Bankruptcy prediction: To what degree does past development count?

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Abstract: - In most cases, bankruptcy models are based on financial indicators (so called predictors) that describe a current condition or a certain area of financial health, like profitability, indebtedness and so on. But they do not tell us anything about relevant past development in this area. The main question of the research presented was, how much of the information about the past development could be useful in predicting bankruptcy. The aim of our research is to analyse the partial potential of financial ratios for predicting bankruptcy and to compare their importance with the importance of commonly used indicators. Twenty eight indicators were examined in a sample of construction companies operating in the Czech Republic, as well as their development over the past five periods. The non-parametric Boosted Trees method was used to evaluate the relative importance of predictors. The results show that the indicators describing past development could be a significant predictor of bankruptcy, however their main potential is in possible synergy with the indicators describing the current state, both being of the same area of financial health.

Key-Words: - construction companies, bankruptcy prediction, financial ratio, dynamic indicators, model accuracy, multi-period transformation, model development

1 Introduction

Many bankruptcy predictors or models capable of predicting bankruptcy based on the use of financial data have been created in the previous decades. The question is: to what extent are these models still useful these days? According to the literature, this use could be controversial, because the economic environment is changing and the ability of these models to recognize 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 [11, 19, 21, 31] 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.

Most of the previously created models [11] 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 [25], who point out the need of creating models for branches such as construction, as the existing models are inappropriate for this branch.

According to [12], 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. Prediction of bankruptcy specifically for construction companies from the Czech Republic is dealt with, for example, by [16, 24]. Literature [24] 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.

As the paper presented deals with the problem of identifying suitable variables, we will discuss this issue in more detail.

The first models [1, 20, 32 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 [7] found that the ranking of predictor significance changes with the receding time. Deakin's conclusion was confirmed by the work of [11]. Literature [23] criticizes the earlier bankruptcy models of [1, 20 and 32] as static since the time factor is ignored. These issue were also considered by [13] who, aided by the Cox's model see [6], analyzed 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. Literature [19] 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, [19] works with the multi-period transformation in four directions, either as:

- the average (for 2, 3 or 5 periods),
- the trend (for 3 or 5 periods), which is 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,
- *"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.

2 The research hypotheses

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). The significance of the indicator employed in the model then determines the significance of the whole model. That is why this issue should be given great attention.

The aim of our research is to analyze partial potential of financial ratios for predicting bankruptcy. As already 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 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 analyze whether the monitoring of a change of the indicator value in time can reach a higher relative importance.

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; especially for bankrupt companies, it is a year of bankruptcy).

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:

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

wherein 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 more distant times from the last known year, i.e. for times t+2, t+3, t+4 and t+5.

We compare the actual value of the indicator with its historical value to describe the evolution of the indicators in the years prior to bankruptcy. We suppose that the situation of the company that is going bankrupt is worsening. That means that the value of its indicators is either rising (like in the case of indebtedness indicators) or it is lowering (like in the case of profitability or solvency indicators). On the other hand, we suppose that the situation of financially healthy companies would be relatively stable over time.

In the course of the research presented the following hypotheses were suggested:

H1: The relative importance of the change ratio is higher than the relative importance of its basic form alternative.

Alternative H2: The relative importance of the change ratio is equal to or lower than the relative importance of its basic form alternative.

3 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.

2.1 Investigated ratios

These ratios are often used in studies on bankruptcy prediction problems [26, 10, 17, 14, 2, 1, 7, 20, 8, 18, 29, 19, 3, 27, 22].

Table 1 The list of investigated ratios

No.	Ratio	Shortcut	T.	No.	Ratio	Shortcut	T.
1.	Current ratio	CR	L	15.	Sales/Stocks	S/St.	T
2.	Working capital/ total assets	WC/TA	L	16.	Sales/Debtors	S/Deb.	T
3.	Working capital/sales	WC/S	L	17.	Quick assets/sales	QA/S	T
4.	EBIT/total assets	EBIT/TA	P	18.	Current liabilities/ total assets	CL/TA	I
5.	EBITDA/total assets	EBITDA/ TA	P	19.	Long-term liabilities/ total assets	LTL/TA	I
6.	EAT/equity	ROE	P	20.	Debt-equity ratio	DER	I
7.	Cash flow/total assets	CF/TA	P	21.	EBIT/Interest	EBIT/Int.	I
8.	Cash flow/sales	CF/S	P	22.	EBITDA/Interest	EBITDA/Int.	I
9.	Cash flow/ total liabilities	CF/TL	P	23.	logarithm of total assets	LogTA	SF
10.	EAT/total assets	EAT/TA	P	24.	logarithm of sales	LogS	SF
11.	EBIT/Sales	EBIT/S	P	25.	Fixed assets/ total assets	FA/TA	SR
12.	EBITDA/Sales	EBITDA/S	P	26.	Sales/Operating revenue	S/OR	SR
13.	Retained Earnings/ total assets	RE/TA	P	27.	Added Value/Sales	AD/S	SR
14.	Sales/total assets	S/TA	T	28.	Cost of employees	CE/S	SR

Note: T. – type, P – profitability, L – liquidity, T- turnover, I – indebtedness, SF -size factors, SR-structural ratios, EAT – net profit, EBIT – operating profit, EBITDA – operating profit plus depreciation.
Source: [26, 10, 17, 14, 2, 1, 7, 20, 8, 18, 29, 19, 3, 27, 22]

3.1 Method to test the significance of indicators

Statistical significance of an indicator for distinguishing active and bankrupt companies was assessed by a non-parametric Boosted Trees.

The method of Boosted Trees (BT) is a combination of the classification and regression trees method (CART) see [5], with a boosting algorithm introduced by J. Friedman see [9]. Using the boosting algorithm raises the accuracy of the classification algorithm, to which it is applied by progressively reducing the error term [4, 9].

The resultant classification rule represents a set of many "weak" learners. The boosting algorithm is most often applied to CART, but an Artificial Neural Network (ANN) application may be encountered as well [15].

A useful feature of this method is that it allows the sorting out of the variables x_j according to their relative influence I_j on the variability of the approximation function $\hat{G}(x)$ across the entire division of input predictors, this measurement can be described as follows, see [9]:

$$I_j = \left(E_x\left[\frac{\partial \hat{G}(x)}{\partial x_j}\right] \cdot \mathrm{var}_x\left[x_j\right]\right)^{1/2} \qquad (2)$$

Among the advantages of the BT method, aside from its nonparametric nature (the data need not be normally distributed), is its tolerance for outliers in the input variable space [28].

In addition, the method can even capture non-linear relationships between the variables, Since the lack of normality and the presence of outliers tend to be commonplace in financial data [23, 30] it can be expected that a method which is immune to these aspects will deliver higher classification accuracy.

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. As the space is limited, we do not show the results of descriptive statistics for all the analysed ratios, only for the first four.

Table 2 Descriptive statistics of active companies

Variable	Active Descriptive statistics								
	Mean	Grubb's Test Statistics	p-value	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.
CR 1	29.436	31.81097	0.000000	1.511528	-4.1	19870.9	623.730	28.86	877.69
WC/TA 1	0.2039	9.37447	0.000000	0.209651	-3.4	1.0	0.382	-1.32	7.16
WC/S 1	14.221	28.43408	0.000000	0.191961	-54373.3	114273.0	4,018.374	18.59	609.85
EBIT/TA 1	0.0357	13.31152	0.000000	0.023617	-1.4	0.7	0.108	-2.62	44.86

Source: Source: Our own analysis of data from the Amadeus database

Table 3 Descriptive statistics of bankrupt companies

Variable	Bankrupt Descriptive statistics								
	Mean	Grubb's Test Statistics	p-value	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.
CR 1	0.794	2.534407	0.946937	0.86327	0.00	1.98506	0.4699	0.19	-0.357
WC/TA 1	-107.57	9.525899	0.000000	-0.11990	-9,420.00	0.48081	977.590	-9.60	92.435
WC/S 1	-22.320	6.780449	0.000000	-0.03511	-729.80	57.76667	104.341	-5.29	29.993
EBIT/TA 1	-0.367	6.583517	0.000000	-0.001397	-8.50	0.49688	1.2354	-4.86	26.390

Source: Source: Our own analysis of data from the Amadeus database

Descriptive statistics clearly show that the data are not normally distributed (particularly in terms of kurtosis) and - according to Grubbs test of outliers - contain an outlier value (except indicators CR 1 on the sample of bankrupt companies). For these reasons, we decided to categorize the data and subsequently apply the Boosted Trees method.

4 Results

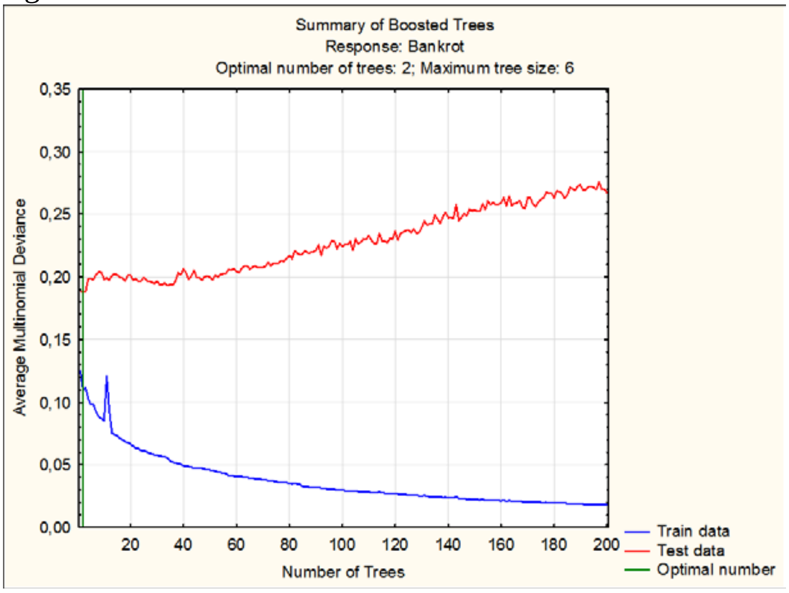
To distinguish static and change ratios, we use numerical abbreviations of the moments to which they relate. For example, the basic form of ratio QA/S is designated QA/S 1, which means that this is a value of the ratio defined for the moment of one year before bankruptcy (time t+1), or more generally,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

4.1 The results of Boosted trees method application

In accordance with the literature, see (Hastie et al, 2009, p. 363), the overall number of terminal nodes was limited up to 6. The parameter of the number of terminal nodes determines the maximum number of iterations between variables.

The model is derived by means of an iterative calculation aimed at obtaining the optimum number of trees where the total error (or deviance in this case) is minimal. The process of the calculation for manufacturing companies is shown in the graph below.

Fig. 1 Process of iterative calculation of Boosted Trees model



Source: Source: Our own analysis of data from the Amadeus database

According to the graph, the optimum number of trees per manufacturing industry sample is 2, while the maximum number of trees was 200. The specific error obtained in the training and test sample for both industries are shown in the table below.

Table 4 Summary of results of Boosted Trees method application – risk estimate and standard error

	Risk estimate	Standard error
Train	0.02724	0.00461
Test	0.04673	0.02040

Source: Source: Our own analysis of data from the Amadeus database

However, for the purposes of the research presented here, the contribution of the individual variables to the discrimination ability of the model is of key importance. This property of variables can be presented within the Boosted Trees method as the relative importance (RI) of an indicator, where number 1 is allocated to the most important indicator, and numbers at an interval (1;0) are allocated to the other indicators. Results for manufacturing companies are summarized in the table below.

An analysis showing the individual variables' representation in the intervals of their significance showed that their distribution was rather uneven. The relative importance of variables in a bankruptcy assessment differs greatly. A significance higher than 15% is achieved only by 22.2% of predictors or 30 out of 135, which appear in the following table.

Tab 5. Summary of results of Boosted Trees method application – relative importance of the analysed indicators

No.	Indicator	Type*	RI	No.	Indicator	Type*	RI
1	SF - logTA 1	B	100.00%	16	S -FA/TA 1	B	20.71%
2	I -CL/TA 1	B	79.36%	17	SF - logS 1	B	20.67%
3	P - RE/TA 1	B	60.57%	18	L -WC/S 1	B	19.71%
4	P - EAT/TA 1	B	38.85%	19	SF - logTA 1/4	C	19.04%
5	L -WC/TA 1	B	38.08%	20	SF - logTA 1/5	C	18.74%
6	P -EBIT/TA 1	B	37.26%	21	SF - logTA 1/2	C	18.71%
7	I - DER 1	B	31.02%	22	P - RE/TA 1/4	C	18.39%
8	P - CF/TA 1	B	30.42%	23	P -ROE 1	B	17.70%
9	P - EBITDA/TA 1	B	29.09%	24	L -WC/S 1/5	C	16.94%
10	L - CR 1	B	27.88%	25	L -WC/S 1/4	C	16.90%
11	I - DER 1/3	C	23.88%	26	I - DER 1/4	C	16.78%
12	A- S/TA 1	B	22.32%	27	P - RE/TA 1/5	C	15.21%
13	I - DER 1/5	C	21.71%	28	S -FA/TA 1/3	C	15.17%
14	P - RE/TA 1/3	C	21.69%	29	P - EBIT/S 1/4	C	15.09%
15	SF - logTA 1/3	C	20.89%	30	S -FA/TA 1/4	C	15.07%

Source: Source: Our own analysis of data from the Amadeus database. *note: B – indicator in the basic form, C – indicator in the change form

The results show that the most important indicator among the ones analysed is the logarithm of the total assets value (log TA 1), followed by the short-term indebtedness (CL/TA 1), followed by the relative size of the retained earnings (RE/TA 1). The table shows 22.4% of the most important indicators among the analysed indicators. In this group, there are indicators both in static and changing form, so one form is not dominant over the other. However, the indicators of the static form are among the ten most important. The most important indicator in the change form is the change of Debt-equity ratio (DER 1/3), with a relative importance of 23.88%. The second most important indicator in the change form is again the change of Debt-equity ratio, only this time defined for a different period (DER 1/5). This is followed by the change of relative size of retained earnings (RE/TA 1/3) and change of the logarithm of total assets (LogTA 1/3).

From the above table a clear pattern is shown, dealing with the relationship between the indicator in the basic form and the indicators in the change forms. If an indicator in the change form is engaged, it is always accompanied by the same indicator in the basic form. Moreover, the indicator in the basic form shows a higher relative importance in comparison to its engaged basic form. For example, the basic form of debt-equity ratio (DER 1) shows a relative importance of 31.02%, the most significant change form of this indicator is DER 1/3 with a relative importance of 23.88%. The same applies for the relative size of retained earnings (RE/TA); the relative importance of the basic form of the indicator (RE/TA 1) is 60.57%, the same value for its change form RE/TA 1/3 is 21.69%, and so on.

However, there is one exception to this observed rule, namely the return on sales indicator (EBIT/S). Only the change form of this indicator is among the most significant indicators (see table 5), the relative importance of the basic form of this indicator was lower than 15%.

According to the above mentioned results, the hypotheses of the research were not confirmed, i.e. the change ratios are not of a higher relative importance than their basic form alternatives. However, this does not mean they do not represent significant predictors of bankruptcy.

5 Discussion

The most significant indicator among the ones analysed was the logarithm of the total assets (LogTA). This indicator represents the factor of company size [8, 19, 22]. Bigger companies are generally perceived by their surroundings as a more stable business partner.

Literature [31] add that bigger firms are considered both more capable of surviving tough economic times and less prone to bankruptcy. This finding is in line with the results of other studies, such as [23], who considers the company size factor as a significant predictor of bankruptcy, however it is worth mentioning that [23] in his research defines company size in the meaning of the market value of the company's shares. Our research is based on the accounting data. The indicator of logTA was not the only size factor among the ones analyzed in our study, we also analysed the logarithm of sales (LogS) as an alternative size factor. However, the relative importance of this indicator was much lower than in the case of the indicator LogTA, namely only 20.67%.

The second indicator in terms of relative importance is the indicator of short-term indebtedness. This is also in the line with the findings of different authors, like [24], who considers this factor as one of the typical characteristics of bankrupt construction companies, [24] mentions that such companies exhibit extreme values of debt ratio (sometimes exceeding 100%), which is mainly caused by a high proportion of current liabilities in their capital structure.

The other most significant ratios among the top five are the relative size of retained earnings (RE/TA 1), the return on asset based on EAT (EAT/TA 1) and the relative size of net working capital (WC/TA 1). These indicator are often mentioned in papers dealing with the topic of bankruptcy prediction as they were used in Altman's model [1] and subsequently in many other models. However, Altman used the return on assets based on the EBIT not on EAT (i.e. EBIT/TA). We also analysed the indicator EBIT/TA and its relative importance was slightly lower than in the case of EAT/TA.

The aim of the research presented was to analyse the potential of the change form of indicators. We found that the change form of indicators does not generally dominate the basic form of the indicator as the basic form of the indicator exhibits higher relative importance in comparison to their change forms. Nevertheless, both forms of the indicator, basic and change forms, can be found among the most significant indicators. This leads us to the idea that there could be a possible synergy between these two types of indicator, and combining them in one model could result in the increase of the potential accuracy of the model.

6 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. We found that the indicators based only on information about past development (the change form indicators) are not superior to the indicators based on information about the current state. However the information about past development could be useful when used together with the indicator describing the current state, as there is the potential for a synergic effect.

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