BUILDING A BANKRUPTCY PREDICTION MODEL: COULD INFORMATION ABOUT PAST DEVELOPMENT INCREASE MODEL ACCURACY?

Karas M., Režňáková M.*

Abstract: In most cases, bankruptcy models are based on financial indicators that describe the current condition or a certain area of financial health, such as profitability, indebtedness and so on, but they do not report on relevant past development. The main question of the research presented in this paper is whether information about past development could enhance the prediction accuracy of the bankruptcy prediction model. The aim of our research is to analyse the partial potential of financial indicators describing past development. Given that the threat of company bankruptcy is the result of a long-term process, the question arises as to whether it is possible to enhance the accuracy of a bankruptcy prediction model by using indicators monitoring the development of the company in the past. On a sample of 1,355 small and medium-sized Czech construction companies were taken into account during the period of 2011–2014. The study analysed two types of indicators – basic-form and change-form indicators. Basic-form indicators show the status of an indicator at a specific point in time; change-form indicators represent a modified base index of the basic-form ratio. The authors derived six different models for the purpose of comparing the two types of indicators. The authors used the method of stepwise discriminant analysis, both forward selection and backward elimination, to create the models. The accuracies of the resultant models were analysed using the methods of ROC curves and the Area Under Curve (AUC). The authors found that the model based solely on change-form indicators is not superior to the model based solely on basic-form indicators. However, the model using both types of indicators achieved a higher AUC in comparison with the models created with only one type of indicator.

Key words: construction companies, bankruptcy prediction, dynamic indicators, model accuracy, multi-period transformation

DOI: 10.17512/pjms.2018.17.1.10

Article history:
Received January 22, 2018; *Revised* March 1, 2018*; Accepted* March 20, 2018

Introduction

The first bankruptcy prediction models, such as Altman (1968) and Zmijewski (1984), were designed based on financial ratios calculated using company data one year prior to bankruptcy (the t+1 period). The models designed in this way included only those indicators (predictors) whose bankruptcy-predicting ability had been established for a single interval only, specifically one year before bankruptcy.

* **Michal Karas,** Eng. PhD, Brno University of Technology, Faculty of Business and Management; **Mária Režňáková,** Prof. Eng. CSc., Brno University of Technology, Faculty of Business and Management
✉ Corresponding author: karas@fbm.vutbr.cz
✉ reznakova@fbm.vutbr.cz

Deakin (1972) found that the ranking of predictor significance changes with receding time. Deakin's conclusion was confirmed by the work of Grice and Dugan (2001). Shumway (2001) criticises the earlier bankruptcy models as static since the time factor is ignored. The changing significance of a model's ratios could also be viewed from the perspective of changes to the environment. According to Boratyńska (2016) there is a link between bankruptcies and the business cycle; however, there is no agreement on the channels by which bankruptcies and the business cycle interact, or on how to measure the link between them. In a wider context, the issue of corporate viability in the context of changing macroeconomic conditions has been addressed by the studies by Kaminsky and Reinhart (1999), Edison (2003) and Knedlik (2014). According to Berent et al. (2017) macro data is shown to be critical, as it adds, on average, more than 10 p.p. to accuracy ratio of the bankruptcy prediction models. These issues were also considered by Henerby (1996) who 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. Some pieces of research point out that performance of the company should also be measured by non-financial indicators (see Knápková et al., 2014). Most of the previously created models (Grice and Dugan, 2001) were derived from data of manufacturing companies. Later research (for example Thomas et al. 2011, though also Karas and Režňáková, 2017) showed that the values of financial ratios are industry-influenced. It is necessary to construct bankruptcy models for specific branches or countries, many authors aim to construct a country-specific model (for example Kovacova and Kliestik, 2017). Thomas et al. (2011) point out the need for creating models for branches such as construction, as the existing models are inappropriate for this branch. The given works are evidence of the fact that information relevant for predicting bankruptcy can be drawn from data preceding the bankruptcy by more than one year. Niemann et al. (2008) point out that the adjustment of indicators to contain information on more than one period ("multi-period transformation") may represent a potential for further development of these models. Niemann et al. (2008) work with multi-period transformation in four directions, either as an average, a trend defined as *"the average absolute change in a factor's values",* volatility – in terms of the value of the standard deviation of the indicator for 5 periods, or *"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 takes the value 0.

The construction of bankruptcy models usually begins by finding a limited number of statistically significant differences (indicators) among active companies and companies in financial distress, i.e. among bankrupt companies. According to Zvarikova et al. (2017), who have studied the variables used by 42 bankruptcy prediction models, these models usually incorporate between 4 and 7 variables. Indicators found in this way are then used to predict the situation occurring in the second group of surveyed companies (financial distress, bankruptcy).

The significance of the indicator employed in the model then determines the significance of the whole model, which is why great attention should be devoted to this issue. The aim of our research is to analyse the partial potential of financial ratios for predicting bankruptcy. As it has already been mentioned, financial ratios based on accounting data 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 as to whether it is possible to enhance the distinguishing ability of the bankruptcy model by using indicators that monitor the past development of the company. Specifically, the study will analyse whether an indicator monitoring a change of value to a static indicator can attain a higher relative importance than the static indicator for time (t+1). The paper aims to contribute to the current literature by exploring the partial potential hidden in the definition of financial ratios. The majority of bankruptcy prediction models do not incorporate the change of these ratios over time, the dynamics of the ratio, which could have potential for bankruptcy prediction.

The article is structured in the following manner. The next part describes the research methodology that introduces the idea of dividing the financial ratios into two parts – static and dynamic; the research hypotheses and the method of their evaluation are also introduced. Following this, the research sample is introduced along with the descriptive statistics of the analysed data. The following part provides details on the models, which are created during the course of testing of the research hypothesis. Testing of the models follows, with comparison of their classification accuracy. Next, conclusions are drawn and discussed in the light of other authors' conclusions.

Research Methodology

For the purpose of this research, the authors divided the indicators analysed into two groups: static (basic-form) ratios and change ratios.

Basic-form ratios show the status of the ratio over a certain time; for bankrupt companies, this 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; for bankrupt companies, it is the year of bankruptcy).

The authors defined *change ratios* in terms of a modified base index where they investigate the potential of the ratios in terms of their change compared to the selected previous value. A change ratio can be described as follows:

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

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

The study compares the actual value of the indicator with its historical value to describe the evolution of indicators in the years prior to bankruptcy. The authors suppose that the situation in a company that is going bankrupt is worsening. This means that the value of its indicators is either rising (as in the case of indebtedness indicators) or falling (as in the case of profitability or solvency indicators). On the other hand, the authors suppose that the situation of financially healthy companies would be relatively stable over time.

The following hypotheses were suggested during the course of the research presented here:

H1: The model derived by using both types of indicator (both static and change forms) will attain a higher overall discriminatory power than the models derived by using only one type of indicator (either static or change form).

The overall discriminatory power was analysed by the terms of Wilks' lambda. Wilks' lambda represents commonly used test statistics for multivariate analysis of variance (MANOVA). The Wilks' lambda is based on three matrices: W (the within-group matrix of the sum of squares and products), T (the total matrix of sums of squares and cross-products) and B (the between-group matrix of sums of squares and cross-products), defined as follows (see Patel and Bhavsar, 2013):

$$T = \sum_{i=1}^{g}\sum_{j=1}^{n_i}(X_{ij}-\bar{X})(X_{ij}-\bar{X}) \quad (2)$$

$$W = \sum_{i=1}^{g}\sum_{j=1}^{n_i}(X_{ij}-\bar{X}_i)(X_{ij}-\bar{X}_i) \quad (3)$$

$$B = \sum_{i=1}^{g} n_i\,(X_{ij}-\bar{X})(X_{ij}-\bar{X}) \quad (4)$$

Where X_{ij}, i=1,…. g, j=1, ……n_i represents the j^{th} multivariate observation in the i^{th} group, g is the number of groups and n_i is the number of observations in the i^{th} group. The mean vector of the i^{th} group is represented by $\bar{X}_i$ and the mean vector of all the observations by $\bar{X}$. These matrices satisfy the equation T = W + B. Wilks' lambda is given by the ratio of the determinants of W and T, i.e.

$$\Lambda = \frac{|W|}{|T|} = \frac{|W|}{|W+B|} \quad (5)$$

The statistic Λ can be transformed to give an F-test to assess the null hypothesis of the equality of the population mean vectors. Wilks' lambda ranges from 0 to 1 and the lower the Wilks' lambda, the larger the between-group dispersion. A small (close to 0) value of Wilks' lambda means that the groups are well separated. A large (close to 1) value of Wilks' lambda means that the groups are poorly separated (see Patel and Bhavsar, 2013). Wilks' lambda makes it possible to test the variables taken together, as their usefulness could lie in combination with other variables.

H2: The accuracy of the model derived by using both types of indicator will be higher than the accuracy of models derived by using only one type of indicator (either static or change form).

The authors used the method of discrimination analysis for the purposes of deriving the model. The given method was chosen as it represents the most commonly used algorithm for deriving bankruptcy prediction models (see Aziz and Dar, 2006). This study uses the stepwise version of this method, both forward selection and backward elimination. The models are derived by the application of either basic-form indicators or change-form indicators. Moreover, a model using both types of indicator is also derived.

Preselection of the indicators is required as the number of analysed indicators is high (140 indicators). First, the authors checked the correlation between the pair of indicators during the course of elimination of the highly correlated indicators. The study has used the Spearman's rank correlation coefficient for this purpose.

The authors then eliminated non-significant indicators. A non-parametric chi-squared test of independence is used for this purpose. Since the analysed variables are continuous, they have to be categorised for the purposes of application of this test. Specifically, the intervals of values of analysed variables are divided into 10 categories. Only the significant indicators are used for further analysis.

The authors have used the method of Linear Discriminant Analysis (LDA), which is the most frequently used algorithm (Aziz and Dar, 2006), for the purpose of deriving the models. Stepwise discrimination analysis can also be used to find suitable bankruptcy predictors with only those predictors that possess sufficient discriminatory power being included in the model see Back et al. (1996) or Hung and Chen (2009). 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. The accuracy of the model is evaluated using ROC curves and the corresponding Area Under Curve (AUC) value. This allows us to measure the accuracy of the model regardless of the current setting of the cut-off score. Unlike Wilks' lambda, the ROC evaluates not only the variables of the model, but also the whole discrimination function, i.e. including the coefficient.

Investigated Ratios

This study analyses a set of 28 financial ratios which have been used on bankruptcy prediction.

To distinguish static and change ratios, the study uses numerical abbreviations of the moments to which they relate. For example, the basic form of ratio CL/TL is designated CL/TL 1 which means that this is the value of the ratio defined for the moment one year before bankruptcy (time t+1), or more generally, for one; the form CL/TL 1/2 means that this is a change ratio defined as ratio CL/TL 1 (for time t+1) and CL/TL 2 (for time t+2), i.e. the index of indicator development.

Table 1. The List of Investigated Ratios *(Altman, 1968; Deakin, 1972; Wang and Lee, 2008; Ding et al., 2008; Niemann et al., 2008; Psillaki et al., 2009; Tseng and Hu, 2010; Lin et al., 2011; Karas and Režňáková, 2013; Laitinen et al., 2014; Tian et al., 2015)*

Ratio	**Abbrev.**	**Ratio**	**Abbrev.**
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

In relation to the properties of the data examined, the following table contains descriptive statistics of selected ratios for the sample of active and bankrupt companies. Due to the huge amount of data involved, it shows only the results of descriptive statistics for the first four indicators.

Table 2. Descriptive Statistics of the Sample
(Own analysis of data from the Amadeus database)

Variable	**Mean**	**Median**	**Min.**	**Max.**	**Std. Dev.**
CR 1 (A)	29.44	1.511	-4.1	19,870.9	623.73
CR 1 (B)	0.794	0.863	0.00	1.985	0.46
EBIT/TA 1 (A)	0.036	0.023	-1.4	0.7	0.10
EBIT/TA 1 (B)	-0.367	-0.001	-8.50	0.496	I.54
WC/S 1 (B)	14.22	0.192	-54,373.3	11,4273.0	4,018.37
WC/S 1 (B)	-22.32	-0.035	-729.80	57.766	104.34
WC/TA 1 (A)	0.2039	0.21	-3.4	1.0	0.38
WC/TA 1 (B)	-107.57	-0.12	-9,420.0	0.480	977.59

The descriptive statistics confirm the expected features of the analysed variables, for example a high level of liquidity in active companies in stark contrast to the low liquidity of bankrupt companies, as is obvious from the values of current ratio (CR) or rather from relative values of net working capital (WC/TA, WC/S). A negative return on assets (EBIT/TA) seems to be typical in construction companies that are threatened by bankruptcy, as around 50% of the bankrupt companies analysed exhibit negative operating profits.

Statistical Characteristics of the Variable

The first step in creating the model is to preselect the variables. This is done by using a chi-squared test. An example of the results is shown in the table below. First, the static-form indicators (Table 3)

Table 3. Example of the Results of the Chi-squared Test Application – Static-form Indicators *(Own analysis of data from the Amadeus database)*

Ratio	Chi-sq.	p-value	Ratio	Chi-sq.	p-value
CL/TL 1**	22.8863	0.001784	EBIT/TA 1**	13.1605	0.000286
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

Note: *statistically significant at the 5% level, **statistically significant at the 1% level

and second, the change-form indicators (Table 4).

Table 4. Example of the Results of the Chi-squared Test Application – Change-form Indicators *(Own analysis of data from the Amadeus database)*

Ratio	1/y	Chi-sq.	p-value	Ratio	1/y	Chi-sq.	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	AD/S	1/2**	28.217	0.000435
S/St.	1/5*	11.2594	0.046472		1/4**	23.073	0.000002
CF/TL	1/5*	12.4277	0.014439		1/5**	17.489	0.007644

Note: *statistically significant at the 5% level, **statistically significant at the 1% level

Before application of the LDA method, it is necessary to analyse the correlation between the indicators, as a strong positive correlation could be harmful to the model. Values of the correlation coefficient higher than 0.9 were identified between three variables measuring the return on assets.

Table 5. Results of Correlation Analysis
(Own analysis of data from the Amadeus database)

The pair of indicators	Spearman's (R)	t(N-2)	p-value
EBIT/TA 1 & EBITDA/TA 1**	0.935233	87.69311	0.000000
EBIT/TA 1 & EAT/TA 1**	0.909407	79.26085	0.000000
EBITDA/TA 1 & EAT/TA 1**	0.860737	56.13085	0.000000

Note: **statistically significant at the 1% level

The correlation between all the three pairs of the given indicator is statistically significant at the 1% level. The information carried by these indicators is extremely similar, for which reason it suffices to use just one of them. We chose EAT/TA as it is the most significant (by the chi-squared test) of the three given predictors. A set of 6 models was created during the course of this research.

Table 6. Overview of the Created Models
(Own analysis of data from the Amadeus database)

Model	Indicator form	LDA Version	Variable no.	Wilks' lambda	F-stat.	p-val.
1	Basic	Forward	6	0.65676	105.83	<0.001
2	Basic	Backward	5	0.65795	126.43	<0.001
3	Change	Forward	15	0.91492	8.7321	<0.001
4	Change	Backward	1	0.94605	54.064	<0.001
5	Basic + change	Forward	16	0.6522	33.206	<0.001
6	Basic + change	Backward	6	0.68063	73.747	<0.001

All the created models are statistically significant at the 1% level in terms of their overall discriminatory power. However, while comparing the models, it can be seen that the models derived by using the backward elimination method are more significant (according to F-statistic) relative to their alternatives created by the forward selection method. Therefore, only Model 2, Model 4 and Model 6 will be further described.

Model 2

This model was created using basic-form indicators and the method of backward elimination only. The details of Model 2 are given in the following table.

Table 7. Details of Model 2

	Wilks' Lambda	Partial Lambda	F to rem.	P-val.	Toler.
WC/TA 1***	0.6666	0.9869	16.11	0.000063	0.1837
CL/TA 1***	0.6793	0.9685	39.46	0.000000	0.1750
logTA 1***	0.8106	0.8116	282.27	0.000000	0.9464
EAT/TA 1***	0.6647	0.9897	12.57	0.000407	0.4586
RE/TA 1***	0.6681	0.9847	18.81	0.000016	0.2553

Note: ***significant at the 1% level

All the variables of Model 2 are statistically significant at the 1% level. The most significant variable of the model is the size factor – the total assets value (Log TA 1). Moreover, its unique information contribution to the model is high (according to the tolerance value). On the other hand, the variable of short-term indebtedness (CL/TA 1) is a variable with a lower unique contribution to the model as the corresponding value of tolerance is lowest.

Model 4

This model was created using change-form indicators and the method of backward elimination only.

Table 8. Details of Model 4

	Wilks' Lambda	Partial Lambda	F to rem.	P-val.	Toler.
WC/TA 1/4***	1.0000	0.9460	54.063	0.000000	1.000000

Note: ***significant at the 1% level

The model contains only one variable; it is significant at the 1% level.

Model 6

This model was created using both basic-form and change-form indicators and the method of backward elimination.

Table 9. Details of Model 4

	Wilks' Lambda	Partial Lambda	F to rem.	P-val.	Toler.
logTA 1/2***	0.6878	0.9895	10.00	0.001612	0.9010
CL/TA 1***	0.7066	0.9631	36.03	0.000000	0.2067
S/OR 1***	0.6917	0.9839	15.37	0.000094	0.9681
logTA 1***	0.7888	0.8628	149.91	0.000000	0.9187
EAT/TA 1***	0.7205	0.9446	55.28	0.000000	0.2917
RE/TA 1***	0.6907	0.9853	14.05	0.000188	0.2520

Note: ***significant at the 1% level

The most significant variable of the model is the total assets value (logTA1), again with the highest unique information contribution to the model (according to the tolerance value). The second most significant variable in the model is the return on assets (EAT/TA), although its unique information contribution is much lower, as 70.82 % of its information content can be explained by the combination of the rest of the model's variables. The discrimination functions of the derived models and the corresponding cut-off values are as follows:

Model 2 = -2.1475*WC/TA_1 - 3.5768*CL/TA_1 + 5.4615*$logTA_1$ -0.057*EAT/TA_1 + 1.8023*RE/TA_1; *bankrupt if Z(2) < 19.3625, otherwise non-bankrupt.*

Model 4 = 0.1193*$WC/TA_{1/4}$; *bankrupt if Z(4) < -3.2698, otherwise non-bankrupt.*

Model 6 = 15.5880*$logTA_{1/2}$ - 3.8639*CL/TA_1 - 0.8485*S/OR_1 + 5.4503*$logTA_1$ - 6.429*EAT/TA_1 + 1.9321*RE/TA_1; *bankrupt if Z(6) < 33.9695, otherwise non-bankrupt.*

Results of Model Testing

The accuracy of the derived models is as follows when using the given value of the cut-off score. In the case of active (non-bankrupt) companies, the percentage of correctly classified companies varies between 99.12 (Model 6) and 99.36% (Model 4).

Table 10. The Accuracy of the Derived Models

Model	Observed	Predicted		
		Active	Bankrupt	%
Model 2	Active	1,215	8	99.34
	Bankrupt	32	61	65.59
	Total	1,247	69	96.96
Model 4	Active	1,102	7	99.36
	Bankrupt	69	7	9.21
	Total	1,171	14	93.58
Model 6	Active	1,133	10	99.12
	Bankrupt	35	44	55.69
	Total	1,168	54	96.31

However, the percentage of correctly classified bankrupt companies differs significantly. The given accuracy is highest (65.59%) in the case of Model 2, with a slightly lower score in the case of Model 6 (55.69%) and significantly, lower accuracy is being identified in the case of Model 4 (9.21%).
The number of observations differs between the models, as the observations of the financial statements of the companies are incomplete and not all the variables can, therefore, be defined. ROC curves were employed for the purposes of comparing the models' accuracy (Figure 1). The corresponding AUC values are shown below.

Table 11. The AUC Values of the Derived Models

Model	Area	Std. Error*	Asymptotic Sig.**	Asymptotic 95 % Confidence Interval	
				Lower Bound	Upper Bound
Model 2	0.889	0.031	0.00000	0.829	0.95
Model 4	0.631	0.045	0.00000	0.543	0.719
Model 6	0.892	0.029	0.00000	0.834	0.949

Note: * Under the non-parametric assumption, ** Null hypothesis: true area = 0.5

All the derived models have attained a significantly higher AUC value than 0.5. However, the AUC value obtained by Model 4 (based solely on change-form indicators) is much lower than in the case of the other models (0.631). While comparing the model based on both forms of indicators (Model 6) with the model based solely on static-form indicators (Model 2), we can see that the model based on both forms of indicator provides slightly better results in terms of AUC (0.892 in the case of Model 2 versus 0.889 in the case of Model 6).

Discussion

The potential of change ratios was analysed in terms of overall model discriminatory power measured by Wilks' lambda and in terms of model accuracy measured by the AUC value.

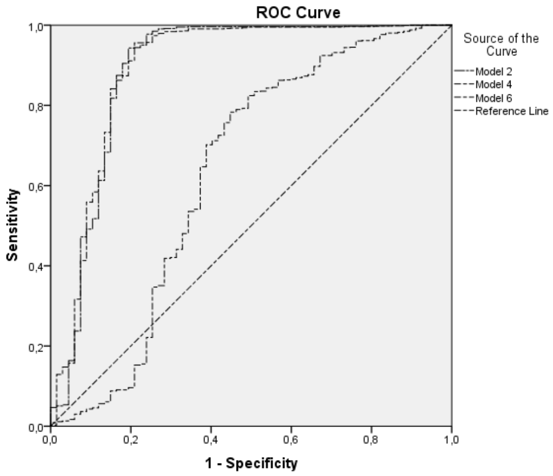

Figure 1. ROC Curves for the Created Models
(Our own analysis of data from the Amadeus database)

The given potential was analysed by means of the comparison of three different models – Model 2 based solely on static-form indicators, Model 4 based solely on a change-form indicator, and Model 6 based on both form of indicator. However, Model 4 incorporates only one variable, which is the change to the relative size of net working capital in time four years prior to bankruptcy. This ratio evaluates the size of the working capital used for financing current assets and is one of the ratios characterising the solvency of a company. A crucial change to this ratio occurs four years prior to bankruptcy. Although the predictive power of the given model is relatively high, its application is limited as the value of one indicator could be manipulated deliberately.

Comparison of the given models found that the model based solely on change-form indicators is not superior to the model based on static-form indicators. However, the change-form indicators are significant enough to enter a model – Model 6 derived by using both types of indicator also incorporates change-form indicators (logTA1/2). This model attained a higher value of Wilks' lambda than the model based solely on static-form indicators (Model 2), which implies a lower discriminatory power. Hypothesis H1 cannot be accepted.

When analysing the models' accuracy (in terms of AUC) the situation is opposite, with the model based on both types of indicator (Model 6) attaining a higher AUC value (0.892) than the model based solely on static-form indicators (0.889). Hypothesis H2 can, therefore, be accepted.

Most of the variables of Model 2 and Model 6 are common to both models, namely the logarithm of total assets value (logTA 1), return on assets (EAT/TA 1), short-term indebtedness (CL/TA 1) and the relative size of retained earnings (RE/TA 1). Model 2 (static-form indicators) incorporates an indicator of the relative size of net working capital (WC/TA 1). In the case of Model 6, indicators of the change

to the logarithm of total assets (LogTA 1/2) and sales to operating revenues (S/OR 1), which can be considered an indicator of the sales structure, are also incorporated.
Of the given indicators, logTA 1 represents the most significant indicator in both models. This factor represents company-size or market-position factors (Niemann et al., 2008) with larger firms considered more able to survive hard times being less prone to bankruptcy (Wu et al., 2010). Shumway (2001) mentions company-size factors as highly significant bankruptcy predictors. The results of research also confirm the significance of this factor.
Speaking of short-term indebtedness (CL/TA 1), according to Spička (2013) one of the typical characteristics of bankrupt construction companies is their extreme debt ratio (sometimes exceeding 100 %), the problem lying mainly in current liabilities. Our study has corroborated his conclusions.
Both Model 2 and Model 6 incorporate a profitability factor in the form of the return on assets (EAT/TA 1). Incorporating a profitability factor into the model is in line with previous research; however, a more favourable form of the return on assets is based on EBIT not EAT. EBIT/TA is often part of other authors' models, for example Li and Sun (2009), Psillaki et al. (2009).
Both forms (EBIT/TA and EAT/TA) were analysed in this research; however, due to the existence of strong correlation between these variables one of them had to be excluded from the sample. EBIT/TA was excluded, as it was a less significant indicator according to the results of the chi-squared test.
Both Model 2 and Model 4 incorporate the same factor – the relative size of the net working capital (WC/TA) – the static form of the ratio (WC/TA 1) was incorporated into Model 2, while the change form of the ratio (WC/TA 1/4) became part of Model 4. It can say that the financial problems of construction companies that result in bankruptcy reflect the relative size of the net working capital. The WC/TA ratio represents a liquidity indicator that is frequently used in bankruptcy models, see Altman (1968), Shumway (2001) or Wu et al. (2010).
The research was conducted on a set of 140 variables; 28 in the static form, the rest in change form. However, only two change-form variables were incorporated into the model, i.e. logTA1/2 and WC/TA 1/4. Both variables, in the static form, are considered significant bankruptcy predictors (see, for example, Ding et al., 2008, Niemann et al., 2008, Psillaki et al., 2009). It is quite surprising that the model based solely on change ratios incorporates only one of them, i.e. WC/TA 1/4. It could be suggested that change to the relative size of the net working capital in the four years prior to bankruptcy is the most significant predictor in the case of construction companies.

Conclusions

The focus of this research is to frame the discriminatory ability of bankruptcy prediction models. The aim of the paper is to analyse the usefulness of information about the past development of a company's financial situation in predicting

bankruptcy. A set of three different models have been created during the course of the research, after which their discriminatory power and accuracy are evaluated. The first model is created with static-form indicators only; the second model is based on change-form indicators only, while the third model uses both types of indicator. The authors have found that a model created with both types of indicator can be superior to a model that incorporates only one type of indicator. The accuracy of the models is evaluated using the methods of ROC curves and AUC.
The results of the research have shown that there is potential for increasing the discriminant power of bankruptcy prediction models by using change-form indicators. However, the information that change-form indicators carries could be viewed as a reflection of internal and external environmental factors. Therefore, further research should focus on the analysis of the link between external environmental factors and bankruptcy predictors (model variables).

References

Altman E.I., 1968, *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy*, "The Journal of Finance", 23.

Aziz M., Dar H., 2006, *Predicting corporate bankruptcy: Where we stand?* "Corporate Governance", 6.

Back B., Laitinen T., Sere K., 1996, *Neural networks and genetic algorithms for bankruptcy predictions*, "Expert Systems with Applications", 11.

Berent T., Bławat B., Dietl M., Krzyk P., Rejman R., 2017, F*irm's default — new methodological approach and preliminary evidence from Poland, "*Equilibrium. Quarterly Journal of Economics and Economic Policy", 12.

Boratyńska K., 2016, *Corporate bankruptcy and survival on the market: Lessons from evolutionary economics*, "Oeconomia Copernicana", 7.

Deakin E.B., 1972, *A discriminant analysis of predictors of business failure*, "Journal of Accounting Research", 10.

Ding Y., Song X., Zen Y., 2008, *Forecasting financial condition of Chinese listed companies based on support vector machine*, "Expert Systems with Application", 34.

Edison H.J., 2003, *Do indicators of financial crises work? An evaluation of an early warning system*, "International Journal of Finance and Economics", 8.

Grice J.S., Dugan M.T., 2001, *The limitations of bankruptcy prediction models: Some cautions for the researchers*, "Review of Quantitative Finance and Accounting", 17.

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.

Hung C., Chen J.H., 2009, *A selective ensemble based on expected probabilities for bankruptcy prediction*, "Expert Systems with Applications", 36.

Kaminsky G., Reinhart C., 1999, *The Twin Crises: The causes of banking and balance-of-payments problems*, "American Economic Review", 89.

Karas M., Režňáková M., 2013, *Bankruptcy prediction model of industrial enterprises in the Czech Republic*, "International Journal of Mathematical Models and Methods in Applied Sciences", 7.

Karas M., Režňáková M., 2017, *Stability of bankruptcy predictors in construction and manufacturing industries at various times before bankruptcy*, "E&M Economics and Management", 20.

Knápková A., Homolka L., Pavelková D., 2014, *Utilization of Balanced Scorecard and the effect of it's on the financial performance of companies in the Czech Republic*, "E&M Economics and Management", 17.

Knedlik T., 2014, *The impact of preferences on early warning systems - The case of the European Commission's Scoreboard*, "European Journal of Political Economy", 34.

Kovacova M., Kliestik T., 2017, *Logit and Probit application for the prediction of bankruptcy in Slovak companies*, "Equilibrium. Quarterly Journal of Economics and Economic Policy", 12.

Laitinen E.K., Lukason O., Suvas A., 2014, *Behaviour of financial ratios in firm failure process: An international comparison*, "International Journal of Finance and Accounting", 3.

Li H., Sun J., 2009, *Predicting business failure using multiple case-based reasoning combined with support vector machine*, "Expert Systems with Applications", 36.

Lin F., Liang D., Chen E., 2011, *Financial ratio selection for business crisis prediction*, "Expert Systems with Applications", 38.

Niemann M., Schmidt J.H., Neukirchen M., 2008, *Improving performance of corporate rating prediction models by reducing financial ratio heterogeneity,* "Journal of Banking & Finance", 32.

Patel S., Bhavsar C.D., 2013, *Analysis of pharmacokinetic data by Wilk's lambda (An important tool of MANOVA)*, "International Journal of Pharmaceutical Science Invention", 2.

Psillaki M., Tsolas I.T., Margaritis M., 2010, *Evaluation of credit risk based on firm performance,* "European Journal of Operational Research", 201.

Shumway T., 2001, *Forecasting bankruptcy more accurately: A simple hazard model,* "Journal of Business", 74.

Špička J., 2013, *The financial condition of the construction companies before bankruptcy*, "European Journal of Business and Management", 5.

Thomas N.S., Wong J.M.W., Zhang J., 2011, *Applying Z-score model to distinguish insolvent construction companies in China*, "Habitat International", 35.

Tian S., Yu Y., Guo H., 2015, *Variable selection and corporate bankruptcy forecasts*, "Journal of Banking and Finance", 52.

Tseng F.M., Hu Y.C., 2010, *Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks*, "Expert Systems with Applications", 37.

Wang Y.J., Lee H.S., 2008, *A clustering method to identify representative financial ratios*, "Information Sciences", 178.

Wu Y., Gaunt C., Gray S., 2010, *A comparison of alternative bankruptcy prediction models*, "Journal of Contemporary Accounting and Economics", 6.

Zmijewski M.E., 1984, *Methodological issues related to the estimation of financial distress prediction models*, "Journal of Accounting Research", 22.

Zvarikova K., Spuchlakova E., Sopkova G., 2017, *International comparison of the relevant variables in the chosen bankruptcy models used in the risk management*, "Oeconomia Copernicana", 8.

BUDOWANIE MODELU PROGNOZOWANIA UPADŁOŚCIOWEGO: CZY INFORMACJE DOTYCZĄCE DOTYCHCZASOWEGO ROZWOJU MOGĄ ZWIĘKSZYĆ DOKŁADNOŚĆ MODELU?

Streszczenie: W większości przypadków modele upadłości opierają się na wskaźnikach finansowych, które opisują obecny stan lub pewien obszar kondycji finansowej, takie jak rentowność, zadłużenie itd., ale nie zawierają informacji na temat istotnego wcześniejszego rozwoju. Głównym zagadnieniem badań przedstawionych w tym artykule jest to, czy informacje na temat wcześniejszego rozwoju mogą zwiększyć dokładność prognozowania modelu prognozowania upadłości. Celem naszych badań jest analiza częściowego potencjału wskaźników finansowych opisujących dotychczasowy rozwój. Biorąc pod uwagę, że groźba bankructwa firmy jest wynikiem długotrwałego procesu, pojawia się pytanie, czy możliwe jest zwiększenie dokładności modelu przewidywania bankructwa za pomocą wskaźników monitorujących rozwój firmy w przeszłości. Badania przeprowadzono w okresie 2011-2014 na próbie 1 355 małych i średnich czeskich firm budowlanych. W badaniu przeanalizowano dwa rodzaje wskaźników - wskaźniki w formie podstawowej i zmienionej. Wskaźniki w formie podstawowej pokazują status wskaźnika w określonym momencie; wskaźniki w formie zmienionej reprezentują zmodyfikowany wskaźnik bazowy współczynnika w formie podstawowej. Autorzy wyprowadzili sześć różnych modeli w celu porównania obu typów wskaźników. Autorzy wykorzystali metodę krokowej analizy dyskryminacyjnej, zarówno do wyboru w przód, jak i do eliminacji wstecznej, w celu stworzenia modeli. Dokładności uzyskanych modeli analizowano za pomocą metod krzywych ROC i obszaru pod krzywą (AUC). Autorzy stwierdzili, że model oparty wyłącznie na wskaźnikach zmian nie jest lepszy od modelu opartego wyłącznie na wskaźnikach podstawowych. Jednak model wykorzystujący oba typy wskaźników osiągnął wyższy obszar pod krzywą w porównaniu z modelami utworzonymi przy użyciu tylko jednego rodzaju wskaźnika.
Słowa kluczowe: firmy budowlane, prognoza upadłości, wskaźniki dynamiczne, dokładność modelu, transformacja w wielu okresach

建立破产预测模型：可以提供关于过去开发的信息增加模型的准确性？

摘要：大多数情况下，破产模型都是基于财务指标来描述财务状况或财务状况的某一领域，如盈利能力，债务等，但它们并没有报告相关的过去发展情况。本文研究的主要问题是关于过去发展的信息是否可以提高破产预测模型的预测准确性。我们研究的目的是分析描述过去发展的财务指标的部分潜力。鉴于公司破产的威胁是长期过程的结果，因此通过使用监控公司过去发展的指标，是否有可能提高破产预测模型的准确性成为问题。在2011-2014年期间，
对1355个中小型捷克建筑公司的样本进行了考虑。该研究分析了两种类型的指标基本形式指标和变化形式指标。基本形式指标显示指标在特定时间点的状态;变化形式指标代表基本形式比率的修改基础指数。为了比较这两种类型的指标，作者得出了六种不同的模型。作者采用逐步判别分析的方法，即前向选择和后向消除来创建模型。使用ROC曲线和曲线下面积（AUC）的方法分析所得模型的准确性。作者发现，仅基于变化形式指标的模型并不优于仅基于基本形式指标的模型。然而，与仅使用一种类型的指标创建的模型相比，使用这两种指标的模型实现了更高的AUC。
关键词：建筑公司破产预测动态指标模型精度多时段变换