Financial Ratios as Bankruptcy Predictors: The Czech Republic Case

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Abstract: The traditional bankruptcy models and their predictors cannot be used to predict bankruptcy in the Czech Republic as they have been intended for different business environments reflecting their specific features. The paper aims to find bankruptcy predictors specific for the Czech companies. An analysis of 44 financial ratios published in bankruptcy model studies from 1966 to 2010 discovered that, in the domestic conditions, only three of them can be used to predict bankruptcy one year ahead with a precision of 81.25%.

Key-Words: financial ratios, bankruptcy prediction, discriminant analysis

1 Introduction

Beaver (1966) and Altman (1968) as first came with an idea of financial ratios being used to sense the risk of a bankruptcy as early as five years ahead. Many similar models have been built since (Deakin, 1972; Altman, 1977; Ohlson, 1980; Zmijewski, 1984; Shumay, 1999, and others). At present, many authors are endeavouring to find a more perfect classification algorithm. Niemann et al. (2008) believe that the choice of classification algorithm offers little leeway for improving the precision of rating models. The remaining potential to increase the precision of a model includes methods of variable choice and methods supporting the statistical significance of predictors. Moreover, there are studies (Grice, Dugan, 2001; Wu, Gaunt, Gray, 2010; Niemann et al. 2008) showing that the precision of a bankruptcy model is significantly degraded if used in a field, period, and/or business environment different from that in which the learning data were observed. Therefore, it is generally not a good idea to use models favoured in the literature believing that they and their predictors will work well even in the domestic conditions. This paper aims to find bankruptcy predictors applicable to Czech-Republic-based industrial enterprises.

2 Literature Review

Many authors have been trying to find suitable bankruptcy predictors (Altman, 1968, 1977; Lin, Liang, Chen 2011; Wang, Lee, 2008; Niemann et al., 2008; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009; Cheng, Chen, Fu, 2006). Using logical regression, Zmijewski (1984) investigated the way model parameter estimation is negatively influenced by a non-random choice of the bankrupt-to-active company ratio in the sample. Shumway (1999) criticizes the above models as static suggesting the use a Cox model for a bankruptcy model (Cox, 1972). The impacts of accounting changes on the capacity of financial statements to foresee the risk of bankruptcy were studied in some detail by Beaver (2005). Zhang et al (1999) points to the limiting assumptions of parametric models such as linearity, normality and independence of predictors. The precision of a model for different application fields was investigated by Grice and Dugana (2001), Wu, Gaunt and Gray (2010) studied the precision of bankruptcy models for business environments other than those for which they were originally designed. Carling et al (2007) were concerned with the possibility to use macroeconomic data to predict bankruptcy. Barnes (1982, 1987) explained the cause of the frequent deviation from normality of ratios. Nikkinen and Sahlstrőm (2004) investigated the application of Box-Cox transformation (Box, Cox, 1964) to accounting data normalisation. Zimmerman (1994, 1995, 1998) was concerned with the influence of non-normality and outliers on the precision of parametric and non-parametric testing. Aziz and Dar (2006) examined 89 studies concerned with models used to predict bankruptcy finding out

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thatdiscrimination analysis (first used by Altman, 1968) is the most frequent classification method used. Aziz and Dar (2006) found no statistically significant difference between the precisions of individual methods even if artificial-intelligence methods scored slightly better on average. According to (Hung, Chen, 2009), no particular method can generally be marked as better that any other. Different methods have different advantages and disadvantages for different data.

3 Sample and Methods Used

The sample consisted of 207 Czech-Republic-based industrial enterprises (joint-stock companies) including 32 bankrupt and 175 active ones. Only companies with complete financial statements were considered even with the awareness of a risk pointed out by Zmijewski (1984). This approach was chosen for the analysis to include a maximum number of potential predictors. The period observed is that of 2007 to 2010. The data were extracted from an Amadeus database containing also information on bankrupt companies. The sample data included financial statements submitted one year prior to the bankruptcy.

3.1 Potential Predictors

As potential predictors, the indicators were analysed used in previous models (Beaver, 1966; Altman 1968; Deakin, 1972; Ohlson, 1980; Ding et al., 2008; Wang, Lee 2008; Niemann et al, 2008; Beaver, 2005; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009). In this way, 53 potential predictors were obtained with 44 potential predictors being calculated from the data available[1].

3.2 Method for Finding Predictors

To find suitable predictors, discrimination analysis was used, 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 being included in the model thatpossess a sufficient discriminating power (see Back et al, 1996; Hung, Chen, 2009). To increase the statistical significance (discrimination capacity) of the predictors as outlined by Niemann et al (2008), factors need to be taken into consideration that influence the validity of a chosen method such as the existence of outliers. When setting up a bankruptcy model, outliers are often winsorized (Shumway, 1999; Wu, Gaunt, Gray, 2010) or even removed (Mileris, Boguslauskas, 2011), the authors, however, do not explain this procedure. It has been proved that outliers do influence both parametric and non-parametric tests (see Zimmerman, 1994, 1995, 1998). Non-normality is another issue encountered quite often in financial ratios (Barnes, 1982, 1987). Normality is among the limiting assumptions when applying discrimination analysis (see Zhang et al, 1999; Hebák et al, 2004; Tseng, Hu, 2010). A Shapiro-Wilks procedure was used to test normality (Shapiro, Wilks, 1964). This test is especially suitable for small-sized samples (Meloun, Militký, 1994; Hebák et al, 2007). In the event that non-normality is proved, two approaches are possible. The indicator in question may be ignored, (see Mileris, Boguslaukas, 2011), which, however, may lead to a disproportionate reduction in the number of the predictors analysed and, therefore, this approach does not seem to be suitable. Another option is to use Box-Cox transformation, which can significantly reduce skewness, but not so much kurtosis, in financial ratios regardless of the accounting concept used (Nikkinen, Sahlstrőm, 2004). For this property, Box-Cox transformation appears to be the most suitable choice. Next the relationship between the predictors found has to be given proper attention, too. The significance of predictors may be given by a combination or correlation with other predictors (see Cochran, 1964; Altman, 1968). Cochran (1964) says that, while a positive correlation diminishes the discrimination capacity of the model, a negative one increases it. The non-parametric Spearman coefficient was chosen to represent the correlation between predictors.

3.2.1 Box-Cox Data Transformation

This is a form of power transformation designed by Box and Cox (Box, Cox, 1964). The transformation formula can be written as:

$$y^{(\lambda)} = \begin{cases} \dfrac{(y+\lambda_2)^{\lambda_1} - 1}{\lambda_1} & ; \ \lambda_1 \neq 0 \\ \ln(y+\lambda_2) & ; \ \lambda_1 = 0 \end{cases} \quad (1)$$

The parameters λ_1, λ_2 are estimated by the maximum likelihood method. Here the indicators of sales (S), total assets (TA), and equity (EQ), originally

[1]Mostly those indicators were not determined using capital market data as the shares of none of the bankrupt sample companies were marketable.

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designed as logarithms, are considered non-logarithm values. The logarithm of a value as such is a special case of Box-Cox transformation for $\lambda_{1,2}=0$ (see equation 1). The values of $\lambda_{1,2}$ taken to be the maximum likely estimate, their value need not be assumed. In some cases, the value of the parameter may diverge or, if strongly non-normal, the transformation may not achieve normality at all within the preset value of the Shapiro-Wilks test. Depending on the approach to the use of the transformation, two models were set up, model 1 and model 2.

3.3 Model 1

The original 44 potential predictors for model 1 creation were reduced in two stages. At stage one, predictors were left out for which either λ was diverging or the transformation had not, in the sense of Shapiro-Wilks test, achieved normality. The significance level of the test was chosen to be p=0.01. Thus the original number 44 of potential predictorswas decreased to 15. Potential predictors for which normality was not rejected by the test at a significance level of at least p=0.01 are listed by the following Table 1, with Table 2 showing more detailed results.

Table 1, Shapiro-Wilks normality test results

Indicator	W	p-value
CD/S	0.98377	0.01752
CR	0.99493	0.71642
EBIT(3vol)	0.99614	0.88503
FA/LTL	0.99239	0.38960
OI/AC	0.99191	0.30744
OR/CA	0.99599	0.86801
OR/CL	0.99622	0.89458
OR/FA	0.99219	0.33672
OR/LTL	0.99382	0.57870
OR/TA	0.99624	0.89728
OR/TL	0.99520	0.75893
QA/S	0.98884	0.10682
S/TA	0.99662	0.93432
TA	0.98603	0.03905
WC/TA	0.98291	0.01298

Source: Our own analysis of data from the Amadeus database

The table contains the following potential predictors: Current debt to sales (CD/S), Current ratio (CR), 3-year EBIT volatility (EBIT 3vol), Fixed assets to longterm liabilities (FA/LTL), operating income to average capital (OI/AC), operating revenue to current assets (OR/CA), operating revenue to current liabilities (OR/CL), operating revenue to fixed assets (OR/FA), operating revenue to total liabilities (OR/TL), quick assets to sales (QA/S), sales to total assets (S/TA), total assets (TA), working capital to total assets (WC/TA).

Table 2, Box-Cox transformation parameters

	λ_1	λ_2	LCL	UCL
CD/S	-3.2487	0.9208	-4.0638	-2.4869
CR	-0.5932	0.7541	-0.9118	-0.2846
EBIT(3-vol)	0.0275	0.0000	-0.0352	0.0903
FA/LTL	-0.2834	0.9768	-0.3667	-0.2078
OI/AC	-0.3900	1.5117	-0.4845	-0.3015
OR/CA	-0.2318	0.6242	-0.4822	0.0163
OR/CL	0.1863	0.5557	-0.0603	0.4336
OR/FA	-0.4434	0.8425	-0.5733	-0.3238
OR/LTL	-0.1743	0.5514	-0.2367	-0.1153
OR/TA	-0.5687	0.8503	-0.8775	-0.2708
OR/TL	0.1341	0.7014	-0.1138	0.3817
QA/S	-1.4560	1.1965	-2.1604	-0.7680
S/TA	-0.4949	0.9306	-0.8215	-0.1794
TA	0.0765	0.0000	0.0109	0.1431
WC/TA	3.7082	2.7676	2.8091	4.7277

Source: Our own analysis of data from the Amadeus database

At the second stage, the number ofpotential predictors was reduced by applying a (forward and backward) stepwise discrimination at a 1% significance level of the F-test. By the forward stepwise discrimination, the 15 potential predictors were reduced to 8. The classification precision achieved was 81.25% of bankrupt companies detected in the sample. For comparison, also the backward stepwise discrimination was applied achieving the same classification precision, but engaging only three predictors. See the following Table 3.

Table 3 Stepwise discrimination results – model 1

	Wilks lambda	Part. lambda	F	p-val.	Toler.
QA/S	0.5334	0.9262	15.5307	0.000113	0.855471
S/TA	0.5343	0.9246	15.9115	0.000094	0.668317
TA	0.9194	0.5373	167.9262	0.000000	0.717309

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.49401, $F(3;195)=66.575$, $p<0.0000$.

3.4 Model 2

For Model 1, only those potential predictors were included meeting the normality condition after being transformed. As this method differs from the previous ones (see Altman, 1968, 1977; Deakin, 1972; Hung, Chen, 2009) also, the possibility was explored of buildinga model with non-transformed data included. Model 2 was created by reducing the original 44 potential predictors to 4 by applying stepwise discrimination at a 1% significance level of the F-test. For results, see the below Table 4.

Table 4 Stepwise discrimination results – model 2

	Wilks lambda	Part. lambda	F	p-val.	Toler.
QA/TA	0.5148	0.9495	10.7473	0.0012	0.8294
QA/S	0.5965	0.8194	44.5266	0.0000	0.8514
NI/FA	0.5060	0.9660	7.1034	0.0083	0.9631
TA	0.8579	0.5697	152.5612	0.0000	0.8161

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.48876, F (4;202) = 52.822, p<0,0000.

3.5 Model 1 and 2 classification precisions

For the sample observed, Models 1 and 2 achieved the same classification precision, see the below Table 5.

Table 5, Model 1 and 2 classification precisions

Observed	Forecast		Total	correct %
	Active	Bankrupt		
Active	173	2	175	98.86
Bankrupt	6	26	32	81.25
Total	179	28	207	96.14
Type I error			7.14%	
Type II error			3.35%	

Source: Our own analysis of data from the Amadeus database

The below Table 6 displays the Spearman correlation coefficient values between the Model 1 and Model 2 predictors. M denotes the model using the indicator in question.

Table 6, Correlation between Model 1 and 2 predictors

M	Indicator	Spearman	t(N-2)	p-val.
1	QA/S & TA	0.0520	0.7452	0.456986
1	S/TA & QA/S*	-0.3155	-4.7603	0.000004
1	S/TA & TA*	-0.4472	-7.1587	0.000000
2	QA/S & QA/TA*	0.2062	3.0171	0.002875
2	NI/FA & TA	0.0734	1.0542	0.293032
2	NI/FA & QA/S	-0.0164	-0.2344	0.814875
2	QA/S & TA	0.0520	0.7452	0.456986
2	QA/TA & TA*	-0.2220	-3.2592	0.001308
2	QA/TA & NI/FA*	0.4516	7.2475	0.000000
1,2	S/TA & QA/TA*	0.4507	7.2297	0.000000
1,2	S/TA & NI/FA*	0.1920	2.8011	0.005580

Source: Our own analysis of data from the Amadeus database

The TA and QA/S ratios are common to both models with a very small and statistically insignificant correlation existing between them. In addition to both these predictors, Model 1 contains a S/TA ratio having a statistically significant negative correlation with both TA and QA/S. Model 2 has NI/FA and QA/TA[3] ratios instead of the S/TA ratio. A statistically significant positive correlation exists between the NI/FA and QA/TA ratios. A statistically significant positive correlation exists between the S/TA ratio (model 1) and the NI/FAor theQA/S ratios (model 2). As model 1 contains more statistically significant negative correlations and a positive correlation exists between the ratios in which the models differ, according to Altman (1968) and Cochran (1964), model 1 can be taken for more suitable.

3.6 The predictors found – model 1

The first predictor found is the quick assets to sales (QA/S) ratio referred to as a quick assets turnover. This ratio measures the activity (Back et al. 1999; Li, Sun, 2009) or liquidity (Deakin, 1972, 1976). In this indicator, Deakin (1976) points to the frequent non-normality and existence of extreme outliers. Non-normality and existence of outliers biases the results of statistical testing even in the case of non-parametric tests (Zimmerman, 1994, 1995, 1998). In the present research, normality was tested and outliers removed. The QA/S ratio, in terms of its discrimination ability, appears to be more suitable than other liquidity indicators traditionally used such as the current ratio (CR) and the relative working capital value (WA/TA). Especially the WC/TA ratio is a liquidity indicator frequently used in bankruptcy models (Beaver, 1966, Altman, 1968, 2006; Ohlson, 1980; Shumway, 1999; Wu, Gaunt, Gray, 2010; Lin Liang, Chen, 2011). The second predictor represents the sales to total assets (S/TA) ratio also referred to as a capital-turnover ratio. According to Altman (1968), this ratio reflects: "*the management capability in dealing with competitive conditions*". In Altman's model (Altman, 1968), this ratio on a univariate basis was not statistically significant with his strength consisting in combination with other predictors, see Altman, 1968: „*this ratio was insignificant on a univariate basis, the multivariate context is responsible for illuminating the importance*". Altman (1968) believed that this was caused by the strong negative

* at a significance level of 1%

correlation to the EBIT/TA[3] ratio. Altman (1968) used non-transformed data. The non-transformed-data-based model 2 did not include this ratio. The significance of this indicator for bankruptcy prediction was only apparent after a transformation (within the meaning of Niemann et al, 2008). The third predictor is the total assets value (TA), which is one of the company-size or market-position factors (Niemann et al, 2008) withlarger firms considered more able to survive hard times being less bankruptcy prone (Wu, Gaunt, Gray, 2010). Shumway (1999) mentions company-size factors as very significant bankruptcy predictors. Unlike the above predictors, this predictor is of a non-ratio character. Financial predictors or indicators usually take the form of ratios. The reason for using ratios is that they make it possible to compare companies of different sizes (Altman, 1968). This approach results in an isolation of the company size factor outside the bankruptcy model. The research carried out corroborates that the size factor itself is an important bankruptcy predictor and should be included in the model, both in its transformed and non-transformed form.

4 Discussion

The authors of the above models (see Altman, 1968, 1977, Zmijewski, 1984, Shumway, 1999) wanted each model variable to describe a different area of a company's financial health (indebtedness, profitability, liquidity, etc.). According to Niemann et al, 2008,this approach results in an increased number of uncorrelated model input parameters increasing its performance. Correlated predictors may be useful because some predictors may not alone be related to a bankruptcy, but they are in combination with other predictors (see Cochran, 1964; Altman, 1968). Model 1, which only included potential predictors with normality proved, reached the same precision as model 2 form non-transformed data. Model 1 shows overall characteristics (Wilks lambda, F value) slightly better than those of model 2 as it also contains more statistically significant correlations (see Cochran, 1964; Altman, 1968). Reducing the original set of predictors to a smaller subset may result in this subset being ineffective when applied to companies or periods other that those used for building the model (Grice, Dugan, 2001;Wu, Gaunt, Gray, 2010). Testing predictors over a time is the subject of further research.

[3]Earnings Before Interest and Taxes to Total Assets.

5 Conclusion

As a result of analysing data of Czech-Republic-based industrial enterprises from the 2007 to 2010 period, three financial predictors were found with a statistically significant relationship to bankruptcy. These are quick assets turnover representing activity or liquidity, capital-turnover ratio describing the ability to succeed in competition, and the total assets value as a company-size factor. The importance of a combination of these three predictors for the model's discrimination capacity is increased by their negative correlation. For a give sample, a model containing these predictors reached a precision of 81.25% of correctly predicted bankrupt companies and 98.86% of correctly predicted activecompanies.

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