Bankruptcy Prediction Model of Industrial Enterprises in the Czech Republic

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***Abstract*—**Imminent bankruptcy endangers the owners and employees of a bankrupting company as well as its creditors such as other companies and banks. The number of the Czech companies going bankrupt from 2008 to 2011 was three to four times higher, which makes it even more necessary to look for early-warning tools. Based on an analysis of the financial statements of Czech industrial enterprises submitted between 2007 and 2010, a bankruptcy prediction model has been devised with a classification precision ranging from 94.03to 97.79 percent.It can identify bankruptcy with a confidence of 90 percent even three years ahead.

***Keywords*—**bankruptcy prediction, discriminant analysis, Box-Cox data transformation, forward and backward discrimination, classification function

I. INTRODUCTION

BYthe neoclassical economic theory, a bankruptcy makes it possible for the management to free the inefficiently used economic resources reallocating them to achieve their more efficient use (see Lízal, Schwarz, 2012).Over a short period, however, bankruptcy brings about huge economic losses for the investors and other stakeholders with the company incurring considerable social and other costs, too(Shuai, Li, 2005).Smrčka et al (2012) see the social costs of a bankruptcy mostly in increased unemployment, loss of qualification of ex-employees, increased costs of the social security system, and loss of specific know-how related to the bankrupt enterprise.Their existence calls for an analysis of the bankruptcy causes and early identification of signs heralding bankruptcy.

By Wu (2010), the internal enterprise causes may be seen in insufficient management skills, marketing,and inability to compete.They are reflected in the company performance as recorded in the books. For this reason, accounting data are a frequent source of information for assessing the stability and viability of an enterprise.

Many authorsare trying to develop a tool for early identification and prevention of bankruptcy. Such a tool is a significant contribution to the efficiency of corporate management and the performance of the national economy.

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Papers by Beaver (1966) and Altman (1968), later referred to by many others such as Deakin, 1972, Altman, 1977, Ohlson, 1980, Zmijewski, 1984, and Shumay, 1999, can be seen as groundbreaking in this area.

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.

Lízal and Schwarz (2012) point out the lack of empirical studiesconcerned with bankruptcies (financial distress) in the CEE region. This paper is concerned with problems encountered when designing a bankruptcy modelapplicable to the Czech environmentwhile presenting the results of our own research leading to the design of a three-factor bankruptcy-prediction model.

II. LITERATURE REVIEW

That financial figures can be used to predict an imminent bankruptcy was first conceived by Beaver (1966).For each figure, he compared the values measured at healthy enterprises with those of bankrupt ones finding out that signs of bankruptcy could be traced as far back as five years. Beaver'sapproach involved investigation of the influence of isolated indicators. Altman (1968) started to take into account the mutual interaction between indicators usinglinear discrimination analysis.Correlated indicators may increase a model's discriminating capacity (see Cochran, 1964). The idea that suitable bankruptcy predictors could be found by comparing corresponding indicators for healthy (prospering) and bankruptcy enterpriseswas used as a basis in many other models(Altman, 1977; Lin, Liang, Chen 2011; Wang, Lee, 2008; Niemann et al., 2008; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009; Cheng, Chen, Fu, 2006, Tomić-Plazibat et al, 2006, Zhou, Elhag, 2007) even if a different approach may also be identified based on using only the bankruptcy data to derive a bankruptcy model (see Wu, 2010).

According to Mandru et al (2010), Altman's model (Altman, 1977) is still robust despite being designed over30 years ago.Later, the method used by Altman (1968) to find suitable variables by reducing the original set to a suitable subsetcame to be known as the building of a reduced model. In the literature, the reduced form is applied most often to the building of a model (Lin, Liang, Chen, 2011; Wang, Lee, 2008; Niemann et al 2008; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009; Cheng, Chen, Fu, 2006).Many other authors were interested in applying the model in periods, areas, and industries different from those for which it was designed – see, for instance,Platt, Platt, 1990, Grice, Dugan, 2001; Carling et al, 2007; Wu, Gaunt, Gray, 2010. Grice and Dugan (2001) investigated Ohlson's (Ohlson, 1980) and Zmijewski's model (Zmijewski, 1984) concluding that the precision of both models was degraded significantly when they were applied to different data samples. They postulate that the relationship between the financial figures and bankruptcy may change over time. This conclusion corresponds with Deakin's view (1972).

A possible explanation of the fact that models are inefficient when applied in different economic environmentsis given by Scott (1981). Scott maintains that the subset created by reducing the original set of variablesin order to be suitable for a particular case (*such as a certain economic environment*) is often inefficient when applied to firms or periods other than those used to construct the model.

Shumway (1999) criticizes the above models as static suggesting the use a Cox model for a bankruptcy model (see 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. 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.They concluded that using this transformation approaches normality considerably as it removes skewness completely while kurtosis only partly. Nikkinen and Sahlstrőm (2004) maintain that positive skewness can be observed in financial indicators, which are inherently positive such as liquidity indicators. Next, they postulate that the skewness of indicators with a lower limit of zero and upper limit of 100 percent(such as the total indebtedness indicator)will tend to be slightly negative. This problem is analysed in more detail in a paper by McLeay and Omar (2000). Zimmerman (1994, 1995, 1998) was concerned with the influence of non-normality and outliers on the precision of parametric (t-test) and non-parametric testing (Mann-Whitney-Wilcoxon U-test).

He found out that non-normality and the existence of *extreme outliers*influences the results of non-parametric tests, too, in terms of the second-type error.A first-type error occurs if a bankruptcy-prone company is assessed as financially stable. A second-type order describes the opposite situation, that is, evaluating a financially stable company as facing a bankruptcy. By Zhou, Elhag (2007), the first-type error is 2 to 20 times more serious (thus costly) than the second-type error.

By Zhou and Elhag (2007),a model's precision is seriously degraded if predicting a bankruptcy lying more than two years ahead. Carling et al (2007) were concerned with the possibility to use macroeconomic data to predict bankruptcymaintaining that adding external environment indicators improves the precision as comparedwith that of a model using purely financial indicators. Aziz and Dar (2006) examined 89 studies concerned with models used to predict bankruptcy finding out thatdiscrimination analysis (MDA), 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 than any other. Different methods have different advantages and disadvantages for different data.

III. SAMPLE AND METHODS USED

The sample consisted of 207 Czech-Republic-based industrial enterprises (joint-stock companies) including 32 bankrupt and 175 prospering ones[1]. The data came from AMADEUS (Analysis Major Database for European Sources).The sample data included financial statements submitted one year prior to the bankruptcy. As Beaver-Altman's matched-pairs approach, that is comparing only enterprises of identical sizes, was not used on purpose, the observed sample includes enterprises of different sizes. The reason is the following: the enterprise size as such may itself be a significant bankruptcy indicator in the first place (see Ohlson, 1980; Peel & Peel, 1987).Second, as bankruptcy is a rare occurrence[2], this matching may influence the sample size and, thus, the number of the degrees of freedom (Taffler, 1982).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. Statistica 10 was used for calculation.

A. 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

[1]Data on 200 active and 92 bankruptcy companies have been gathered over three years, which is a total of 876 observations. Complete financial records one year before bankruptcy were only available at 32 bankrupt and 175 prospering enterprises. The remaining observations were used to test the model over time, see further.

[2]In the Czech Republic from 2006 to 2010, the number of wound-up joint-stock companies ranged between 2 and 2.6% (Felcman, 2010).

2008; Niemann et al, 2008; Beaver, 2005; Tseng, Hu, 2010; Psillaki, Tsolas, Margaritis, 2009).In this way, 53potential predictors were obtained with 44 potential predictors being calculated from the data available[3].

Table 1 lists potential predictors and the methods of their calculation.The CR, OP/OR, TL/TA, WC/OE, OR/TA, and EBT/OR indicators were not included in the sample because of being strongly[4] correlated with other indicators.The total number of indicators tested was 38.

B. 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).According to McLeay, Omar (2000), normalityof financial indicators improves the classification precision of a linear-discrimination-analysis-based model. A Shapiro-Wilks procedure (SW test) was used to test normality (Shapiro, Wilks, 1964). This test is especially suitable for small-sized samples (Meloun, Militký, 1994; Hebák et al, 2007).The Shapiro-Wilks test tests the null hypothesis that a sample $x_1, x_2,\ldots,x_n$came from a normally distributed population. The test statistics is (Hebák et al, 2007):

$$SW = \frac{\left[\sum_{i=1}^{n} a_i x_{(i)}\right]^2}{Q(x)} \tag{1}$$

where

$$Q(x) = \left(x_i - \bar{x}\right)^2 \tag{2}$$

and

$x_{(i)}$ are order statistics,

a_i are constants specially derived by Shapiro and Wilks for the purposes of this test, these constant are tabulated.

Table 1 List of analyzed indicators

CA/TA	Current assets/total asset	OI/AC	Oper. income (loss)/avarage capital
CD/S	Current debt/sales	OP/OR	(Oper. revenue - oper. cost)/oper. revenue
CF/S	Cash flow/sales	OR/CA	Oper. revenue/current assets
CF/TA	Cash flow/total asset	OR/CL	Oper. revenue/current liabilities
CF/TD	Cash flow/total debt	OR/FA	Oper. revenue/fixed assets
CR	Current ratio	OR/LTL	Oper. revenue/long-term liabilities
DR	Debt ratio	OR/TA	Oper. revenue/total assets
E/TA	EBIT/total asset	OR/TL	Oper. revenue/total liabilities
EBIT (E-vol)	EBIT (3-yers volatility)	PM	profit margin (3-year average)
EBIT/Int.	EBIT/interest	QA/S	Quick asset/sales
EBITDA/Int.	EBITDA/interest	QA/TA	Quick asset/total asset
EBITDA/TL	EBITDA/total liabilities	RE/TA	Retained earnings/total asset
EBT/OR	Income (loss) before tax/Oper. Revenue	S	Log of sales
EQ	log of equity	S/TA	Sales/total asset
FA/LTL	Fixed assets/long-term liabilities	TA	Total assets
NI/AC	Net income (loss)/avarage capital	TD/EDA	Total debt/EBITDA
NI/CA	Net income/current assets	TL/TA	Total liabilities/total assets
NI/FA	Net income/fixed assets	WC/OE	Working capital/operating cost
NI/OR	Net income/Oper. revenue	WC/S	Working capital/sales
NI/TA	Net income/total asset	WC/TA	Working capital/total asset
NI-change	[NI(t) - NI(t-1)]/[|NI(t)| +|NI(t-1)|]	Tan. A/Tot. A	Tangible assets/total assets
OC/OR	Oper. cost/oper. revenue	Int. A/Tot. A	Intangible assets/total assets

Source: Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980), Ding et al. (2008), Lin, Liang, Chen (2011),Wang, Lee (2008), Niemann, Schmidt, Neukirchen (2008), Beaver (2005), Tseng, Hu (2010), Psillaki, Tsolas, Margaritis (2009)

In the event that non-normality is proved, two approaches are possible.

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

[4]Correlation was determined by a non-parametric Spearman coefficient with the statistically significant correlations above 0.9 at 1-percent level of significance being thought of as very strong.

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 (Watson, 1990, 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.

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:

$$y^{(\lambda)} = \begin{cases} \dfrac{(y+\lambda_2)^{\lambda_1}-1}{\lambda_1} & ; \quad \lambda_1 \neq 0 \\ \ln(y+\lambda_2) & ; \quad \lambda_1 = 0 \end{cases} \tag{3}$$

The parameter λ_1 can be estimated by maximizing the log-likelihood function (Nikkinen, Sahlstrőm, 2004):

$$\ell = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln\sigma^2 - \frac{1}{2\sigma^2}\sum_{t=1}^{n}\left(y_t^{(\lambda)}-\mu\right)^2 + (\lambda-1)\sum_{t=1}^{n} y_t \tag{4}$$

In the case of a negative value of the financial ratio *(y)*, a positive constant *(λ_2)* is added to ensure positivity of the variable *($y+\lambda_2$)* to be transformed.

Here the indicators of sales *(S)*, total assets *(TA)*, and equity *(EQ)*, originally 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 3). The value of (λ_1) is taken to be the maximum likely estimate, its 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 present value of the Shapiro-Wilks test.

IV. RESULTS

Testing normality

By the Shapiro-Wilks test,none of the 38 non-transformed indicators appeared to be normally distributed at a significance level of at least 1%.After transformation, the following 13 financial quotients (which is only 34.2%) passed the normality test at a significance level of at least 1%[5]:

1. Current Debt To Sales (CD/S),
2. 3-Year EBIT Volatility (EBIT 3vol),
3. Fixed Assets To Long Term Liabilities (FA/LTL),
4. Operating Income To Average Capital (OI/AC),
5. Operating Revenue To Current Assets (OR/CA),
6. Operating Revenue To Current Liabilities (OR/CL),
7. Operating Revenue To Fixed Assets (OR/FA),
8. Operating Revenue To Long-Term Liabilities (OR/LTL),
9. Operating Revenue To Total Liabilities (OR/TL),
10. Quick Assets To Sales (QA/S),
11. Sales To Total Assets (S/TA),
12. Total Assets (TA),
13. Working Capital to Total Assets (WC/TA).

Depending on the approach to the use of the SW tests results, two models were set up, model 1 and model 2.

Model1 – forward discrimination

The original 38potential 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 achieved normality by Shapiro-Wilks test. The significance level of the test was chosen to be p=0.01. Thus, the original number 38 of potential predictorswas decreased to 13. At the second stage, the number of potential 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 13potential predictors were reduced to 6. See the below table.The effect of the variables marked with (*) is significant at a 5% level so they cannot be excluded from the model.

Table 2 Results of forward step discrimination – model 1

	Wilk. Lambda	Parc. Lambda	F to remove	p-value	Toler.
TA*	0,8803	0,5480	158,390	0,00000	0,696249
QA/S*	0,5190	0,9294	14,589	0,00018	0,786518
S/TA*	0,5014	0,9621	7,572	0,00650	0,109173
OR/CA	0,4911	0,9822	3,473	0,06391	0,393127
OR/FA	0,4872	0,9900	1,936	0,16570	0,150260
OI/AC	0,4856	0,9934	1,274	0,26041	0,596475

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.48239 approx. F (6,192)=34.337 p<0.0000. Model 1 generated by forward discriminationis statistically significant by an F-test at a 1% significance level.The model correctly identified99.43% of prosperingenterprises and 84.38% bankrupt ones with an overall precision of 97.1%. The first-type error was 3.57% and the second-type error was 2.79%.

Reduced model 1

The following model can be obtained by ignoring variables not statistically significant as determined by a 5%-level F test.

[5]The details of the SW test and the transformation parameters are included in the appendix.

Table 3 Reduced model 1

	Wilk. Lambda	Parc. Lambda	F to remove	p-value	Toler.
QA/S*	0,9193	0,5433	170,646	0,00000	0,703231
TA*	0,5444	0,9175	18,258	0,00003	0,663768
S/TA*	0,5417	0,9220	17,172	0,00005	0,860823

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.49945, F (3.203)=67.815 p<0.0000.

The reduced variant of model 1 scored slightly worse while involving only half of the indicators. Such a model with only three variables could correctly identify 98.86% of prospering and 81.25% bankrupt enterprises with an overall precision of 96.13%. The first-type error is 7.14%, the second-type error is 3.35%, with the first-type error being committed if a bankrupt enterprise is evaluated as financially healthy (prospering) by the model;the second-type error then occurs in the opposite situation.

Classification function

To evaluate the bankruptcy risk of a particular enterprise, a classification function can be used. Two classification functions are available in Statistica 10, the software used, (table 4). An enterprise is assigned to a group if the value of the classification function pertaining to the group is greater than the value of the second classification function. This is a clear-cut decision with no grey zone of equivocal results as it is the case in a discrimination function.

Table 4Classification function of reduced model 1

	Active	Bankruptcy
S/TA	44,8240	38,9665
QA/S	44,5134	59,0637
TA	3,2356	2,4002
Constant	-65,6812	-47,6496

Source: Our own analysis of data from the Amadeus database

Model1 – backward discrimination

For comparison, backward discrimination analysis was applied, too, with F-test at a 1% level of significance. This method resulted in finding different predictors with the exception of*(TA).*

Table 5Results of backward discrimination – model 1

	Wilk. Lambda	Parc. Lambda	F to remove	p-value	Toler.
TA*	0,8583	0,5627	150,7880	0,0000	0,8527
CD/S*	0,5400	0,8943	22,9338	0,0000	0,0814
OR/CL*	0,5359	0,9012	21,2660	0,0000	0,0717
OR/TL*	0,5161	0,9357	13,3331	0,0003	0,3476

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.48295, F (4,194)=51,924 p<0,0000. Model 1 created by backward discrimination is statistically significant by an F-test at a 1% significance level.However, this model achieves a classification precision that is identical with that of reduced model 1, correctly identifying 98.86% prosperingenterprises and 81.25% bankruptones.The model overall precision was 96.13%.First-type erroris 7.14%, second-type error 3.35%.

Table 6Classification function of model 1 – backward discrimination

	Active	Bankruptcy
CD/S	875,133	944,800
OR/CL	90,115	97,920
OR/TL	9,379	6,284
TA	1,504	0,763
Constant	-166,928	-170,323

Source: Our own analysis of data from the Amadeus database

Model 2 – forward discrimination

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 modelregardless of the conclusions of a SW test.

Model 2 was created by reducing the original 38potential predictors to 16 by applying forward discrimination at a 1% significance level of the F-test. For results, see the below Table 7.

Table 7Results of forward discrimination – model 2

	Wilk. Lambda	Parc. Lambda	F to remove	p-value	Toler.
TA*	0,38080	0,80962	41,8576	0,00000	0,01690
QA/S*	0,37453	0,82316	38,2409	0,00000	0,20118
S*	0,34793	0,88610	22,8802	0,00000	0,02610
OR/CL*	0,34212	0,90114	19,5282	0,00002	0,05017
QA/TA*	0,34210	0,90119	19,5172	0,00002	0,11648
S/TA*	0,33082	0,93193	13,0021	0,00040	0,04694
EQ*	0,32978	0,93488	12,3998	0,00055	0,36927
TD/EDA*	0,32513	0,94824	9,7166	0,00213	0,73783
CF/S*	0,32228	0,95662	8,0725	0,00502	0,51456
OR/TL*	0,32069	0,96136	7,1539	0,00818	0,18323
CD/S*	0,31759	0,97076	5,3622	0,02172	0,04839
WC/S*	0,31562	0,97681	4,2253	0,04129	0,23852
EBIT(3vol)	0,31410	0,98154	3,3483	0,06895	0,43597
Tan.A/ Tot.A	0,31264	0,98613	2,5040	0,11533	0,21324
EBITDA/Int.*	0,31169	0,98913	1,9559	0,16370	0,84206
CA/TA	0,31156	0,98952	1,8848	0,17152	0,08169

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda 0.30830, F (16,178)=24,960 p<0,0000. Model 2 created byforward discriminationachieved the lowest values of the (best) overall characteristics, but using the greatest number of variables.The classification precision of this model is100% of correctly identified prosperingenterprises and 84.37% bankruptones, the overall precision being 97.53%. First-type erroris 0%, second-type error 2.79%.

Model 2 – backward discrimination

For comparison, a backward variant of step discrimination was applied, too.The resultsare displayed by Table 8.

Table 8 Results of backward discrimination – model 2

	Wilk. Lambda	Parc. Lambda	F to remove	p-value	Toler.
QA/TA*	0,4972	0,8930	22,635	0,00000	0,61034
QA/S*	0,5863	0,7573	60,559	0,00000	0,63510
WC/S*	0,4756	0,9336	13,439	0,00032	0,61119
NI/FA*	0,4598	0,9658	6,696	0,01041	0,94985
TA*	0,8465	0,5246	171,297	0,00000	0,65959

Source: Our own analysis of data from the Amadeus database

The model overall characteristics: Wilks lambda: 0.44402, F (5,189)=47,331 p<0.0000. Because of the number of its variables, model 2 created by backward discrimination hasexceptional characteristics.Its classification precision is remarkable, too;the model can correctly identify 99.42% of prosperingenterprises and 84.37% bankruptones. Its overall precision is 97.10% with the first-type error being 3.57% and the second-type error 2.79%.

Table 9Classification function of model 2 – backward discrimination

	Active	Bankruptcy
QA/TA	34,116	15,6212
QA/S	-9,255	21,8732
WC/S	-0,084	1,4505
NI/FA	0,000001	0,000001
TA	2,090	1,1823
Constant	-103,643	-84,1530

Source: Our own analysis of data from the Amadeus database

The models present 4 different methods of using step discrimination analysis to find suitable bankruptcy predictors. By their conclusions, theyaresubstantially different. As our aims include anexplanationof the way in which bankruptcy is reflected in financial figures,we must also pay attention to the mutual relationship between the models' indicators. To this end, the Spearman correlationcoefficient was used for its non-parametric assumptions. The values of this coefficient are listed by Table 10.

The statistically significant correlationsat a 1% level of significanceare shown in bold face.

From Table10,it is clear that the variables of model 1 created by forward discrimination (TA, S/TA, and QA/S) are significantly correlated with the variables of other models. As the models do not significantly differ from each other in their overall characteristics (that is, Wilks lambda, F-stat)even by the overall classification precision demonstrated on the sample observed[6], which ranges between 96.13 % and 97.10%,it can be concluded that the predictors,*(TA)*, *(S/TA)*, and*(QA/S)*,contain aggregated information that, in other models, is accounted for by a greater number of other variables.

Another explanation is that model 1 contains only indicators confirmed as normally distributed by a SW test (seeTable 15).By McLeay and Omar (2000),normality contributes to a higher classification precision of models based on linear discrimination analysis *even more than 3 years before bankruptcy*. Moreover, the model is derived by a forward procedure, which byHair et al (1998 in: Zhou, Elhag, 2007) is more suitable for looking for suitable predictors among a large number of possible explanation variables.

Because of the number of predictors and the precision shown, model 1 created by forward discriminationappears to be the best.

C. 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 relative working capital value *(WA/TA)*,which 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).

Table 10 Spearman correlation coefficient values

	CD/S	NI/FA	OR/CL	OR/TL	QA/S	QA/TA	S/TA	TA	WC/S
CD/S	1,00000	-0,15403	**-0,96352**	**-0,77826**	**0,75250**	0,02334	**-0,41497**	-0,04502	**-0,28638**
NI/FA	-0,15403	1,00000	0,11344	**0,28281**	-0,01637	**0,45162**	**0,19200**	0,07343	**0,32693**
OR/CL	**-0,96352**	0,11344	1,00000	**0,80397**	**-0,74582**	-0,07180	**0,36509**	0,03878	**0,26110**
OR/TL	**-0,77826**	**0,28281**	**0,80397**	1,00000	**-0,64157**	0,16647	**0,59686**	-0,13332	**0,19792**
QA/S	**0,75250**	-0,01637	**-0,74582**	**-0,64157**	1,00000	**0,20619**	**-0,31549**	0,05198	**-0,31670**
QA/TA	0,02334	**0,45162**	-0,07180	0,16647	**0,20619**	1,00000	**0,45074**	**-0,22195**	**0,35878**
S/TA	**-0,41497**	**0,19200**	**0,36509**	**0,59686**	**-0,31549**	**0,45074**	1,00000	**-0,44720**	-0,17087
TA	-0,04502	0,07343	0,03878	-0,13332	0,05198	**-0,22195**	**-0,44720**	1,00000	0,12527
WC/S	**-0,28638**	**0,32693**	**0,26110**	**0,19792**	**-0,31670**	**0,35878**	-0,17087	0,12527	1,00000

Source: Our own analysis of data from Amadeus

[6]This original sample usedis denoted by 1 y. (in), see tables 11 and 12.

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*".This conclusion is consistent withthe theoretical assumptions on bankruptcy that see insufficient management skills as major causes of enterprisebankruptcy (seeLízal, Schwarz, 2012, Zhou, Elhag, 2007, Wu, 2010).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 correlation to the EBIT/TA[7] ratio. In the present model, the predictor*(S/TA)*is also significantly correlated with other indicators (seeTable 10), which suggests that it contains more comprehensive information.

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 (see Ohlson, 1980; Peel & Peel, 1987).

The models presented above have been derived from transformedfinancialindicatorsand, thus, the stability of their predictors (with changing time and industries) is also conditioned by the stability of the transformation parameter estimates. By McLeay and Omar (2000), the estimates of the parameters of Box-Cox transformation are relative stable over timer.

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).Therefore, the model has also been tested using data from further enterprises in the same period as well as data from other periods (seeTables 11 and 12).

D. Testing model 1 overtime

The originally observed sample only contained enterprises with complete financial statements so that all the 38potential predictors could be analysed. Model 1 was derived using 207 observations one year before bankruptcy (1 y. (in)). For its application, however, only data on three indicators are needed, which increases the number of observations by 61 (1 y. (out)) used to test the module designed. Next, data from enterprises two or three years before bankruptcy were used for testing (2 y. or 3y.).Model 1 was tested using another 593 observations.The model robustnesswas further tested using data of 153enterprises going bankrupt in 2011 and 391 enterprises prosperous in the same year (sample marked 2011). Table 11 shows the observation numbers for each year.

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

Table 11 Observation numbers for testing the model

Number of observation			
Time	Active	Bankrupt	Total
1 y. (in)	175	32	207
1 y. (out)	23	38	61
2 years	194	76	270
3 years	182	80	262
2011	391	153	544
Total	965	379	1344

Source: Our own analysis of data from the Amadeus

The model reliability was tested by its classification function (seeTable 9) and the transformation parameters(λ_1, λ_2)pertaining to each predictor,seeTable 13.The testing results are shown by Table 12.

Table 12Model testing over time–percentage of correctly classified enterprises

Time	Active	Bankrupt	Total	Type I error	Type II error
1 y. (in)	98.86%	81.25%	96.14%	7.14%	3.35%
1 y. (out)	78.26%	92.11%	86.89%	12.50%	14.29%
2 years	97.42%	85.53%	94.07%	7.14%	5.50%
3 years	96.70%	90.00%	94.66%	7.69%	4.35%
2011	98.21%	96.73%	97.79%	4.52%	1.29%
average	**93.89%**	**89.12%**	**93.91%**	**7.80%**	**5.75%**

Source: Our own analysis of data from the Amadeus

The model's high prediction capacity was proved by testing. One year ahead, the model can identify the risk of bankruptcy with a precision of 87.14%, with two years ahead it is 85.53%, andwith three years ahead 90.00%.

The overall classificationprecision of the model[8]over time ranges between 94.03% and 97.10% of correctly classified enterprises.

V. 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

[8]The overall classificationprecision was calculated as a weighted average of the number of correctly classified active and bankrupt enterprises with weights given by the number of observations. Observation one year before bankruptcy (1 y.) was calculated using a weighted average between 1 y. (in) and 1 y. (out) to be 94.03%.

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).

By the correlation values (seeTable 10), it can be concluded that, in its predictors, the preferred model 1 created by forward discrimination aggregates information accounted for by several other indicators in other models. Moreover, theseindicators also relate to another area of financial health. These are, for instance, factors of indebtedness (*CD/S, OR/CL, and OR/TL)* andprofitability*(NI/FA)*included in the model implicitly rather than explicitly by their correlations with the *(S/TA)*predictor. The robustnessof this model in terms of profitability and indebtedness is based on the stability of such correlations.

The importance of the *(S/TA)* predictor is also corroborated by the fact that, although first used by Altman (1968), it 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).McLeay and Omar (2010) further point out the *(S/TA)*quotient as a financial quotient indicator distinguished among others by its normality.In the present research, this indicator shows stabilityof its descriptive characteristics(variance, mean value), seeTable 17as well as stability of its position within the model (correlationto QA/S), which exists between different times and industries, thus contributing to the model's robustness (seeTable 18).

Model 1 appears to be more precise when applied to a sample including enterprisesfrom different industries (sample 2011), than when applied to samples of a selected industry. This conclusion is at variance with the theoretical assumptions that the precision of a model will decrease as the model is applied to data of enterprises from different industries. (see Platt, Platt, 1990, Grice, Dugan, 2001; Carling et al, 2007; Wu, Gaunt, Gray, 2010). One could assume that the predictors found are not industry-specific. However, such an assumption requires further research.

An analysis of the descriptive characteristics of the samples observed discovered that the volatilityof the predictors was many times higher in samples of bankruptenterprises, than in those of prosperingones (seeTable 17).Such a high volatility results in a lower ability of the model to correctly identify bankrupt enterprises (*see type I error*), which was also the case of the model created by us (seeTable 12).An exception is the group of enterprises one year before bankruptcy, which were not used in the model design (1 y. (out)). The reason was a small number of observations in this group and frequent occurrence of outliers, which results in extremely high mean values of the predictor (seeTable 17). To eliminate this deficiency, more robust classification algorithms could be used such as artificial neural networks, which perform better than methods using multi-criteria discrimination analysis (such as Back, Laitinen, Sere, 1996; Shin, Lee, 2002; Wilson, Sharda, 1994). On the other hand, it is a drawback of these methods that their inner structure cannot be analysed and they must be seen as black boxes. Thus, they cannot be used to identify factors that may signalise a potential bankruptcy risk.

VI. CONCLUSION

As a result of analysing data of 207 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. The model robustnessover time and different industries was subsequently tested using another 1137 observations. The model overall classificationprecision ranges between 94.03% and 97.79% of correctly classifiedenterprises.

APPENDIX

Table 13. Parameter estimates of Box-Cox transformation (1y. in sample)

Table 14, Results of Shapiro-Wilks test results of non-transformed data (1y

Ratio	λ_1	λ_2	LCL (-95%)	UCL (+95%)	Ratio	λ_1	λ_2	LCL (-95%)	UCL (+95%)
CA/TA	0,8799	0,9663	0,0435	1,7337	OC/OR	5,0000*	1,2154		
CD/S	-3,2487	0,9208	-4,0638	-2,4869	OI/AC	-0,39	1,5117	-0,4845	-0,3015
CF/S	1,6696	1,7775	0,9666	2,4308	OP/OR	5,0000*	2,2154		
CF/TA	5,0000*	2,4268			OR/CA	-0,2318	0,6242	-0,4822	0,0163
CF/TD	-0,8357	1,6335	-1,269	-0,4094	OR/CL	0,1863	0,5557	-0,0603	0,4336
CR	-0,5932	0,7541	-0,9118	-0,2846	OR/FA	-0,4434	0,8425	-0,5733	-0,3238
DR	-0,9379	0,8963	-1,5098	-0,412	OR/LTL	-0,1743	0,5514	-0,2367	-0,1153
E/TA	5	2,0425			OR/TA	-0,5687	0,8503	-0,8775	-0,2708
EBIT(3-vol)	0,0275	0	-0,0352	0,0903	OR/TL	0,1341	0,7014	-0,1138	0,3817
EBIT/Int.	0,0207	2938	-0,0091	0,0517	PM	5,0000*	5,0439		
EBITDA/Int.	-0,0752	693	-0,1051	-0,0446	QA/S	-1,456	1,1965	-2,1604	-0,768
EBITDA/TL	0,839	2,9357	0,5222	1,1806	QA/TA	-1,6071	0,9796	-2,5073	-0,7145
EBT/OR	4,4808	2,311	3,5142	5,5928	RE/TA	4,7995	3,7693	3,8575	5,9092
EQ	0,197	2854652	0,158	0,2423	S	0,1486	0	0,0809	0,2174
FA/LTL	-0,2834	0,9768	-0,3667	-0,2078	S/TA	-0,4949	0,9306	-0,8215	-0,1794
Int. A/Tot. A	-4,2689	1,2123	-5,0365	-3,5242	TA	0,0765	0	0,0109	0,1431
NI/AC	-0,2346	15,4024	-0,2994	-0,1696	Tan. A/Tot. A	0,0049	0,9978	-0,7925	0,7908
NI/CA	2,0262	3,4695	1,5489	2,5607	TD/EDA	0,8511	65,6618	0,7241	0,9874
NI/FA	5,0000*	57,1132			TL/TA	-0,938	0,8963	-1,5098	-0,4122
NI/OR	5,0000*	2,3133			WC/OE	3,0683	2,9058	2,4709	3,7274
NI/TA	5,0000*	2,476			WC/S	[illegible]	[illegible]	[illegible]	[illegible]
NI-change	0,7582	2	0,3475	1,1736	WC/TA	[illegible]	[illegible]	[illegible]	[illegible]

Source: Our own analysis of data from the Amadeus database

Source: Our own analysis of data from the Amadeus database

Ratio	SW	p-value	More than 1%	More than 5%	More than 10%	Ratio	SW	p-value	More than 1%	More than 5%	More than 10%
CA/TA	0,97494	0,00094				OC/OR	0,67806	0,00000			
CD/S	0,73854	0,00000				OI/AC	0,16340	0,00000			
CF/S	0,84343	0,00000				OP/OR	0,67806	0,00000			
CF/TA	0,60931	0,00000				OR/CA	0,84513	0,00000			
CF/TD	0,77269	0,00000				OR/CL	0,92851	0,00000			
CR	0,80014	0,00000				OR/FA	0,08884	0,00000			
DR	0,81964	0,00000				OR/LTL	0,14050	0,00000			
E/TA	0,70822	0,00000				OR/TA	0,79354	0,00000			
EBIT(3-vol)	0,3375	0,00000				OR/TL	0,92234	0,00000			
EBIT/Int.	0,11587	0,00000				PM	0,28459	0,00000			
EBITDA/Int.	0,11457	0,00000				QA/S	0,89543	0,00000			
EBITDA/TL	0,76464	0,00000				QA/TA	0,92687	0,00000			
EBT/OR	0,69612	0,00000				RE/TA	0,68565	0,00000			
EQ	0,37021	0,00000				S	0,46353	0,00000			
FA/LTL	0,08686	0,00000				S/TA	0,82285	0,00000			
Int. A/Tot. A	0,23855	0,00000				TA	0,42715	0,00000			
NI/AC	0,09843	0,00000				Tan. A/Tot. A	0,97039	0,00024			
NI/CA	0,7674	0,00000				TD/EDA	0,63474	0,00000			
NI/FA	0,10708	0,00000				TL/TA	0,81934	0,00000			
NI/OR	0,65464	0,00000				WC/OE	0,74871	0,00000			
NI/TA	0,59918	0,00000				WC/S	0,86486	0,00000			
NI-change	0,952090	0,00000				WC/TA	0,87421	0,00000			

Table 15, Results of Shapiro-Wilks test results of transformed data (1y. in sample)

Ratio	SW	p-value	More than			Ratio	SW	p-value	More than		
			1%	5%	10%				1%	5%	10%
CA/TA	0,9753	0,001050				OC/OR	0,88269	0,00000			
CD/S	0,98377	0,017520	x			OI/AC	0,99191	0,30744	x	x	x
CF/S	0,8516	0,000000				OP/OR	0,88269	0,00000			
CF/TA	0,90394	0,000000				OR/CA	0,99599	0,86801	x	x	x
CF/TD	0,91921	0,000000				OR/CL	0,99622	0,89458	x	x	x
CR	0,99493	0,716420	x	x	x	OR/FA	0,99219	0,33672	x	x	x
DR	0,96877	0,000150				OR/LTL	0,99382	0,57870	x	x	x
E/TA	0,90409	0,000000				OR/TA	0,99624	0,89728	x	x	x
EBIT(3-vol)	0,99614	0,885030	x	x	x	OR/TL	0,9952	0,75893	x	x	x
EBIT/Int.	0,22135	0,000000				PM	0,77717	0,00000			
EBITDA/Int.	0,31618	0,000000				QA/S	0,98884	0,10682	x	x	x
EBITDA/TL	0,76437	0,000000				QA/TA	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT/OR	0,87393	0,000000				RE/TA	0,97304	0,00053			
EQ	0,68301	0,000000				S	0,95281	0,00000			
FA/LTL	0,99239	0,389600	x	x	x	S/TA	0,99662	0,93432	x	x	x
Int. A/Tot. A	0,34896	0,000000				TA	0,98603	0,03905	x		
NI/AC	0,31079	0,000000				Tan. A/Tot. A	0,97405	0,00071			
NI/CA	0,80617	0,000000				TD/EDA	0,652	0,00000			
NI/FA	0,41065	0,000000				TL/TA	0,96865	0,00014			
NI/OR	0,86194	0,000000				WC/OE	0,87771	0,00000			
NI/TA	0,89175	0,000000				WC/S	0,91385	0,00000			

Source: Our own analysis of data from the Amadeus database

Source: Our own analysis of data from the Amadeus database

Table 16, Stabilityof the parameters of Box-Cox transformationbetween samples

QA/S				
Sample	λ1	λ2	LCL (5%)	UCL (95%)
1 y. (in)	-1,45598	1,196505	-2,16044	-0,76800
1y. (out)	-0,60013	1,127255	-0,81069	-0,41519
2 y.	-1,55642	0,964648	-1,76790	-1,36062
3 y.	-1,41811	1,000000	-1,60673	-1,24297
2011	-1,67423	1,044444	-1,83946	-1,51913
S/TA				
Sample	λ1	λ2	LCL (5%)	UCL (95%)
1 y. (in)	-0,49488	0,930605	-0,82151	-0,17943
1y. (out)	-0,60510	0,999904	-1,16209	-0,09763
2 y.	-0,09537	0,999998	-0,32835	0,13100
3 y.	-0,24782	0,999960	-0,46950	-0,03542
2011	-0,52384	0,999981	-0,62968	-0,42365
TA				
Sample	λ1	λ2	LCL (5%)	UCL (95%)
1 y. (in)	0,07648	0,000000	0,01095	0,14305
1y. (out)	-0,02841	0,000000	-0,11796	0,06007
2 y.	0,06588	0,000000	0,01718	0,11470
3 y.	0,07039	0,000000	0,02179	0,11889
2011	0,15581	0,000000	0,12671	0,18525

Table 17, Descriptive characteristicsof predictors – prospering enterprises (A), bankrupt enterprises (B)

QA/S (B)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-val.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	32	0,398	0,3793	2,8818	0,063802	0,0451	1,2657	0,30104
1y. (out)	38	360,864	133,0652	5,7746	0,000000	0,0348	8671,75	1 439,22
2 y.	74	90,068	45,8627	6,2319	0,000000	0,0354	2090,00	320,92
3 y.	80	210,899	48,7576	7,5129	0,000000	0,0000	7240,00	935,60
2011	153	446,385	21,1917	11,6519	0,000000	-0,0444	41180,30	3 495,92
S/TA (B)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-val.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	32	1,32222	1,3184	2,3676	0,433229	0,1518	3,3219	0,8446
1y. (out)	38	0,76961	0,72852	3,4196	0,007178	0,0001	4,0850	0,96955
2 y.	74	1,07494	1,02882	3,4755	0,021512	0,0001	4,7594	1,06012
3 y.	80	1,06253	0,96306	6,2920	0,000000	0,0000	10,6257	1,51989
2011	153	4,81647	1,47468	12,2201	0,000000	0,0000	462,5000	37,45322
TA (B)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-val.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	32	487 055	403 352	3,4098	0,004590	13 077	3 162 368	784 593,12
1y. (out)	38	277 008	244 094	4,4226	0,000005	1 259	2 627 965	531 577,60
2 y.	74	361 955	284 934	4,6032	0,000044	1 088	3 538 439	690 062,58
3 y.	80	283 043	190 106	6,2198	0,000000	1 561	4 325 195	649 889,47
2011	153	88 429	67 871	5,4131	0,000002	2	1 302 736	224 328,50
QA/S (A)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-val.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	175	0,21382	0,2075	3,9330	0,010203	-0,19651	0,9945	0,1985
1y. (out)	23	0,24928	0,23101	3,3558	0,001678	-0,12725	1,11873	0,25909
2 y.	196	153,4665	0,33048	13,9286	0,000000	0,0483	30002	2142,97176
3 y.	182	0,35804	0,33467	7,1748	0,000000	0,0352	2,51875	0,30115
2011	391	0,31001	0,29635	10,2914	0,000000	0,00585	3,13652	0,27465
S/TA (A)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-val.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	175	1,41805	1,36523	6,7481	0,000000	0,0694	8,0880	0,98843
1y. (out)	23	1,65632	1,54219	3,3688	0,001522	0,1928	7,1945	1,64397
2 y.	196	1,53362	1,45805	5,8744	0,000000	0,0000	8,1406	1,1247
3 y.	182	1,51574	1,42952	6,0520	0,000000	0,0493	8,3823	1,13459
2011	391	3,06742	2,31081	18,1422	0,000000	0,0694	170,85	9,2481
TA (A)	**N**	**Mean**	**Wins. Mean**	**Grubbs Test**	**p-hod.**	**Min.**	**Max.**	**Std.dev.**
1 y. (in)	175	7 353 172	5 763 969	8,9362	0,000000	267 425	138 464 258	14 671 915
1y. (out)	23	27 143 654	14 523 172	4,4393	0,000000	309 845	392 593 000	82 321 963
2 y.	196	9 838 098	6 820 771	10,9486	0,000000	46 002	313 894 000	27 771 159
3 y.	182	8 520 799	5 309 289	11,1756	0,000000	54 225	303 124 000	26 361 219
2011	391	5 871 375	4 684 916	10,9411	0,000000	3 201	138 464 258	12 118 784

Source: Our own analysis of data from the Amadeus database

Table 18, Stabilityof the model inner structure (correlationbetween predictors)

	1 y. (in)	**1 y. (out)**	**2 y.**	**3 y.**	**2011**
QA/S vs. TA	0,0520	**-0,4477**	-0,0898	-0,1415	0,0056
S/TA vs. QA/S	**-0,3155**	**-0,8455**	**-0,6993**	**-0,6975**	**-0,7169**
TA vs. S/TA	**-0,4472**	0,2443	-0,1128	0,0315	**-0,2014**

Source: Our own analysis of data from the Amadeus database

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