THE POTENTIAL OF DYNAMIC INDICATOR IN DEVELOPMENT OF THE BANKRUPTCY PREDICTION MODELS: THE CASE OF CONSTRUCTION COMPANIES

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Abstract

KARAS MICHAL, REŽŇÁKOVÁ MÁRIA. 2017. The Potential of Dynamic Indicator in Development of the Bankruptcy Prediction Models: the Case of Construction Companies. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis,* 65(2): 641–652.

The current development of bankruptcy models usually goes in the direction of testing different classification algorithms, while the potential hidden in financial indicators is given less attention. Their analysis is often only restricted to the comparison between their respective statuses in bankrupt and healthy companies, while the dynamics of the indicators, i.e. the change in their values in time, is not paid much attention. The aim or our research is to analyse partial potential of financial ratios for predicting bankruptcy. Twenty-eight indicators were examined in a sample of 1,355 construction companies operating in the Czech Republic, as well as their development over the past five periods. A non-parametric chi-square test was used to evaluate the significance of predictors. The variables were categorised for the application of the test. Our research confirmed the assumption as to the importance of using the indicators in dynamic (change) form. Indicators that are significant only in their change form were identified. Moreover, the use of the dynamic form of the indicators can increase the significance of the bankruptcy model. This was tested by using the stepwise version of linear discrimination analysis.

Keywords: construction companies, bankruptcy prediction, financial ratio, dynamic indicators, linear discrimination analysis, model accuracy

INTRODUCTION

Early detection of the signals of bankruptcy in companies is one of the main motives leading to the creation of bankruptcy models, i.e. models on the basis of which it is possible to distinguish prosperous (financially sound) companies from companies threatened by bankruptcy. To assess the financial situation, financial ratios are normally used, and this is the reason why – in the construction of bankruptcy models – indicators contained in the financial statements are extensively exploited – especially financial ratios.

The scientific efforts of predicting corporate bankruptcy based on the analysis of financial ratios dated back to 1960's. Beaver (1966) and Altman (1968) were among the first authors who

had the idea of predicting bankruptcy only from financial indicators. They found that the signs of bankruptcy can be traced back for five years. Using a discrimination analysis, Altman (1968) created the first bankruptcy model. According to many authors Altman's model still represents an effective tool to predict bankruptcy (see Li, Ragozar, 2012, Satish, Janakiram, 2011, El Khoury, Al Beaïno, 2014).

It is not unusual to use know how of other authors and/or institutions, so we frequently come across the effort to use previously created models. However, this use is controversial, because the economic environment is changing and the ability of these models to recognise companies threatened by bankruptcy decreases with the passage of time. Another problem arises with

the use of the models in an environment other than that in which the model was created.

From a different point of view authors such as Platt and Platt (1990), Grice and Dugan (2001), Niemann et al (2008) and Wu, Gaunt and Gray (2010), have pointed out this problem and indicated that the predication accuracy of bankruptcy models (their ability to differentiate correctly between a company threatened by bankruptcy and a prospering company) falls markedly when they are applied to a different branch, period or economic environment than original environment.

These arguments motivate efforts to create new models. The need for new models is particularly evident for less traditional sectors in terms of a study on the prediction of bankruptcy. Most of the previously created models (Grice, Dugan, 2001) were derived from the data of manufacturing companies. Given that the values of financial ratios are industry-influenced, there is a need to construct bankruptcy models directly for individual fields of activities. This problem is noted, for example, by Thomas, Wong and Zhang (2011), who point out the need of creating models for branches such as construction, as the existing models are inappropriate for this branch.

According to Heo, Yang (2014), the specifics of construction companies show high values of liquidity ratios, high debt, and also the fact that the positive cash flow generated from contracts is concentrated only in their later stages. Sun, Liao, Li (2013) add some more specifics of this sector: *The construction industry is a capital-intensive industry that requires long-term project periods, huge investment, and takes a long time to receive returns from the investment. Therefore, it has a different capital structure from other industries, **and the same criteria used for other industries cannot be applied to effectively evaluate its financial risk*** (Sun, Liao, Li, 2013 in: Heo, Yang, 2014). The said opinion is also confirmed by another study (Barrie, Paulson, 1992 in: H. P. Tserng *et al.*, 2014), as follows: *"due to the distinctive operational behaviours of the construction industry, **its financial characteristics also differ from other industries***". Prediction of bankruptcy specifically for construction companies from the Czech Republic is dealt with, for example, by Kuběnka, Králová (2013) and Špička (2013). Špička (2013) states that the typical manifestation of bankruptcy of construction companies in the Czech Republic is high indebtedness, especially in the short term, as well as low labour productivity and negative return on assets.

The research on bankruptcy prediction models could be divided into two lines:

1) Testing various methods that can improve the prediction accuracy of models.

Historically, various algorithms have been employed to devise models of bankruptcy. The first was the linear discrimination analysis (LDA) method (Altman, 1968), developed by Fisher (1936). In reaction to its shortcomings, other algorithms were applied.

2) Identifying suitable variables of a model (so called predictors).

The first models (Altman, 1968; Ohlson, 1980; Zmijewski, 1984, and others) were designed on the basis of financial ratios calculated using company data one year prior bankruptcy ($t + 1$ period). The models so designed included only those indicators (predictors) whose bankruptcy-predicting ability had been established for a single interval only, specifically one year before the bankruptcy. Deakin (1972) found that the ranking of predictor significance changes with the receding time. Deakin's conclusion was confirmed by the work of Grice and Dugan (2001). Shumway (2001) criticises the earlier bankruptcy models (of Altman, Zmijewski and Ohlson) as static since the time factor is ignored. These issue were also considered by Henerby (1996) who, aided by the Cox's model (see Cox, 1972), analysed the appropriateness of cash flow-based indicators for predicting bankruptcy, and concluded that these indicators are statistically most significant 3 years before the event and can therefore serve as early indicators. **The said works are the evidence that the information relevant for predicting bankruptcy can be drawn also from the data preceding the bankruptcy for more than one year.** Niemann *et al.* (2008) point out that the adjustment of indicator for them to contain the information for more than one period (the so-called multi-period transformation) may represent the potential for further development of the models. Niemann *et al.* (2008) works with the multi-period transformation in four directions, either as:

a) the average (for 2, 3 or 5 periods),

b) the trend (for 3 or 5 periods), which is defined as *"the average absolute change in a factor's values"*

c) volatility – in terms of the value of the standard deviation of the indicator for 5 periods,

d) *"ever-negative"* – a dichotomous indicator, which takes value 1 if the given indicator (e. g. EBIT) is negative over multiple periods; in other cases it becomes 0.

MATERIALS AND METHODS

The construction of bankruptcy models usually starts with finding a limited number of statistically significant differences (indicators) among active companies and companies in financial distress, i.e. among bankrupt companies. Indicators so found are then used to predict the situation, in which the latter of the surveyed companies occurred (financial distress, bankruptcy).

When constructing models, a set of possible variables is reduced to a subset with the most informative value; i.e. there is an effort to eliminate

redundant variables. Such an approach is known in the literature as the creation of the reduced form of the model, and represents the most common approach to the creation of the model that was used, for example, in the studies (Lin, Liang, Chen, 2011; Wang, Lee, 2008; Niemann et al, 2008; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009; Cheng, Chen, Fu, 2006).

Literature study identified two approaches to reduce the variables or to identify the variables with sufficient information ability, namely:

e) **Based on the frequency at which the relevant indicator appears in the literature**

Those indicators are selected, which – according to the prevailing opinion in the literature – best describe the relevant area of the company economy (profitability, liquidity, etc.). This approach can be problematic, because: *"…reliance on these financial ratios can be problematic. The order of their importance, for example, remains unclear as different studies suggest different ratios as the major indicators of potential financial problems."* (Lin, Liang, Chen, 2011).

f) **According to the degree of statistically significant influence**

The model includes only variables with a sufficient informative value. First, several to several dozens of candidates are identified for the explanatory variable, and then their statistical dependence is examined towards the explained variable, i. e. the occurrence of bankruptcy.

The model should be made only from relevant variables, i.e. those whose inclusion in the model increases its predictive ability. The number of variables is undergoing optimisation, when the criterion is their contribution to the informative ability of the model.

The aim of our research is to analyse the ability of alternatively defined financial ratios to distinguish active (financial healthy, non-defaulted companies) and bankrupt (defaulted) companies in the construction branch. As already mentioned, financial ratios based on accounting data (usually on manufacturing companies) are used to construct bankruptcy models. Given that the threat of bankruptcy to a company is the result of a long-term process, the question arises whether it is possible to enhance the distinguishing ability of the bankruptcy model by using indicators that will monitor the development of the company in time. Specifically, we will analyse whether the monitoring of a change of the indicator value in time can increase its statistical significance. Analysed will be indicators, which are already significant for predicting bankruptcy, but also indicators that are not significant. Unlike in publications of Niemann *et al.* (2008), we do not analyse the significance of the new multi-period indicator for predicting bankruptcy, but the significance of the change of the definition of the current indicator, which we

compare with its initial form. For research purposes, the following hypothesis was determined:

The overall significance of the model is higher when the change form ratios are included.

The increase in the overall significance of the model will be analysed by means of a stepwise discrimination analysis (or rather the forward selection) by which the model is built in the following stepwise manner. The procedure starts by finding the most significant indicator, then only an indicator that leads to higher overall model significance can be entered into the model.

Sample and method used

The data were obtained from AMADEUS (Analysis Major Database for European Sources). The bankrupt companies in our sample declared bankruptcy during years 2011 and 2014. The field examined is construction (NACE: F Construction). The sample included only small- and medium-sized companies operating in this field with the value of assets ranging between 2 and 50 million EUR in at least one of the analysed periods. These criteria were accommodated by 1257 active companies and 98 companies in bankruptcy, which made up the original sample. We analyse a set of 28 financial ratios covering several aspects of company's financial health.

Investigated ratios

These ratios are often used in studies on bankruptcy prediction problems (see Tian et al, 2015, Gordini, 2014, Laitinen et al, 2014, Carling et al, 2007, Karas, Režňáková, 2013a, Beaver, 1966, Altman, 1968, Deakin, 1972, Ohlson, 1980, Ding *et al.*, 2008, Lin, Liang, Chen, 2011, Wang, Lee, 2008, Niemann *et al.* 2008, Beaver, 2005, Tseng, Hu, 2010, Psillaki, Tsolas, Margaritis, 2009).

I: *The list of investigated ratios*

Ratio	Abbreviation	Ratio	Abbreviation
Current ratio	CR	Sales/Stocks	S/St.
Working capital/total assets	WC/TA	Sales/Debtors	S/Deb.
Working capital/sales	WC/S	Quick assets/sales	QA/S
EBIT/total assets	EBIT/TA	Current liabilities/total assets	CL/TA
EBITDA/total assets	EBITDA/TA	Long-term liabilities/total assets	LTL/TA
EAT/equity	ROE	Debt-equity ratio	DER
Cash flow/total assets	CF/TA	EBIT/Interest	EBIT/Int.
Cash flow/sales	CF/S	EBITDA/Interest	EBITDA/Int.
Cash flow/total liabilities	CF/TL	logarithm of total assets	LogTA
EAT/total assets	EAT/TA	logarithm of sales	LogS
EBIT/Sales	EBIT/S	Fixed assets/total assets	FA/TA
EBITDA/Sales	EBITDA/S	Sales/Operating revenue	S/OR
Retained Earnings/total assets	RE/TA	Added Value/Sales	AD/S
Sales/total assets	S/TA	Cost of employees	CE/S

Source: Tian *et al.*, 2015, Gordini, 2014, Laitinen *et al.*, 2014, Carling *et al.*, 2007, Karas, Režňáková, 2013a, Beaver, 1966, Altman, 1968, Deakin, 1972, Ohlson, 1980, Ding *et al.*, 2008, Lin, Liang, Chen, 2011, Wang, Lee, 2008, Niemann *et al.*, 2008, Beaver, 2005, Tseng, Hu, 2010, Psillaki, Tsolas, Margaritis, 2009

Method to test the significance of indicators

Preselection is needed as the number of analysed indicators is high (140 indicators). First we checked the correlation between the pair of indicators in course of elimination of the high correlated ones. Then we eliminated non-significant indicators. This was done by using a non-parametric chi-square test of independence. Since the analysed variables are continuous, they had to be categorised for the purposes of applying this test. Specifically, the intervals of values of analysed variables were divided into 10 categories. Finally, the stepwise discrimination analysis was applied. Now about the properties of the data examined: the following table contains descriptive statistics of selected ratios of the sample of active or passive companies.

Another view of the characteristics of the data is offered, for example, by the following mean plot of the EBIT/TA ratio, from which the number of outliers is obvious particularly on the sample of bankrupt companies.

II: *Descriptive statistics of active companies*

	Mean	Grubb's Test Statistics	p–value	Median	Min.	Max.	Std. Dev.
CR 1	29.436	31.81097	0.000000	1.511528	−4.1	19870.9	623.730
WC/TA 1	0.2039	9.37447	0.000000	0.209651	−3.4	1.0	0.382
WC/S 1	14.221	28.43408	0.000000	0.191961	−54373.3	114273.0	4,018.374
EBIT/TA 1	0.0357	13.31152	0.000000	0.023617	−1.4	0.7	0.108

Source: Our own analysis of data from the Amadeus database

III: *Descriptive statistics of bankrupt companies*

	Mean	Grubb's Test Statistics	p–value	Median	Min.	Max.	Std. Dev.
CR 1	0.794	2.534407	0.946937	0.86327	0.00	1.98506	0.4699
WC/TA 1	−107.57	9.525899	0.000000	−0.11990	−9,420.00	0.48081	977.590
WC/S 1	−22.320	6.780449	0.000000	−0.03511	−729.80	57.76667	104.341
EBIT/TA 1	−0.367	6.583517	0.000000	−0.001397	−8.50	0.49688	1.2354

Source: Our own analysis of data from the Amadeus database
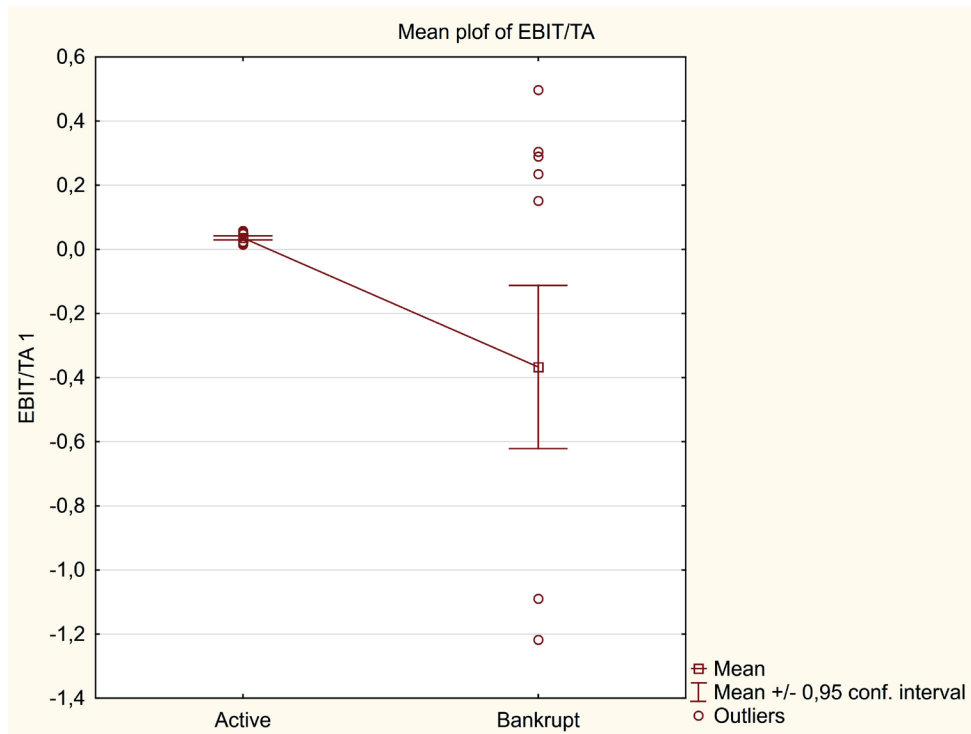
1: *Mean plot of EBIT/TA 1*
Source: Our own analysis of data from the Amadeus database

The applied chi-square test of independence tests the null hypothesis that the two qualitative features are independent. Tests statistics, for the contingency table of *r* rows and *s* columns, can be written in the following form (see Hindls, Hronová, Novák, 2000):

$$G = \sum_{i=1}^{r} \sum_{j=1}^{s} \frac{\left(n_{ij} - \psi_{ij}\right)^2}{\psi_{ij}}$$

where
n_{ij} are associated frequencies, ψ_{ij} – *are hypothetical associated frequencies,*
wherein *i = 1,2,…,r, and j = 1,2,…,s, respectively.*
Under the null hypothesis, test statistics χ^2 has a distribution with $(r-1)\cdot(s-1)$ degrees of freedom.

So far the significance of the indicators has been verified using a one-dimensional approach, namely the chi-square test. However, it could be argued that the significance of the indicator could differ when evaluated complexly, i.e. when the variables are incorporated into a model. For this purpose we used the method of linear discrimination analysis (LDA) which is the most frequently used algorithm (Aziz, Dar, 2006). Stepwise discrimination analysis can also be used to find suitable bankruptcy predictors with only those predictors that possess sufficient discriminating power being included in the model (see Back *et al.*, 1996; Hung, Chen, 2009).

The objective of the LDA method is, according to (Hebák *et al.*, 2004), *"to find a **linear** combination of p monitored predictors, i.e. Y = bTx, where b^T = [b₁, b₂,…, bₚ] 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 LDA method produces a discriminatory rule (function) which according to calculated predictors assigns each company to a group of enterprises either threatened or not threatened by bankruptcy.

Discriminant analysis works with the assumption of multivariate normal distribution of data.

The density of probability of multivariate normal distribution of a variable *x* can be written as follows (Hastie, 2009, p. 108]:

$$f_k(x) = \frac{1}{(2p)^{p/2} |S_k|^{1/2}} \exp\left[-\frac{1}{2}\left(x - m_k\right)^T S_k^{-1}\left(x - m_k\right)\right]$$

where
x is the vector of independent predictors, where
$\quad x = (x_1, x_2, …, x_p)$,
μ_k is the vector of middle values of the quantity *x k*-th group,
Σ_k is the covariance matrix of the *k*-th group.

Linear discriminant analysis (LDA) is a special kind of discriminant analysis which adds the assumption of identical covariance matrices (Σ_k). Under these assumptions, the discriminant rule, based on the Mahalanobis distance, can be written as follows (Hebák *et al.*, 2004):

$$x^T \Sigma^{-1}(\mu_1 - \mu_2) > 1/2(\mu_1 + \mu_2)^T \Sigma^{-1}(\mu_1 - \mu_2)$$

$$\rightarrow \text{group 1 (e.g. active)}$$

$$x^T \Sigma^{-1}(\mu_1 - \mu_2) < 1/2(\mu_1 + \mu_2)^T \Sigma^{-1}(\mu_1 - \mu_2)$$

$$\rightarrow \text{group 2 (e.g. bankrupt)}$$

where

π_1 or π_2 is a priori the probability of units belonging to the group corresponding to the range group 1 or 2.

The method of defining changes

For the purpose of our research, we divided the indicators analysed into two groups: namely to the static (basic form) ratios and change ratios.

Basic form ratios show the status of the ratio over a certain time; for bankrupt companies, it is one period prior to bankruptcy. It generally applies to one period preceding the last known period (time t + 1, where t – is the last known period.

We defined *change ratios* in terms of the modified base index, when we investigate the potential of the ratios in terms of their change compared to the selected previous value. The change ratio can be described as follows:

$$\frac{X(t+1)}{X(t+1+i)}, \text{wherein } i = 1, 2, 3, 4,$$

wherein X (t + 1) is a basic form ratio defined for time t + 1, i – the number of previous periods, X (t + 1 + i) is a basic form ratio defined by more distant times from the last known year, i.e. for times t + 2, t + 3, t + 4 and t + 5.

RESULTS

To distinguish static and change ratios, we use numerical abbreviations of the moments to which they relate. For example, the basic form of ratio S/TA is designated S/TA 1, which means that this is a value of the ratio defined for the moment of one year before bankruptcy (time t + 1), or more generally, for one; the form S/TA 1/2 means that this is a change ratio defined as ratio S/TA 1 (for time t + 1) and S/TA 2 (for time t + 2), i. e. the index of the indicator development. The basic form ratios that are statistically significant at least at 5 % level are shown in the Tab. IV.

The change form ratios that are statistically significant at least at 5 % level are shown in the Tab. V.

Creating a multidimensional model

For the purpose of verifying the research hypothesis, we used the stepwise version of the LDA method, specifically forward selection. The probability to enter the model was set at the 5 % level of the F-test. Before application of the method, it is necessary to analyse the correlation between the indicators, as a strong positive correlation could be harmful to the model. For this purpose, we used the Spearman's correlation coefficient. Values of the correlation coefficient higher than 0.9 were identified between three variables measuring the return on assets – EBIT/TA, EBITDA/TA and EAT/TA. The details are listed in the Tab. VI.

IV: *Results of ratio analysis – basic form ratios*

Ratio	Chi²	p-value	Ratio	Chi²	p-value
S/TA 1**	49.5952	0.000000	CF/TA 1**	16.8217	0.000041
CL/TL 1**	22.8863	0.001784	EBIT/TA 1**	13.1605	0.000286
CL/TA 1**	26.3411	0.000000	ROE 1**	12.9256	0.000324
WC/TA 1**	13.1605	0.000286	FA/TA 1**	98.7253	0.000000
EAT/TA 1**	211.214	0.000000	S/OR 1**	14.3458	0.013556
EBITDA/TA 1**	16.8217	0.000041	logS 1**	107.282	0.000000
RE/TA 1**	13.1605	0.000286	logTA 1**	54.7209	0.000000

Source: Our own analysis of data from the Amadeus database.
Note: *statistically significant at 5 % level, **statistically significant at 1 % level.

V: *Results of ratio analysis – change form ratios*

Ratio	1/y	Chi-square	p-value	Ratio	1/y	Chi-square	p-value
QA/S	1/3**	22.1895	0.000184	CL/TA 1/3	1/3*	12.2045	0.015893
	1/4*	12.002	0.017336		1/2**	28.217	0.000435
S/St.	1/5*	11.2594	0.046472	AD/S	1/4**	23.073	0.000002
CF/TL	1/5*	12.4277	0.014439		1/5**	17.489	0.007644
EBIT/Int.	1/3**	16.9321	0.000039	EBITDA/S	1/2**	17.763	0.000025
	1/4**	18.2014	0.000112		1/4**	22.924	0.000002
	1/5**	20.0281	0.000008	EBITDA/TA	1/2**	18.351	0.000018
EBITDA/Int.	1/2**	18.3833	0.000018		1/4**	14.518	0.000139
	1/3**	21.3424	0.000004	CF/TA	1/4**	23.936	0.000006
	1/4**	23.6057	0.000001		1/5**	24.290	0.000191
	1/5**	26.8246	0.000000	RE/TA	1/3**	34.522	0.000001
EBITDA/TA	1/4**	47.9562	0.000000	S/OR	1/3**	16.882	0.009729
WC/S	1/4**	15.6397	0.000077	EBIT/TA	1/3**	14.518	0.000139
	1/5**	17.8121	0.000481	S/OR	1/3**	16.882	0.009729
WC/TA	1/3**	14.0358	0.000179	logS	1/2**	21.965	0.008990
	1/4**	72.6676	0.000000		1/3**	63.202	0.000000
	1/5**	35.8812	0.000000		1/4**	52.605	0.000000
EAT/TA	1/2**	17.495	0.007627		1/5**	55.807	0.000000
	1/3**	14.586	0.000680	logTA	1/2**	26.883	0.000001
	1/4**	15.164	0.000099		1/3**	155.544	0.000000
	1/5**	17.112	0.000035		1/4**	125.430	0.000000
					1/5**	66.862	0.000000

Source: Our own analysis of data from the Amadeus database.
Note: *statistically significant at 5 % level, **statistically significant at 1 % level.

VI: *Results of correlation analysis*

The pair of indicators	No.	Spearman (R)	t(N-2)	p-value
EBIT/TA 1 & EBITDA/TA 1**	1104	0.935233	87.69311	0.000000
EBIT/TA 1 & EAT/TA 1**	1316	0.909407	79.26085	0.000000
EBITDA/TA 1 & EAT/TA 1**	1104	0.860737	56.13085	0.000000

VII: *Results of ratio analysis – LDA results*

	Wilk's Lambda	Partial Lambda	F-value to remove	p-value	Toler.	1-toler. (R^2)
logTA 1**	0.712505	0.915356	86.36758	0.000000	0.762280	0.237720
CL/TA 1**	0.676670	0.963831	35.04918	0.000000	0.105625	0.894375
EAT/TA 1**	0.687827	0.948198	51.02668	0.000000	0.282070	0.717930
S/OR 1**	0.666270	0.978876	20.15570	0.000008	0.828554	0.171446
RE/TA 1**	0.660889	0.986846	12.44931	0.000439	0.220531	0.779469
logTA 1/2**	0.658600	0.990276	9.17187	0.002525	0.457497	0.542503
WC/TA 1/5*	0.655900	0.994353	5.30453	0.021489	0.848726	0.151274
WC/TA 1/4**	0.659147	0.989453	9.95549	0.001655	0.829131	0.170869
logS 1**	0.659678	0.988657	10.71562	0.001101	0.622161	0.377839
WC/TA 1*	0.655969	0.994247	5.40429	0.020301	0.129751	0.870250
logS 1/5*	0.655582	0.994835	4.84881	0.027909	0.888692	0.111308
logTA 1/4**	0.656903	0.992834	6.74150	0.009568	0.482147	0.517853
S/OR 1/3	0.653992	0.997254	2.57199	0.109109	0.870253	0.129747
logTA 1/3	0.653043	0.998702	1.21362	0.270900	0.366033	0.633967
EAT/TA 1/2	0.652966	0.998820	1.10328	0.293819	0.983129	0.016871

Source: Source: Our own analysis of data from the Amadeus database. **Note:** *statistically significant at 5 % level, **statistically significant at 1 % level.

The correlation between all the three pairs of the mentioned indicator are statistically significant at the 1 % level. The information carried by these indicators is very similar, for which reason it suffices to use just one of them. We chose EAT/TA as it is the most significant predictor (by the chi-square test) of these three given predictors. Now to the results of the application of the LDA method.

The LDA method enables us to evaluate the overall significance of the whole model and the significance of each indicator involved. The Wilk's lambda of the whole model is 0.6522, which can be transformed into an F-distribution with corresponding F-statistics of 33.206 for which the p-value of lower than 0.0000. The significance of the each of the indicators is summarised in the Tab. VII.

The resultant model incorporates 15 indicators, 12 of which are statistically significant at least at the 5 % level.

The most significant indicator of the model is the logarithm of total assets in the basic form (i.e. LogTA 1), however the change form of the indicator is also statistically significant in the model (namely Log TA 1/2 or 1/4). Other company size factors are also included in the model, for example the logarithm of sales, again both in the basic (LogS 1) and change (LogS 1/5) form.

The second most significant indicator in the model is the return on assets in the basic form (EAT/TA 1). The change form of the indicator (EAT/TA 1/2) was also included in the model, though it is not statistically significant.

The third most significant indicator is short-term indebtedness in its static form (CL/TA 1), and although the change form of this indicator (CL/TA 1/3) was significant (in terms of the chi-square test) it was not included in the model. The same situation appears in the case of another significant indicator, namely the relative size of retained earnings (RE/TA). In the case of the ratios of sales and operating revenue (S/OR), the change form was included in the model (S/OR 1/3), although it is not significant.

The last indicator that was included in the model is the relative size of net working capital which is significant both in its static form (WC/TA 1) and change form (WC/TA 1/4 or 1/5).

DISCUSSION

In this part of the paper, attention will be paid to the discussion of the variable choice in the light of the results of the previous pieces of research, as well as to discussion of the research hypothesis verification.

The return on assets is generally considered a strong predictor of bankruptcy – whether in its basic form (Altman, 1968, Li, Sun, 2009, Psillaki, Tsolas, Margaritis, 2009), or when respecting the factor of time (Shumway, 2001). Specifically for the bankrupt construction companies in the Czech Republic, negative return on assets (EBIT/TA) is

typical according to Špička (2013). This is consistent with our results, however in our research we used return on assets based on EAT not on EBIT, as both variants of indicators were highly correlated and the return on assets based on the EAT was slightly more significant in terms of the chi-square test.

The declining performance of a company and a drop in its value, which can lead to bankruptcy of the company, is often associated with high indebtedness of the company (see Chandrapala, Knápková, 2013). In our research, the total indebtedness did not show as a significant predictor, but ratios evaluating short-term indebtedness (CL/TA 1) on the other hand, did manifest itself as one of the most important predictors of bankruptcy. This is in line with the findings of Špička (2013) who concluded that typical bankruptcy manifestations in construction companies in the Czech Republic included high indebtedness due in particular to current liabilities. The change forms of the CL/TA indicator, however, are not significant. The CL/TA was also included in the model. We can assume the bankruptcy of construction companies is connected with the growth of short-term debts. It is rather surprising that the ratios evaluating interest coverage (EBIT/Int. 1 or EBITDA/Int. 1), which is generally considered a significant predictor of bankruptcy (see, for example, Neumaier, Neumaierová, 2005), are not significant in their basic forms, but only in their change forms (all except EBIT/Int. 1/2). Interest coverage ratios often reach high values for profitable and low-indebted companies; where the level of indebtedness is stable and the profit develops in a relatively stable manner, the indicator may also show stable development. However, in a declining company it can be assumed that there will be an increase in paid interest and a decline in profit, both of which will cause the decline of the values of interest coverage. This trend reflects change indicators in a better way than the basic form ratio. The low significance of interest coverage indicators for distinguishing prosperous companies and companies at risk of bankruptcy can be explained by the change in credit financing: companies threatened by bankruptcy cannot use loan financing and do not, therefore, pay interest. This may cause the interest coverage indicators to take similar values in companies threatened by bankruptcy as in thriving companies.

Another example of a usually employed bankruptcy predictor is the indicator of assets turnover (S/TA). This indicator was first used by Altman (1968) and is still used as a significant predictor even by the current models designed for different environments (see Wu, 2010; Wang, Ma, 2011; Sánchez-Lasheras *et al.*, 2012). It indicates that bankrupt companies are unable to effectively use their assets to achieve sales. In our research, the turnover of total assets is significant in its basic form; surprisingly this indicator was not included in the model. What's more, the ratios of turnover of working capital items, specifically inventories

and debts (S/St. and S/Debt.), were not significant either (with the exception of S/St. 1/5 which was not included in the model). This could be explained by the length of construction projects and their seasonal nature. In addition, contracts are usually backed up and purchased inventory immediately used.

The importance of working capital in bankruptcy prediction problems has been confirmed by many papers (Beaver, 1966; Altman, 1968; Ding *et al.*, 2008; Wu, Gaunt, Grey, 2010). The results of our study also confirm the importance of this indicator. The indicator is significant especially in the form of the ratio of the working capital and total assets (WC/TA), which is significant both in its basic and change form (as WC/TA 1 or 1/4 or 1/5). It suggests the thesis that a construction company at risk is unable to adapt the changes of the working capital to the changes in total assets. The ratio WC/TA can be understood as the relative size of the working capital, which is significantly different in bankrupt companies and in active companies; also the development of this value is different. The above also suggests the inability of the declining companies to control cash flow, which is reflected in the marked increase of short-term liabilities and in the negative working capital. The company could deal with this situation only by a substantial change in the operating funding. This conclusion is consistent with findings of other authors (Stehlikova 2013; Svobodova 2013 in: Špička, 2013), who consider, inter alia, "*financial inflexibility in response to the decline in sales*" as a frequent source of bankruptcies of construction companies.

We can assume that companies at risk of bankruptcy try to replenish cash by selling assets which results in the declining value of total assets. This assumption is confirmed also by the significance of the company size indicator (log TA) as a predictor of bankruptcy when monitoring the change already four years before bankruptcy. This indicator was included in the model. The importance of the company's size in predicting bankruptcy is highlighted by the fact that alternative company size factors are also included in the model; namely the logarithm of sales, again both in the basic (LogS 1) and change form (LogS 1/5). The importance of company size, where bigger companies are evaluated as not threatened by bankruptcy, has been confirmed by previous research (see, for example, Shumway, 2001; Wu, Gaunt, Gray, 2010). This assumption is generally associated with larger companies which are perceived by their surroundings as a more stable business partner.

The factor of sales was further analysed in the form of the structure of revenues (Sales to Operating Revenues, S/OR). The indicator operating revenues represents sales of goods, services and production, increased by revenues from the sale of assets. As already mentioned, it can be assumed that companies at risk of bankruptcy will sell off their assets (fixed assets, stocks of material), so the structure of the operating sales in the observed groups of companies will be different. Our assumption was confirmed, i.e. the ratio of the composition of revenues is also a significant indicator in the form S/OR 1 which means that companies decline have a different proportion of sales from the sale of assets.

The results of one-dimensional testing (by using the chi-square test) showed that even an indicator that is not significant in its basic form could be significant in its change form.

In the case of construction companies, such indicators are: the ratio of quick assets to sales (QA/S 1/3 and QA/S 1/4), working capital to sales (WC/S 1/4 and WC/S 1/5), added value to sales (ADS/S 1/2, ADS/S 1/4 and ADS/S 1/5), EBIT to interest (EBIT/Int. 1/3, EBIT/Int. 1/4 and EBIT/Int. 1/5), EBITDA to interest (EBITDA/Int. 1/2, EBITDA/Int. 1/3, EBITDA/Int. 1/4 and EBITDA/Int. 1/5) and EBITDA to sales (EBITDA/S 1/2 and EBITDA/S 1/4). An increase in the discrimination ability of the bankruptcy prediction model could be achieved by including such indicators in the model. This assumption was further analysed. We used the stepwise version of the LDA method to verify this presumption; the results are summarised in Tab. VII.

The hypothesis of the presented research was: *The overall significance of the model is higher when change form ratios are included.* A model was created for the purpose of verification of this hypotheses. This model was created in stepwise manner, specifically by the forward selection procedure, where only indicators that are able to enhance the overall significance of the model (or rather the discrimination ability of the model) are incorporated into the model. The results showed that 5 of 12 indicators that are statistically significant in the created model are in their change form. As the model was created by a forward selection method, this means that these indicators represent a contribution to overall model significance. This contribution is most obvious in case of the logTA and WC/TA indicators. These two indicators are more significant in their change form (namely logTA 1/2 and WC/TA 1/5, WC/TA 1/4) than in the basic form of the logarithm of sales (logS 1) indicator and the working capital to total assets (WC/TA 1). One of the indicators is more significant in its change form in comparison to its basic form – this is the ratio of the working capital and total assets (WC/TA 1/5, WC/TA 1/4).

As change indicators were included in the model and are statistically significant in the model, we can say that the hypothesis of this research was confirmed.

CONCLUSION

The aim of the article was to analyse a partial potential of financial indicators of the construction industry for predicting bankruptcy. The usual approach to examining the significance of the ratios for prediction of bankruptcy is often limited to comparisons of the status between the sample of bankrupt and active companies. The limitation of this approach is that it does not take into account previous development of the company and – consequently – of the financial ratios. But bankruptcy is not a state in which the company appears suddenly; bankruptcy is preceded by a certain negative development for several periods. The importance of taking into account past information is highlighted by Niemann *et al.* (2008), who examined the significance of indicators covering more periods by their definition. In the research presented herein, we took a slightly different way. The main question for this research was to determine whether taking the past development into account may increase the significance of the predictors and created model. If the distinguishing ability increases of the indicator, which is already included in the model, we can raise the information already contained in the model to a higher power. If the accuracy increases of the indicator, which originally was not significant, it is possible to introduce a new piece of information into the model that might otherwise be overlooked. The more significant information can be incorporated into the model, the higher its potential accuracy.

The hypothesis whether the statistical significance of the indicator can be increased by monitoring its development in time was verified. For monitoring the development in time, modified basic indexes of the indicators were used for the period of five years before bankruptcy. A chi-square test and a linear discrimination analysis were used for testing.

The results of one-dimensional testing (by using the chi-square test) showed that even the indicator that are not significant in their basic form, could be significant in their change form.

Such indicators are, for example, the ratio of quick assets to sales, working capital to sales, added value to sales, EBIT to interest, EBITDA to interest and EBITDA to sales.

There is a chance that it is possible to enhance the discrimination ability of the bankruptcy prediction model by including these indicators in the model. This assumption has been further verified by using of the stepwise version of the LDA method, forward selection. The LDA method makes it possible to evaluate the overall significance of the whole model and the significance of each indicator involved. The application of the mentioned method led to the creation of a model of 15 indicators of which 8 were in the change form. The basic form indicators represent the most significant variables of the created model (namely logarithm of total assets and the ratios of current liabilities to total assets, EAT to total assets, the structure of sales and retained earnings to total assets). It is possible to enhance the overall significance of the model by incorporating the change form indicators. Specifically, by incorporating the following indicators: the change of logarithm of total assets (logTA 1/2) and change of ratio of working capital and total assets (WC/TA 1/5, WC/TA 1/4).

REFERENCES

ALTMAN, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance,* 23(4): 589–609.

AZIZ, M. and DAR, H. 2006. Predicting corporate bankruptcy: where we stand? *Corporate Governance,* 6(1): 18–33.

BACK, B., LAITINEN, T. and SERE, K. 1966. Neural networks and genetic algorithms for bankruptcy predictions. *Expert systems with applications*, 11(4): 407–413.

BARRIE, D. S. and PAULSON, B. C. 1992. *Professional construction management: including CM, design-construct, and general contracting.* 3rd edition. Hightstown: McGraw-Hill.

BEAVER, W. H. 1966. Financial ratios as predictors of failure. *Journal of accounting research. Empirical research in accounting: selected studies*, 4(1): 71–111.

BEAVER, W. H., MCNICHOLS, M. F. and RHIE, J. W. 2005. Have financial statements become less Informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting studies*, 10(1): 93–122.

COX, D. R. 1972. Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2): 187–220.

DEAKIN, E. B. 1972. A discriminant analysis of predictors of business failure. *Journal of accounting research*, 10(1): 167–179.

DING, Y., SONG, X. and ZEN, Y. 2008. Forecasting financial condition of Chinese listed companies based on support vector machine. *Expert systems with application,* 34(4): 3081–3089.

EL KHOURY, R. and AL BEAÏNO, R. 2014. Classifying manufacturing firms in Lebanon: An application of Altman's model. *Procedia – social and behavioral sciences,* 109(8): 11–18.

FISHER, R. A. 1936. The use of multiple measurements in taxonomic problems. *Annals of human genetics*, 7(2): 179–188.

GORDINI, N. 2014. A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. *Expert systems with applications*, 41(14): 6433–6445.

GRICE, J. S. and DUGAN, M. T. 2001. The limitations of bankruptcy prediction models: Some cautions for the researchers. *Review of quantitative finance and accounting*, 17(2): 151–166.

HASTIE, T., TIBSHIRANI, R. and FRIEDMAN. J. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2nd ed. Springer.

HEO, J. and YANG, J. Y. 2014. AdaBoost based bankruptcy forecasting of Korean construction companies. *Applied soft computing*, 24(1): 494–499.

HENERBY, K. L. 1996. Do cash flows variables improve the prediction accuracy of a Cox proportional hazards model for bank failure? *The quarterly review of economics and finance*, 36(3): 395–409.

HINDLS, R., HRONOVÁ, and S., NOVÁK, I. 2000. *The Methods of Statistical Analysis for the Economists* [in Czech: *Metody statistické analýzy pro ekonomy*]. 2nd edition. Praha: Management Press

HEBÁK, P., HUSTOPECKÝ, J. JAROŠOVÁ, E. and PECÁKOVÁ, I. 2004. *Multivariate Statistical Methods* [in Czech: *Vícerozměrné statistické metody*]. Praha: Informatorium.

HUNG, C. and CHEN, J. H. 2009. A selective ensemble based on expected probabilities for bankruptcy prediction. *Expert systems with applications*, 36(3): 5297–5303.

CHANDRAPALA, P. and KNÁPKOVÁ, A. 2013. Firm-specific factors and financial performance of firms in the Czech Republic. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, 61(7): 2183–2190

CHENG, C. B., CHEN, C., L. and FU, C. J. 2006. Financial distress prediction by a radial basis function network with logit analysis learning. *Computers and mathematics with applications*, 51(3–4): 579–588.

KARAS, M. and REŽŇÁKOVÁ, M. 2013a. Bankruptcy prediction model of industrial enterprises in the Czech Republic. *International journal of mathematical models and methods in applied sciences*, 7(5): 519–531.

KARAS, M.; REŽŇÁKOVÁ, M. 2013b. Identification of financial signs of bankruptcy: A case of industrial enterprises in the Czech Republic. In: *Proceedings of the 6th International Scientific Conference: Finance and the performance of firms in science, education, and practise*. Zlín: Tomas Bata University, 324–335.

KIM, M. J., and KANG, D. K. 2010. Ensemble with neural networks for bankruptcy prediction. *Expert systems with applications*, 37(4): 3373–3379.

KUBĚNKA, M. and KRÁLOVÁ, V. 2013. Use of Z" score in evaluating the financial health of the construction sector. [in Czech: Využití Z" score při hodnocení finančního zdraví odvětví stavebnictví]. *E + M Ekonomie a Management*, 16(1): 101– 112.

LAITINEN, E. K., LUKASON, O. and SUVAS, A. 2014. Behaviour of Financial Ratios in Firm Failure Process: An International Comparison. *International journal of finance and accounting*, 3(2): 122–131.

LI, J. and RAGOZAR, R. 2012. Application of the Z-Score model with consideration of total assets volatility in predicting corporate financial failures from 2000–2010. *Journal of accounting and finance*, 12(2): 11–19.

LI, H., and SUN, J. 2009. Predicting financial failure using multiple case-based reasoning combine with support vector machine. *Expert systems with applications*, 36(6): 10085–10096.

LIN, F., LIANG, D. and CHEN, E. 2011. Financial ratio selection for business crisis prediction. *Expert systems with applications*, 38(12): 15094–15102.

NEUMAIEROVA, I., and NEUMAIER, I. 2005. Index IN05. In: *Sborník příspěvků mezinárodní vědecké konference „Evropské finanční systémy"*. Brno, 21.–23. 6. 2004. Brno: Ekonomicko-správní fakulta Masarykovy university v Brně, 143–148.

NIEMANN, M., SCHMIDT, J. H., and NEUKIRCHEN, M. 2008. Improving performance of corporate rating prediction models by reducing financial ratio heterogeneity. *Journal of banking and finance*, 32(3): 434–446.

OHLSON, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 18(1): 109–131.

PLATT, D. H. and PLATT, M. B. 1990. Development of a class of stable predictive variables: the case of bankruptcy prediction. *Journal of Business Finance and Accounting*, 17(1): 31–51.

PSILLAKI, M., TSOLAS, I. T. and MARGARITIS, M. 2010. Evaluation of credit risk based on firm performance. *European journal of operational research*, 201(3): 873–881.

SATISH, Y. M. and JANAKIRAM, B. 2011. Turnaround strategy using Altman model as a tool in solar water heater industry in Karnataka. *International journal of business and management*, 6(1): 199–206.

SHUMWAY, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. *Journal of business*, 74(1): 101–24.

STEHLIKOVA, A. 2013. Development of insolvency proposals in 2008–2012 in the context of macroeconomic indicators of The Czech Republic. In: *Proceedings of the international scientific conference Insolvency 2013 – The end of one phase, beginning of another one?* Prague: Czech National Bank, 103–112.

SUN, J., LIAO, B. and LI, H. 2013. AdaBoost and bagging ensemble approaches with neural network as base learner for financial distress prediction of Chinese construction and real estate companies. *Recent patents on computer science*, 6(1): 47–59.

SVOBODOVA, L. 2013. Development in the insolvency procedure in the Czech Republic. *Ekonomika a management*, 7(1): 39–50.

ŠPIČKA, J. 2013. The financial condition of the construction companies before bankruptcy. *European journal of business and management*, 5(23): 160–166.

THOMAS, N, S., WONG, J. M. W. and ZHANG, J. 2011. Applying Z-score model to distinguish insolvent construction companies in China. *Habitat international*, 35(4): 599–607.

TIAN, S., YU, Y., and GUO, H. 2015. Variable selection and corporate bankruptcy forecasts. Journal of banking and finance, 52(1): 90–100.

TSENG, F. M. and HU, Y. C. 2010. Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert systems with applications*, 37(4): 1846–1853.

TSERNG, H. P., CHEN, P., HUANG, W. H., LEI, M. CH. and TRAN, Q. H. 2014. Prediction of default probability for construction firms using the logit model. *Journal of civil engineering and management*, 20(2): 247–255.

WANG, Y. J. and LEE, H. S. 2008. A clustering method to identify representative financial ratios. *Information Sciences*, 178(4): 1087–1097.

WU, Y., GAUNT, C. and GRAY, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, 6: 34–45.

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