Yes	2743	40,8
	Total	6730	100,0
Serbia	No	31754	75,6
	Yes	10263	24,4
	Total	42017	100,0
Slovenia	No	37935	82,8
	Yes	7869	17,2
	Total	45804	100,0
Total	No	156096	76,7
	Yes	47504	23,3
	Total	203600	100,0

To identify relevant predictors and create financial distress prediction model, Multidimensional Discrimination Analysis was used, which is probably the most frequently used algorithm. Using stepwise discrimination analysis we find relevant predictors of financial distress, with only those predictors being included in the model that possess a sufficient discriminating power. The choice of relevant predictors can also be done on the basis of the test of equality of means between groups of companies that are in financial distress and that are not, but the stepwise method, besides selecting variables, also solves the problem of multi-collinearity.

The main result of this analysis is Fisher canonical discriminant function. It is a linear function of the relevant predictors that separates companies into group of companies in financial distress or healthy companies. For classification of company into one of these two groups, using this discriminant function we can calculate discriminant score. We compare this score with the weighted averages of centroids (average scores in the groups of companies). If we use a constant in discriminant function, it is enough to compare the discriminant score value to zero. Analogously, we could decide on the company's engagement on the basis of the value of Fisher's linear discriminant functions.

If we want to assess the overall quality of the model, we will assess the statistical significance of canonical discriminant function. The contribution of individual predictors to explaining the overall variability can be judged by standardized coefficients of discriminant function and their statistical significance. The classification ability of the obtained model is evaluated by the classification table. This table contains data of the percentages of mistakenly and correctly classified objects in each group. If the model is validated on the sample it was designed for, the classification ability is slightly overvalued. It is appropriate to divide the data into the training sample, used for the model creation and the testing sample, where we verify the classification ability of the model. The size of a training sample is commonly 80 %, and 20 % for testing sample.

3. RESEARCH RESULTS

As already mentioned, we use the stepwise Multidimensional Discriminant Analysis to create a prediction model. First, we look at the results of One-way ANOVA to identify predictors that differentiate companies into a group of companies in financial distress and healthy companies. Table 4 shows these results. We can exclude variables X16, X18, X21 and X24 from the next analysis because we cannot claim that their mean values for the two groups of companies are significantly different.

Table 4: Tests of Equality of Group Means

Predictor	***Wilks' Lambda***	***F***	***df1***	***df2***	***Sig.***
X01	,999	60,619	1	81705	,000
X02	,998	202,352	1	81705	,000
X04	,999	51,565	1	81705	,000
X07	,999	117,866	1	81705	,000
X08	,997	206,373	1	81705	,000
X09	,995	372,558	1	81705	,000
X10	,968	2693,394	1	81705	,000
X11	1,000	28,749	1	81705	,000
X12	1,000	11,874	1	81705	,001
X15	,968	2671,314	1	81705	,000
X16	1,000	,107	1	81705	,744
X18	1,000	,042	1	81705	,838
X20	1,000	27,066	1	81705	,000
X21	1,000	2,119	1	81705	,145
X22	,999	87,517	1	81705	,000
X24	1,000	,146	1	81705	,702
X25	,998	202,355	1	81705	,000
X26	,998	161,802	1	81705	,000
X27	,995	375,779	1	81705	,000
X28	,996	317,439	1	81705	,000
X30	1,000	4,746	1	81705	,029
X35	,993	574,576	1	81705	,000
X36	1,000	13,947	1	81705	,000
X37	1,000	8,566	1	81705	,003
Country=Croatia	,999	87,811	1	81705	,000
Country=Macedonia	1,000	36,123	1	81705	,000
Country=Montenegro	1,000	21,029	1	81705	,000
Country=Serbia	,999	68,605	1	81705	,000
Country=Slovenia	1,000	13,803	1	81705	,000
Size=Small	,997	281,895	1	81705	,000
Size=Medium	,997	237,597	1	81705	,000
Size=Large	1,000	27,225	1	81705	,000

The canonical correlation of discriminant function is significant, but is not very high (only 0,224).

Table 5: Canonical correlation

Function	***Eigenvalue***	***% of Variance***	***Cumulative %***	***Canonical Correlation***
1	,053	100,0	100,0	,224
Test of Function(s)	***Wilks' Lambda***	***Chi-square***	***df***	***Sig.***
1	,950	4218,298	17	,000

The stepwise method included variables to the model one by one. Table 5 shows final list of relevant predictors in our model. Moreover, Table 6 describes the discrimination ability of individual variables. Variables X10 and X15 have the greatest discrimination ability.

Table 6: Standardized Canonical Discriminant Function Coefficients

Variable	***Coefficient***
X01	,082
X02	,242
X04	-,095
X09	-,205
X10	,525
X11	-,148
X12	,104
X15	,517
X20	-,062
X22	-,051
X27	,362
X28	-,373
X35	-,206
Country=Montenegro	,040
Country=Serbia	-,164
Country=Slovenia	-,062
Size=Small	,237

By using unstandardized canonical discriminant function coefficients (in Table 6); we can calculate a discriminant score for every company that allows to include a company into the group of companies in financial distress or healthy companies.

Table 7: Canonical Discriminant Function Coefficients

Predictor	***Coefficient***
X01	,025
X02	,037
X04	-,016
X09	-1,111
X10	3,861
X11	-,511
X12	,527
X20	-,015
X21	-1,928
X22	-,016
X27	2,077

X28	-,467
X35	-1,290
Country=Montenegro	,226
Country=Serbia	-,371
Country=Slovenia	-,135
Size=Small	,567
(Constant)	-1,977

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 8: Classification Function Coefficients

Predictor	***Distress***	
	No	***Yes***
X01	,053	,084
X02	,187	,233
X04	-,004	-,024
X09	,035	-1,360
X10	9,249	14,096
X11	8,012	7,370
X12	1,465	2,127
X20	-,003	-,021
X21	6,313	3,893
X22	-,082	-,102
X27	5,385	7,993
X28	-,725	-1,312
X35	1,736	,116
Country=Montenegro	3,393	3,676
Country=Serbia	3,490	3,025
Country=Slovenia	3,542	3,373
Size=Small	3,992	4,704
(Constant)	-9,470	-12,685

For practical use of the model it is necessary that the model has sufficient discrimination ability. We evaluate this ability on the basis of a classification table. Based on the Table 8, it is clear that the model has a high ability to identify company financial distress (93,5 % for the training sample and 90,9 % for the testing sample). The prediction model has relatively high overall discrimination ability. This is because 75,6 % of companies in the testing sample were correctly classified. This prediction ability is 76,0 % for the training sample cases.

Table 9: Classification Results

			Predicted Group Membership		
Sample		***Distress***	***No***	***Yes***	***Total***
Training Sample	Count	No	88259	36577	124836
		Yes	2473	35571	38044
	%	No	70,7	29,3	100,0
		Yes	6,5	93,5	100,0
Testing Sample	Count	No	22127	9082	31209
		Yes	866	8645	9511

	%	No	70,9	29,1	100,0
		Yes	9,1	90,9	100,0

4. CONCLUSION REMARKS

We have designed a prediction model for companies from Croatia, Macedonia, Montenegro, Serbia and Slovenia predicting the risk of financial difficulties one year in advance. Multidimensional Discriminant Analysis was used for its creation. We use data calculated form real financial statements of more than 200,000 companies obtained from database Amadeus - A database of comparable financial information for public and private companies across Europe. From the original 32 predictors (24 financial indicators and 8 dummy variables), 17 predictors remained in the model. These predictors are not burdened by multi-collinearity, and provide the best identification of financial distress of companies.

Using canonical discriminant function from our model one can calculate discriminant score of a company and based on this score, it is possible to predict the financial distress of this company. Overall prediction ability of the model is relatively high (about 76 %). But financial distress prediction ability is more than 90 %. Therefore, we can consider the model to be relatively reliable for prediction of financial distress one year in advance. Although the model was created for companies in selected Balkan countries, it may be applicable also to other emerging market countries.

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