The Impact of Methodology on the Effectiveness of Bankruptcy Modeling

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***Abstract*—The prevailing opinion in literature is that the accuracy of bankruptcy models cannot be appreciably improved by the choice of classification algorithm. A reflection of this conviction is the frequent usage of parametric methods. However, the nature of financial data places a limitation on the accuracy of these methods. An analysis of 1908 Czech industrial enterprises from 2004 to 2011 reveals that a nonparametric method, if used for the selection of model variables as well as the actual classification, can yield significantly better results than the traditional parametric approach.**

Keywords—bankruptcy prediction models, boosted trees, stepwise discriminant analysis

I. Introduction

Bankruptcy of a company represents a sizeable economic loss not only to the owners of the company and its creditors, but to the entire society. In an effort to identify the risk of bankruptcy, many authors investigate bankruptcy modeling and try to improve the accuracy with which the threat of bankruptcy can be detected. Building such a model involves two phases: finding suitable variables (called predictors), and choosing a classification algorithm that can effectively utilize those predictors.

The objective of this paper is to determine how the effectiveness of a bankruptcy model is influenced by the choice of a method, specifically a linear Multiple Discriminant Analysis Method (hereinafter MDA method) and a Boosted Trees Method (hereinafter BT method).

II. Literature Review

Historically, various algorithms have been employed to devise models of bankruptcy. The first was the MDA method [1], developed by Fisher [17]. In reaction to its shortcomings, other algorithms were applied. A number of parametric methods exists, such as logistic regression [27, 30], a probit model [40], or a Cox model [21, 33]. Over time, nonparametric methods were also tried, such as artificial neural networks (ANN) [4, 26], Data Envelopment Analysis (DEA) methods [12, 16], even some combinations of parametric and non-parametric methods [13, 22]. Nevertheless, the MDA method remains the most widely used classification algorithm [2].

One of the reasons may be the prevalent opinion that the choice of classification method does not offer much potential to improve the bankruptcy model [28], i.e. that there is not a statistically significant difference in accuracy between the individual methods [2].

III. Sample and Methodology

In the course of this research, a total of 44 financial indicators were tested. They had been used in previous bankruptcy studies, especially those of [1, 5, 6, 14, 15, 28, 30, 32, 34, 36]. The sample consisted of 1908 enterprises from processing industries (1,500 active and 408 bankrupt) that operated in the territory of the Czech Republic within the period of 2004-2011. The data were obtained from Amadeus Database, and the calculations utilized Statistica 10 statistical software.

A. MDA Method

The objective of this method is, according to [20], *"to find a linear combination of p monitored variables, i.e. $Y = bTx$, where $b^T = [b_1, b_2, \ldots, b_p]$ is a vector of parameters, that would segregate, better than any other linear combination, the H groups under consideration so that its variability within the groups would be minimal and its variability between the groups maximal"*. The MDA method produces a discriminatory rule (function) which allows to assign, according to calculated predictors, each company to a group of enterprises either threatened or not threatened by bankruptcy. The factors beneficial for the accuracy of this method are: at least roughly normal distribution of data [31], negatively correlated indicators [1, 11], and the absence of extreme values [38, 39, 40].

B. Boosted Trees Method

The method of Boosted Trees (BT) is a combination of the *classification and regression trees* method (CART) [10], with a boosting algorithm introduced by J. Friedman [10]. Using the boosting algorithm raises the accuracy of the classification algorithm, to which it is applied by progressively reducing the error term [3, 10, 19]. The resultant classification rule represents a set of many "weak" learners. The boosting algorithm is most often applied to CART, but an ANN application may be encountered as well [26].

Among the advantages of the BT method, aside from its nonparametric nature (the data need not be normally distributed), is its tolerance for outliers in the input variable space [35]. In addition, the method allows to capture even complex (non-linear) relationships between the variables [18]. Since the lack of normality and the presence of outliers tend to be commonplace in financial data [7, 8, 33, 37], it can be expected that a method which is immune to these aspects will deliver a higher classification accuracy. In other words, we assumed that the BT method would produce better results than the MDA method.

To better assess the potential of these methods, we will use them for the selection of suitable predictors as well as for the classification algorithm itself.

C. *Bankruptcy Model Derived from the MDA Method*

Finding the suitable predictors was done with a stepwise forward variant of the MDA method, where only the variables with sufficient discriminatory ability are included in the model [4, 23]. The model thus contained 22 out of 44 analyzed variables. Only 8 variables were statistically significant by the F-test at 1% level (see Model 1).

Model 1 was derived from those 8 predictors. As a whole, Model 1 was statistically significant by the F-test at 1% level (see Wilks' lambda 0.60090, F-value 82.107, p-value < 0.0000). The details are shown in the following table:

TABLE I. MODEL 1

Variable		Wilks' Lambda	Parc. Lambda	F-val.	p-val.	Toler.
NI/OR	Net income/operation revenue	0.759688	0.790987	261.3368	0.000000	0.975716
EQ	Log of equity	0.726385	0.827251	206.5256	0.000000	0.637913
NI/FA	Net income/fixed assets	0.618759	0.971143	29.3878	0.000000	0.873026
EBIT(5-vol)	EBIT (5-year volatility)	0.6185	0.971548	28.9627	0.000000	0.664436
NI-change	Ohlson's change of net income	0.606973	0.989999	9.991	0.001621	0.957358
CD/S	Current debt/sales	0.61127	0.98304	17.063	0.000039	0.798648
WC/TA	Working capital/total assets	0.606051	0.991506	8.4725	0.003686	0.678442
IntA/TotA	Intangible assets/total assets	0.605248	0.99282	7.1519	0.007612	0.983283

D. *Bankruptcy Model Derived from the BT Method (Model 2)*

The BT method allows to rank predictors by their relative significance (the degree of their contribution to final classification capability). An analysis showing the individual variables' representation in the intervals of their significance showed that their distribution was rather uneven.

The relative importance of variables in a bankruptcy assessment differs greatly. The significance higher than 60% is achieved only by 13.64% predictors or 6 out of 44, and above 40% are only 43.18% or 19 predictors, which appear in the following table. Those were the only predictors used to build Model 2.

TABLE II. PREDICTORS USED TO CONSTRUCT MODEL 2

Variable		Import.	Variable		Import.
NI/OR	Net income/operation revenue	100.00%	EQ	Log of equity	50.41%
TA	Log of total assets	97.1%	NI/TA	Net income/total asset	47.23%
S	Log of sales	91.19%	NI/CA	Net income/current assets	46.95%
EBIT (5-vol)	EBIT (5-year volatility)	90.17%	WC/TA	Working capital/total asset	46.28%
TL/TA	Total liabilities/total assets	63.23%	OR/CA	Operation revenue/current liabilities	45.32%
OR/CL	Operation revenue/current liabilities	60.40%	S/TA	Sales/Total Assets	44.73%
OR/TL	Operation revenue/total liabilities	56.19%	OR/TA	Operation revenue/total assets	43.85%
CR	Current ratio	53.40%	CF/TD	Cash flow/total debt	43.56%
DR	Debt-Equity-Ratio	52.83%	CF/TA	Cash flow/total asset	41.90%
RE/TA	Retained earnings/total asset	51.34%			

Next was an analysis for the presence of multicollinearity in the model. Variance Inflation Factor (VIF) method was employed for this purpose. The indicators with the value greater than 4 were removed from the model [26]. Twelve additional variables were removed in this manner.

TABLE III. REDUNDANT VARIABLES IN MODEL 2

Variable	Tolerance	R^2	VIF	Variable	Tolerance	R^2	VIF
TA	0.024713	0.975287	**40.46443**	**EQ**	0.029369	0.970631	**34.0499**
S	0.039066	0.960934	**25.59799**	**NI/TA**	0.074339	0.925661	**13.45195**
TL/TA	0.085819	0.914181	**11.65243**	**S/TA**	0.025036	0.974964	**39.94234**
OR/CL	0.166148	0.833852	**6.01873**	**OR/TA**	0.025395	0.974605	**39.37737**
OR/TL	0.112006	0.887994	**8.9281**	**CF/TD**	0.15941	0.84059	**6.27314**
CR	0.171264	0.828736	**5.83895**	**CF/TA**	0.071528	0.928472	**13.98061**

A similar analysis was performed for Model 1, but no predictor had the VIF value greater than 4. After removing the less important variables, and those that were redundant (because of multicollinearity), Model 2 emerged in its final form with only 7 variables.

TABLE IV. FINAL MODEL 2

Variable	Import.	Variable	Import.
NI/OR	100.00%	WC/TA	50.73%
EBIT (5-vol)	87.64%	RE/TA	50.62%
DR	68.78%	OR/CA	36.52%
NI/CA	51.48%		

The following table contains the minimal values of the loss function attained. This value demonstrates the informative quality of the model, referred to as the "goodness of fit".

TABLE V. GOODNESS OF FIT, MODEL 2

	Risk estimate	Standard error
Train	0.04745000	0.00565800
Test	0.01593600	0.00558900

E. Accuracy Comparison of Model 1 and Model 2

The models were evaluated on the given sample. The results of testing (percentage of correctly identified cases) are shown in the following table.

TABLE VI. COMPARISON OF MODEL ACCURACY

Model	Active	Bankrupt	Type I error	Type II error
Model 1	99.78%	60.0%	6.25%	2.18%
Model 2	93.61%	100.00%	15.55%	0.00%

A type I error occurs when a bankruptcy-prone company is assessed as financially stable. A type II error describes the opposite situation, i.e. perceiving a financially stable company as facing bankruptcy. According to [42], the type I error is 2 to 20 times more serious (thus costly) than the type II error. The test results indicate that Model 2, generated by the nonparametric BT method, is clearly superior in its ability to identify the risk of bankruptcy, relative to Model 1 based on the parametric MDA method.

IV. DISCUSSION

The opinion that the choice of classification method does not offer much possibility for improvement in bankruptcy modeling predominates in contemporary literature [2, 23, 28]. The consequence of this notion is a frequent usage of the MDA method which, to be effective, requires compliance with some specific conditions, most notably normality of data and the absence of outliers. However, the nature of financial indicators used to build these bankruptcy models is very often quite different: the data deviate from normality and contain outliers [25]. However, the lack of normality and the presence of outliers in financial ratios may in fact be viewed as natural, because they often stem from their very definition [31]. The fact that the classification accuracy of MDA is affected by the natural properties of inputted data, to which BT is immune, means that the choice of method used to create a predictive model can surely influence the classification accuracy of that model.

Unlike the previous approaches (especially [2]), the methods evaluated in our research were used for classification purposes as well as for finding some suitable predictors. This caused the two models to feature different predictors, the selection of which is the consequence of applying a certain method. The potential of the MDA method can be enhanced by an appropriate data transformation, particularly the Box-Cox transformation [9, 29]. A bankruptcy model can then be derived from the transformed indicators that exhibit normal distribution [25]. Our research did not resort to data transformation except for a logarithmic transformation of indicators TA, S, and EQ, for two reasons:

1. Transformation of a monotone function has no effect on the conclusions with the BT method.
2. In the case of MDA, the Box-Cox transformation was not done because the combination of transformation and the method itself would have affected the model accuracy.

V. CONCLUSION

The research presented herein examined the effectiveness of creating a bankruptcy model taking two different approaches, namely the commonly used MDA method and the newer BT nonparametric method. Both methods were applied to the same sample of companies and the same initial set of indicators. Some of the predictors in the resultant models were identical (NI/OR, EBIT (5-vol) and WC/TA), others were different. The largest differences occurred in the use of indicators expressing indebtedness. Model 2, derived by means of the nonparametric BT method, achieved much better accuracy in the assessment of bankruptcy risk than the model based on the parametric MDA method.

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