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Modelling bankruptcy prediction models in Slovak companies

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Abstract. An intensive research from academics and practitioners has been provided regarding models for bankruptcy prediction and credit risk management. In spite of numerous researches focusing on forecasting bankruptcy using traditional statistics techniques (e.g. discriminant analysis and logistic regression) and early artificial intelligence models (e.g. artificial neural networks), there is a trend for transition to machine learning models (support vector machines, bagging, boosting, and random forest) to predict bankruptcy one year prior to the event. Comparing the performance of this with unconventional approach with results obtained by discriminant analysis, logistic regression, and neural networks application, it has been found that bagging, boosting, and random forest models outperform the others techniques, and that all prediction accuracy in the testing sample improves when the additional variables are included. On the other side the prediction accuracy of old and well known bankruptcy prediction models is quiet high. Therefore, we aim to analyse these in some way old models on the dataset of Slovak companies to validate their prediction ability in specific conditions. Furthermore, these models will be modelled according to new trends by calculating the influence of elimination of selected variables on the overall prediction ability of these models.
Key words: bankruptcy, prediction models, company

1 Introduction

Prediction of financial distress is very critical in enterprise risk management, especially for financial institutions. In particular, financial institutions have to develop various risk management models, such as bankruptcy prediction and credit scoring models. For bankruptcy prediction, financial institutions need effective prediction models in order to make appropriate lending decisions. On the other hand, credit scoring models are used for the management of large loan portfolios and/or credit admission evaluation.

Also the 2008 global financial crisis and its aftermath have shown the ability to predict bankruptcy to be a vital management skill. So methodologies used for that purpose should

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be as close to reality as possible as bankruptcy prediction is one of the most important business decision-making process [1].

Default of companies as well as default of other subjects represents occasion which happens not only in the market economy. Even with the maximum effort is not possible to avoid bankruptcy. Consequences of these defaults are extensive and have impact not only on the company itself, but it influences all stakeholders and if we look on the company as on the part of market economy it effects all its participants.

The problem of bankruptcy forecasting is one of the most actively studied nowadays among practical and theoretical issues of company management. Assessment of the current financial status and determination of bankruptcy probability are of interest to shareholders, suppliers, creditors and others aiming is to deal with perspective and reliable business partners.

By present, many models of bankruptcy forecasting have been developed, but this area remains still a field of research activity. On the other side little is known about the practical application of existing models mainly because the use of existing models is limited by the conditions in which they are developed. Another question concerns the factors that can be significant for forecasting [2].

This is given by the fact that since different economic environments have various properties that do not allow reusing models and related sets of factors in other conditions. This fact has been also confirmed by comparative studies of models for different countries [3, 4].

For developing countries, with the economic structure significantly different from the developed countries this fact is particularly significant [5].

Consequently, respecting the prerequisite that efficient methods can only be applied to companies of the same group in the same economic situation in the period for which the models were originally designed, we aim to analyse, these in some way old models on the dataset of Slovak companies, to validate their prediction ability in specific conditions.

Furthermore, these models will be modelled according to new trends by calculating the influence of elimination of selected variables on the overall prediction ability of these models.

2 Literature Review

Currently a huge number of studies are devoted to the issue of bankruptcy prediction. All researches can be divided into two groups. First group of researchers focus their attention on forecasting methodology while second group concentrate on the choice of proper variables providing the highest prediction ability.

Based on the used forecasting methodology can be bankruptcy prediction models divided into three main categories: statistical models, artificial intelligence and theoretical models [6]. Until the end of twenty century the basic prediction methodologies were based on statistical methods, such as the most common discriminant analysis [7, 8, 9], logit [10] and probit [11, 12]. These statistical methods are quiet popular among researchers and practitioners even nowadays as their prediction ability is relatively high and the way of processing not so difficult.

On the other side in the beginning of 21st century artificial intelligence expert systems including machine-learning techniques became the primary method for bankruptcy prediction. Mainly artificial neural networks (ANN) were used [13]. Although the prediction ability of ANNs is comparatively higher there are reasonable limitations such as the need to have a great experience in order to select the control parameters properly and difficulties with building the model itself [14, 15].

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In addition, some authors have investigated the applicability of other artificial intelligence methods to bankruptcy prediction, for example, the principal component analysis [16, 17], support vector machines [18, 19], decision trees [20, 21], rough sets, [12, 22], data envelopment analysis [23, 24], and others.

Focusing on the second group of researchers concentrating on the choice of proper variables providing the highest prediction ability can be stated that financial indicators are the most popular [25, 21].

In addition to these indicators are added other, such as corporate management factors [26, 27], environmental factors [28, 29], level of legislation development [30] and so on.

Finally, we can summarize that forecasting models usually include indicators from all of these factors [31]. Additionally can be noted that in spite of the average number of indicators is ten, a large number of indicators doesn´t increase the predictive ability of the model [32]. It is important also to note that even though there are more than 500 prediction models worldwide, many of which have shown high predictive ability, they are poorly used in practice and the focus is mainly on developing new ones reflecting specific individual environment.

Therefore, we aim to analyse these in some way old models on the dataset of Slovak companies to validate their prediction ability in specific conditions. Furthermore, these models will be modelled according to new trends by calculating the influence of elimination of selected variables on the overall prediction ability of these models.

3 Data and Methodology

For the presented study we have used dataset of annual financial reports of Slovak companies, which were gained through the Register of financial statements, Ministry of Finance of the Slovak Republic. Calculations were provided on the basis of the year 2015.

To validate the prediction ability of selected old models in specific conditions of Slovak environment we had to set criterions to classify company as bankrupt or non-bankrupt. These criterions were set according to Slovak legal system in combination with other significant characteristics respecting specifics of Slovak environment [33, 34].

Based on the given criterions we consider company as bankrupt if:
- negative value of earnings after taxes,
- the value of financial independence indicator is less than 0.04,
- the value of current ratio indicator is less than 1,
- company has at least two liabilities 30 days after due date from different creditors,
- the total amount of payable and not payable liabilities is higher that the value of company´s assets.

According to these specifics we have randomly chosen 768 companies (50% bankrupt and 50% non-bankrupt) for which we calculated selected bankruptcy prediction models to validate their prediction ability in specific conditions.

Additionally, these models will be modelled according to new trends by calculating the influence of elimination of selected variables on the overall prediction ability of these models.

To fulfil the aim of the presented study and further calculations we selected bankruptcy prediction models shown in table 1, applied them on the dataset of Slovak companies to validate prediction ability of these models.

Table 1. Description of applied bankruptcy prediction models. (Source: self-processed based on [11,35,36, 37, 9])

Author	Year	Country of origin	Formula	Indicators	Criterion for bankrupt
Zmijewski	1984	USA	$ZM = -4{,}336 - 4{,}513X_1 + 5{,}679X_2 + 0{,}004X_3$	X1 = Net Income / Total Assets X2 = Total Liabilities / Total Assets X3 = Current Assets / Current Liabilities ZM = Overall index	$P(b) = \frac{1}{\left(1+\exp^{(-ZM)}\right)}$ P(b) > 0,5
Taffler	1983	UK	$TM = 0{,}53X_1 + 0{,}13X_2 + 0{,}18X_3 + 0{,}16X_4$	X1 = Earnings Before Taxes / Short Term Liabilities X2 = Current Assets / Total Liabilities X3 = Short Term Liabilities / Total Assets X4 = Sales / Total Assets TM = Overall index	TM > 0,3 Enterprise creates value 0,2 ≤ TM ≤ 0,3 Grey zone TM < 0,2 Enterprise is going to bankruptcy
Fulmer	1984	USA	$H\ Factor = 5.528X_1 + 0.212X_2 + 0.73X_3 + 1.27X_4 - 0.12X_5 + 2.335X_6 + 0.575X_7 + 1.083X_8 + 0.894X_9 - 6.075$	X1 = Avg Retained Earnings / Average Total Assets X2 = Revenues / Average Total Assets X3 = EBIT / Total Equity X4 = Cash Flows from Operations / Avg Total Debt X5 = Avg Total Debt / Total Equity X6 = Total Current Liabilities / Avg Total Assets X7 = log (Avg Tangible Assets) X8 = Avg Working Capital / Avg Total Debt X9 = log (EBIT) / Interest Expense	FM > 0 Good financial health of the company FM < 0 Bad financial health of the company
Altman	2017 (originally 1968)	USA	$Z = 0{,}035 - 0{,}495X_1 - 0{,}862X_2 - 1{,}721X_3 - 0{,}017X_4$	X1 = Working Capital / Total Assets X2 = Retained Earnings / Total Assets X3 = EBIT / Total Assets X4 = Book Value of Equity / Book Value of Total Liabilities Z = Overall index	Z > 2,6 "Safe" Zone 1,1 < Z < 2,6 "Grey" Zone Z < 1,1 "Distress" Zone
Springate	1978	Canada	$SM = 1{,}03X_1 + 3{,}07X_2 + 0{,}66X_3 + 0{,}4X_4$	X1 = Net Working Capital / Total Assets X2 = EBIT / Total Assets X3 = Earnings Before Taxes / Short Term Liabilities X4 = Sales / Total Assets SM = Overall index	0,862 < S Good financial health of the company S < 0,862 Possible financial problems of the company

Confusion matrix and receiver operating characteristic curve (ROC) are considered as the most relevant and appropriate tools for the validation of predictive ability of tested models [38].

Table 2. Confusion matrix (Source: self-processed)

		Predictive value		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	TP	FN	TP+FN
	1 (bankrupt)	FP	TN	FP+TN
		TP+FP	FN+TN	Total

Confusion matrix (see table 2) can be stated as contingency table linking the number of proper and improper company´ classification based on the actual and predicted values and indicating following relevant characteristics:
- Type I. error (false positive) – percentage of bankrupt companies predicted by the model as non-bankrupt,
- Type II. error (false negative) – percentage of non-bankrupt companies predicted by the model as bankrupt,
- sensitivity (positive predictive value) – percentage of correct classification of non-bankrupt companies,
- specificity (negative predictive value) – percentage of correct classification of bankrupt companies,
- model accuracy – overall prediction ability of the model according to data set of companies also known as accuracy of prediction model.

4 Results and Discussion

To fulfil the given aim of the presented study we have provided calculation and application of five famous bankruptcy prediction models presented in table 1 on the dataset of Slovak companies. Results are shown in following table 3 and table 4.

Based on these results can be assumed that all calculated prediction models have reached about 50% prediction accuracy on the dataset of Slovak companies. This is given mainly because of the high type I. error in models of Fulmer (62%), Altman (99%) and Springate (78%).

On the other side in models of Zmijewski and Taffler the type I. error and type II. error were similar about 50%. Accoriding to provided calculation we can assume that we haven´t found important differences between tested model´s ability to predict future bankrupt of the company.

Table 3. Calculated confusion matrix of chosen models (Source: self-processed)

Zmijewski model		*Predictive value*		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	201	183	384
	1 (bankrupt)	186	198	384
		387	381	768
Taffler model		*Predictive value*		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	231	153	384
	1 (bankrupt)	205	179	384
		436	332	768
Fulmer model		*Predictive value*		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	273	111	384
	1 (bankrupt)	237	147	384
		510	258	768
Altman model		*Predictive value*		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	375	9	384
	1 (bankrupt)	380	4	384
		755	13	768
Springate model		*Predictive value*		
		0 (non-bankrupt)	1 (bankrupt)	
Actual value	0 (non-bankrupt)	322	62	384
	1 (bankrupt)	299	85	384
		621	147	768

Calculations of relevant characteristics regarding assessing tested models are provided in table 4.

Table 4. Calculated characteristics of chosen models (Source: self-processed)

Model	*Zmijewski model*	*Taffler model*	*Fulmer model*	*Altman model*	*Springate model*
Type I. error	0.4844	0.5339	0.6172	0.9896	0.7786
Type II. error	0.4766	0.3984	0.2891	0.0234	0.1615
Sensitivity	0.5234	0.6016	0.7109	0.9766	0.8385
Specificity	0.5156	0.4661	0.3828	0.0104	0.2214
Model accuracy	51.95%	53.39 %	54.69 %	49.35 %	52.99 %

Furthermore, we have modelled these models according to new trends by calculating the influence of removal of individual variables on the overall prediction ability of these models. Therefore, we provided new calculations for each model while removing each indicator and testing the new overall prediction ability. The aim was to assess the impact of these removal on the model accuracy, which will serve as a basis for future research.

Table 5. Calculated new model´s accuracies after removal of individual indicators (Source: self-processed)

Model	Model accuracy	Indicator removed	New model accuracy
Zmijewski model	51,95 %	X1 = Net Income / Total Assets	51.43%
		X2 = Total Liabilities / Total Assets	50.65%
		X3 = Current Assets / Current Liabilities	52.21%
Taffler model	53,39 %	X1 = Earnings Before Taxes / Short Term Liabilities	53.65%
		X2 = Current Assets / Total Liabilities	51.95%
		X3 = Short Term Liabilities / Total Assets	52.73%
		X4 = Sales / Total Assets	53.91%
Fulmer model	54,69 %	X1 = Avg Retained Earnings / Average Total Assets	54.95%
		X2 = Revenues / Average Total Assets	54.95%
		X3 = EBIT / Total Equity	54.95%
		X4 = Cash Flows from Operations / Avg Total Debt	54.17%
		X5 = Avg Total Debt / Total Equity	54.43%
		X6 = Total Current Liabilities / Avg Total Assets	52.99%
		X7 = log(Avg Tangible Assets)	53.65%
		X8 = Avg Working Capital / Avg Total Debt	52.99%
		X9 = log(EBIT) / Interest Expense	54.04%
Altman model	49,35 %	X1 = Working Capital / Total Assets	49.22%
		X2 = Retained Earnings / Total Assets	49.22%
		X3 = EBIT / Total Assets	50.00%
		X4 = Book Value of Equity / Book Value of Total Liabilities	49.35%
Springate model	52,99 %	X1 = Net Working Capital / Total Assets	52.21%
		X2 = EBIT / Total Assets	51.30%
		X3 = Earnings Before Taxes / Short Term	53.52%

		Liabilities	
		X4 = Sales / Total Assets	53.26%

Results of modelling provided in table 5 have shown us that removal of individual indicators of models doesn´t lead to significant improvement of their overall prediction accuracy. There are only small differences gained by provided calculations and mainly the removal has led to decrease of ability of the model to predict future bankrupt of the company.

These findings confirmed that there is a need to adjust bankruptcy prediction models to different economic environments. These contrasts cause the limited options to reuse models and related sets of indicators in other conditions. This is highly important also in the case of Slovak Republic. Our calculations have shown that the use of foreign models has led only to 50% prediction accuracy. Although these models are well known and were constructed in developed countries their applicability in developing countries, with the economic structure significantly different from the developed countries this fact is particularly substantial [5].

Our findings are in strong correlation with findings of other research studies confirming the need to develop specific models for different countries [3]. Additionally also new indicators, not only financial, should be included for forecasting in such surroundings [31].

This limitation was in some way eliminated by designation of a predictive model that can be easily adapted to any new situation, both in terms of model architecture and the indicators used [2].

5 Conclusion

In spite of numerous researches focusing on forecasting bankruptcy using not only traditional statistics techniques, but also artificial intelligence models, they are rarely used in practise. This is given mainly by the fact which was confirmed also in the presented study that the prediction ability of the model developed in specific conditions of individual country can´t be successfully applied in the conditions of other country or environment.

Therefore, we aim to analyse in some way old models on the dataset of Slovak companies to validate their prediction ability in specific conditions. Results have shown that the prediction accuracy of these models was about 50%, which is quiet low.

Furthermore, these models were modelled according to new trends by calculating the influence of elimination of selected variables on the overall prediction ability of these models. This modelling hadn´t led to significant improvement of the overall prediction accuracy of tested models. There were only small differences gained by provided calculations and mainly the removal had led to decrease of ability of the model to predict future bankrupt of the company.

Results obtained in the presented study have confirmed in some way conclusions of previously published researches. However, the issue of bankruptcy prediction is widely spread worldwide for many years and there have been developed numerous models, since nowadays there hasn´t been developed any generally accepted bankruptcy prediction model which can be generally applied regardless specific environment of individual countries.

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