CORPORATE FINANCIAL DISTRESS PREDICTION OF SLOVAK COMPANIES: Z-SCORE MODELS VS. ALTERNATIVES

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Abstract

In the recent paper "The portability of Altman's Z-score model to predicting corporate financial distress of Slovak companies" published in 2016 in Technological and Economic Development of Economy, its authors claim that, under some assumptions, "Altman's bankruptcy formula is portable into the Slovak economic conditions and useful for predicting financial difficulties". The main goal of our paper is to compare the ported Z-score prediction models from their paper, which are based on linear discriminant analysis, to prediction models based on other standard supervised classification methods, e.g. logistic regression, decision trees, random forests. In our comparison, we take into account accuracy as well as interpretability of the models. In order to assure comparability of results we use the same data set as it was utilized in the above-mentioned paper.

Key words: *financial distress prediction, alternative models, Altman-like models.*

1. Introduction

There is no doubt that data mining and statistical methods play an important role in decision making processes of companies including construction of corporate financial distress or bankruptcy prediction models (Balcaen and Ooghe, 2006). Despite the fact that huge amount of various financial distress prediction models was fitted by different authors utilizing the wide range of different statistical methods, the well-known and long existing financial distress and/or bankruptcy models still dominate their recent modifications or new counterparts (Altman et al., 2014). There is a constant effort to use such models for enterprises in different economies, even if decision makers know or at least should know that assumptions used for fitting the original models are probably not valid anymore, for example due to changes in economic environments, law frameworks, incomparability of populations of interest, etc. As a result, we very often see non-critical adoption various financial distress prediction models without deeper analysis of country specific assumptions.

In Boďa and Úradníček (2016), authors present and thoroughly discuss the Altman's Z-score prediction models (Altman, 1968; Altman et al., 1977; Altman, 1983; Altman, 2013) ported into Slovak economy, i.e., linear discriminant models predicting the financial health of selected Slovak enterprises based on the past information about their financial indicators (such as liquidity, capital structure, or profitability ratios). For simplicity we call these Altman like models in the rest of the paper. The results of Boďa and Úradníček (2016) indicate, quite surprisingly, that the Altman like models, to some degrees, have relatively high accuracy and stable performance over an extended time period. The main goal of our contribution is to compare Altman like models to alternative prediction models based on other standard supervised classification methods, namely quadratic discriminant analysis (QDA), logistic regression (LR), classification tree (CT) and random forest (RF). To assure comparability of results, we fit these models on exactly the same data as used by them and compare their classification accuracy and other properties. The paper is outlined as follows. In Section 2 we present a briefly overview of our data sets; Section 3 consists of description of models and analyses utilized in the paper; in Section 4 we list selected characteristics of Altman like models adopted from the aforementioned paper; Section 5 presents the alternative models fitted using various supervised classification methods.

2. Data

In our paper, we use the data sets utilized in Boďa and Úradníček (2016). According to Boďa and Úradníček (2016) "the data set for the analysis was obtained from the leading Slovak corporate analytical agency CRIF – Slovak Credit Bureau, s. r. o., and comprised detailed financial statements of a large proportion of Slovak enterprises with activities falling into all business sectors of the Slovak economy. The data set involved all the four legal forms of enterprises common in Slovakia (i.e. v.o.s. – general partnership, k.s. – limited partnership, s.r.o. – private limited company, a.s. – joint-stock company) and related to a range of five fiscal periods: from 2009 to 2013." The data sets consist of five financial ratios (predictors) and one binary response variable – a status of a company – taking values "being in distress" and "not being in distress". The predictors are mimicking those in the Altman's model, namely
X1– working capital / total assets,
X2– retained earnings / total assets,
X3– earnings before interest and taxes / total assets,
X4– book value of equity / book value of debt, and
X5– sales / total assets.

In Boďa and Úradníček (2016), the response has been defined as follows. "An enterprise was considered financially distressed if
a) its equity was negative,
b) its EAT (earnings after taxes) was negative,
c) its current ratio attained a value lower than 1.

All the three conditions had to be satisfied in order for an enterprise to be considered financial distressed". Of course, there exist other valid alternatives how to define financially distressed enterprises (see e.g. Fleischer, 2016).

3. Methodology

In order to fulfill the goal of our paper we must ensure, that our analyses can be seen as comparable to those performed by Boďa and Úradníček (2016). Besides using the same data sets, it means that we neither apply any further data cleaning procedures to our data nor impose further restrictions on companies included in our analysis. Standardization of continuous variables is the only transformation procedure applied universally as a part of all model fitting procedures. Analogously to Boďa and Úradníček (2016), the data set for each year was split into a training set and test set assuming 75:25 ratio. The training set is used to fit the model and evaluate its predictive accuracy via tenfold cross-validation, the test set further verifies predictive accuracy indicated by cross-validation on the training set. To unify the fitting procedures as much as possible we fit all models within the same framework utilizing the R package `caret` (Kuhn et al., 2016) assuming that companies being in financial distress form our target category. Among other benefits, the unified framework of the package allows us to change flexibly performance metrics used for model optimization if the fitted model includes some tuning parameters. We can even define our own metric for model tuning. In the paper, we utilize the sensitivity analysis, overall accuracy and AUC (area-under-curve) statistic for tuning of models in order to assess predictive accuracy of the model. As in Boďa and Úradníček (2016), we ignore possible violations of assumptions of classifications methods. We base such a non-rigorous and non-statistical approach on two very simple assumptions. First, if we apply a classification method to a data set violating assumptions of that method, it should deteriorate predictive accuracy of the fitted model. Second, if predictive accuracy of the model estimated using cross-validation on a training set and further verified by a test set is satisfactory, deviations from model assumptions can be ignored to some extent. Because we are not primarily interested in fitting and deployment of corporate financial distress (bankruptcy) prediction models into a real production systems, we do not perform any kind of sensitivity analysis. According to our assumptions, methods we choose should result in conditional probabilities for being distressed and thus in binary classification based on Bayesian classifier where a company belongs to a category for which the conditional probability exceeds 0.5. Since the two classes we assume in our classification models are heavily imbalanced, we can think about two possible solutions of this problem, optimization of a cut-point according to a predictive accuracy (or any other metric) on training or test set and balancing data into 50:50. We do not apply any of them in our analyses. Optimization of cut-point is really discouraged by Harrell (2001) as data driven approach that can lead to over-fitting on a training set and to poor performance on an imbalanced test set. Moreover, for methods being able to incorporate prior probabilities into computation, e.g. logistic regression, the balancing can be harmful. For simplicity, we restrict ourselves to models based on quadratic discriminant analysis, logistic regression, classification trees based on CART algorithm and random forests (Breiman, 2000; Hastie et al., 2001; James et al., 2015; Therneau et al., 2015). We have chosen these methods because predictive ability of resulting models should be at least comparable to those based on linear discriminant analysis. Moreover, their interpretability is not inferior, their assumptions are less restrictive than those of linear discriminant analysis, and some of them are able to deal with imbalances of classes in our data sets using prior probabilities. And finally, all these methods are widely used as alternatives to linear discriminant analysis.

3.1 An Overview of the Re-Estimated and Altman's Z-score Models from Boďa and Úradníček (2016)

The classification accuracy of the models fitted by Boďa and Úradníček (2016) is listed in Table 1 including overall accuracy, sensitivity and specificity. The comparison of models based on AUC statistic can be seen in Table 2.

Table 1: Classification accuracy of the re-estimated and Altman's Z-score models

Initial year	% of correctly classified enterprises	1968 original Altman's model		1983 revised Altman's model		Re-estimated Z-score model	
		Training sample	Test sample	Training sample	Test sample	Training sample	Test sample
2009	Overall	77.89%	79.01%	82.42%	83.14%	61.53%	60.33%
	Non-distresses	81.69%	81.60%	87.71%	87.25%	60.04%	58.47%
	Distresses	40.00%	53.57%	29.70%	42.86%	76.36%	78.57%
2010	Overall	76.99%	78.21%	80.45%	80.55%	56.26%	56.93%
	Non-distresses	83.00%	84.05%	87.96%	88.03%	53.41%	54.03%
	Distresses	34.44%	36.82%	27.31%	27.53%	76.45%	77.45%
2011	Overall	76.81%	76.15%	79.45%	79.32%	66.07%	66.14%
	Non-distresses	82.64%	82.47%	87.08%	87.42%	66.04%	66.38%
	Distresses	37.79%	33.85%	28.35%	25.03%	66.25%	64.50%
2012	Overall	76.56%	76.83%	79.66%	79.51%	70.53%	70.54%
	Non-distresses	82.04%	82.38%	86.75%	86.84%	72.92%	72.78%
	Distresses	39.08%	38.82%	31.07%	29.35%	54.19%	55.21%

Source: Boďa and Úradníček (2016).

Table 2: AUCs of the re-estimated and Altman's Z-score models

Initial year	1968 original Altman's model		1983 revised Altman's model		Re-estimated Z-score model	
	Training sample	Test sample	Training sample	Test sample	Training sample	Test sample
2009	0.708	0.632	0.701	0.625	0.740	0.736
2010	0.649	0.626	0.639	0.616	0.710	0.703
2011	0.636	0.650	0.624	0.639	0.708	0.715
2012	0.642	0.640	0.631	0.632	0.684	0.673

Source: Boďa and Úradníček (2016).

4. Alternative Models

Results of our analyses are listed in the following tables. Table 3 includes performance measures of models based on quadratic discriminant analysis and logistic regression non optimized with respect to cut-points. Tables 4 – 6 consists of performance measures of decision trees and random forest which were optimized with respect to sensitivity, overall accuracy and AUC statistic. Table 7 lists AUC statistic for the selected alternative models computed using training sets.

Table 3 shows that overall accuracy and specificity of logistic regression are far better then those for Altman's models but the corresponding low sensitivity and occurrence of numerical problems make these models unuseful and unreliable. On the other hand, models based on quadratic discriminant analysis are comparable to original Altman's models but inferior to re-estimated Z-score with respect to sensitivity. It could be caused by departures from assumptions of normality as it is well known that linear discriminant analysis is more robust to those than quadratic discriminant analysis. Finally, time stability of the models is not satisfactory and these models should be refitted each year in order to be apply them as a support tool for decision-making in corporate environment.

Table 3: Classification accuracy of quadratic discriminant analysis and logistic regression

Initial year	% of correctly classified enterprises	QDA model		LR model	
		Training sample	Test sample	Training sample	Test sample
2009	Overall	51.08 %	48.76 %	90.66* %	90.58* %
	Non-distresses	48.24 %	45.17 %	99.76* %	99.82* %
	Distresses	79.45 %	83.93 %	0* %	0* %
2010	Overall	77.22 %	81.78 %	87.51* %	87.67* %
	Non-distresses	83.93 %	89.98 %	99.71* %	99.9* %
	Distresses	29.74 %	23.72 %	1.11* %	0.83* %
2011	Overall	74.81 %	78.20 %	86.85* %	86.95* %
	Non-distresses	80.39 %	85.22 %	99.69* %	99.77* %
	Distresses	37.43 %	31.20 %	0.88* %	1.1* %
2012	Overall	86.92 %	87.18 %	86.92 %	87.24 %
	Non-distresses	99.36 %	99.82 %	99.36 %	99.88 %
	Distresses	1.77 %	0.73 %	1.77 %	0.73 %

Note: *fitted probabilities numerically 0 or 1 occurred.
Source: the authors.

Table 4: Classification accuracy of the trees and forests tuned using sensitivity

Initial year	% of correctly classified enterprises	Tree model		Rand. forest model	
		Training sample	Test sample	Training sample	Test sample
2009	Overall	87.84 %	88.1 %	90.82 %	90.58 %
	Non-distresses	95.25 %	96.17 %	99.21 %	99.64 %
	Distresses	14.01 %	8.93 %	7.35 %	1.79 %
2010	Overall	84.02 %	83.87 %	87.29 %	87.24 %
	Non-distresses	93.66 %	93.58 %	98.97 %	99.16 %
	Distresses	15.75 %	15.09 %	4.59 %	2.82 %
2011	Overall	84.27 %	84.62 %	86.18 %	86.21 %
	Non-distresses	94.92 %	95.19 %	98.31 %	98.49 %
	Distresses	12.98 %	13.78 %	4.93 %	3.97 %
2012	Overall	85.67 %	85.68 %	86.77 %	86.74 %
	Non-distresses	96.7 %	97.06 %	98.55 %	98.60 %
	Distresses	10.18 %	7.79 %	6.10 %	5.61 %

Source: the authors.

Table 5: Classification accuracy of the trees and forests tuned using overall accuracy

Initial year	% of correctly classified enterprises	Tree model		Rand. forest model	
		Training sample	Test sample	Training sample	Test sample
2009	Overall	90.71 %	90.74 %	90.66 %	90.91 %
	Non-distresses	99.76 %	100 %	99.33 %	100 %
	Distresses	0.6 %	0 %	4.24 %	1.79 %
2010	Overall	87.04 %	87.63 %	87.36 %	87.42 %
	Non-distresses	98.66 %	100 %	99.24 %	99.56 %
	Distresses	4.75 %	0 %	3.26 %	1.49 %
2011	Overall	86.63 %	87.01 %	86.52 %	86.58 %
	Non-distresses	99.04 %	100 %	98.90 %	99.03 %
	Distresses	3.45 %	0 %	3.57 %	3.20 %
2012	Overall	87.15 %	87.25 %	86.84 %	86.9 %
	Non-distresses	99.73 %	100 %	98.98 %	98.98 %
	Distresses	1.24 %	0 %	4.30 %	4.22 %

Source: the authors.

Table 6: Classification accuracy of the trees and forests tuned using AUC

Initial year	% of correctly classified enterprises	Tree model		Rand. forest model	
		Training sample	Test sample	Training sample	Test sample
2009	Overall	89.66 %	88.43 %	90.60 %	90.74 %
	Non-distresses	97.44 %	96.54 %	99.09 %	99.82 %
	Distresses	12.24 %	8.93 %	5.99 %	1.79 %
2010	Overall	85.56 %	86.5 %	87.20 %	87.40 %
	Non-distresses	97.65 %	97.47 %	98.98 %	99.30 %
	Distresses	7.52 %	8.79 %	3.81 %	3.15 %
2011	Overall	85.3 %	85.93 %	86.62 %	86.55 %
	Non-distresses	96.68 %	97.65 %	98.98 %	98.91 %
	Distresses	9.12 %	7.5 %	3.86 %	3.75 %
2012	Overall	85.91 %	85.76 %	86.90 %	86.85 %
	Non-distresses	96.98 %	97.18 %	98.98 %	98.94 %
	Distresses	10.18 %	7.65 %	4.23 %	4.08 %

Source: the authors.

Results listed in Tables 4 – 6 can be interpreted as follows. We get the best balance of overall accuracy, sensitivity and specificity for classification trees and random forests tuned using sensitivity although models tuned using AUC have very similar performance. Moreover, trees surprisingly over-performed forests in all cases. Models seem to be quite stable during the whole period of interest.

According to Table 7 there are negligible differences among all presented models with respect to the AUC measure.

Table 7: AUCs of the selected alternative models

Initial Year	QDA	LR	Tree(Sens.)	Tree(AUC)	Rand.F(Sens.)	Rand.F(AUC)
2009	0.707	0.73	0.635	0.676	0.727	0.73
2010	0.709	0.702	0.675	0.686	0.705	0.707
2011	0.696	0.716	0.696	0.709	0.727	0.725
2012	0.675	0.697	0.708	0.705	0.723	0.731

Source: the authors.

5. Conclusion

The main goal of our contribution was to compare the Z-score prediction models ported to Slovak companies in the period 2009 – 2013 from the paper by Boďa and Úradníček (2016), which are based on linear discriminant analysis, to prediction models based on other standard supervised classification methods, namely quadratic discriminant analysis, logistic regression, decision tree and random forest. Our results indicate that the so called alternative models beat the Altman like models in overall accuracy and specificity and are far worse in sensitivity (except QDA in some years) even in the case of models optimized with respect to sensitivity. Both sets of models are comparable with respect to AUC statistic. Therefore, in their current state they can be seen as supplementary to each other, if applied. In the future research, we plan to increase the range of our comparative study including additional methods, e.g. conditional tress, KNN (k-nearest neighbors), SVM (support vector machines), as well as to check the presented models for possible improvements in their predictive performance measures, especially sensitivity, utilizing balanced sampling of training sets, balancing of training sets and cut-point selection.

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