Accuracy of Models Predicting Corporate Bankruptcy in a Selected Industry Branch

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Abstract

The paper's main aim is an accuracy verification of dozens models predicting financial distress. The evaluated models were created in the past in developed countries and especially in transition economies. High probability of bankruptcy does not affect only an ailing enterprise itself but it also influences other business related entities or counterparties and therefore the results provided by models predicting financial distress have their serious usage as scoring models. Models predicting financial distress help the decision making process by predicting future development of selected business entities. Research hypotheses are based on the idea that already existing models predicting financial distress still have enough explanatory power and accuracy for decision making and there is no need for the creation of a new one. The research should answer the question which models should nowadays be recommended the most for practical use. The paper uses for the verification tools such as Type I Error, Type II Error, ROC Curves and related AuROC coefficients.

Keywords: *financial distress, bankruptcy models, CZ-NACE 25, Czech Republic*

JEL Classification: G30, G33, M20

Introduction – Importance of Models Predicting Financial Distress

Prediction of corporate financial distress is a serious research topic whose beginnings are connected with economists such as Altman (1968) or Beaver (1966). The approaches predicting corporate financial distress or viability can be classified as a specific tool of financial analysis. Corporate bankruptcy also influences many other related entities such as suppliers, customers, financial institutions, the government etc. Due to the cooperation with an ailing partner

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they may threaten their own viability. The models predicting financial distress provide a quick and inexpensive answer and are therefore determined for related entities and not for the company itself which should monitor its own performance regularly.

The debate about prediction models and their explanatory power is usually re-opened by serious political and economic changes. No need to emphasize that it is the case of the last global economic crisis. It is impossible to cover all methods and approaches predicting financial distress since 1960's because many of them were not published as a part of entities' know-how and they are not aggregate mentioned anywhere. Even though dozens of different corporate models and approaches are introduced in this paper. The research hypotheses are based on the idea if the already existing models have still enough explanatory power for decision making. If the models still have a high accuracy there is no need for the creation of new tools. The verification will be done on the Czech enterprises whose data are expressed in financial accounting. At the end the paper should recommend the models which are the best for practical use nowadays.

The paper is divided into several parts. The first part is dedicated to theoretical background of models predicting financial distress. The second part is focused on the paper's objectives and used research methodology. The third part introduces gained results and answers on research questions. The fourth part contains discussion and it is followed by conclusion.

1. Theoretical Basis

Financial viability is the key issue for every enterprise because surviving in a long run is not possible in case of poor financial performance. Kapliński (2008) summarizes the components on which financial standing depends – the company's financial structure, financial liquidity, solvency, the company's ability to adapt, economic resources, ability to generate profit, ability to maximize the company's market value. Models predicting financial distress are based on the following ideas. According to their financial performance it is possible to distinguish companies with high and low probability of bankruptcy. The models included in the paper use the financial data derived from financial statements for prediction. Statistical methods as the discriminant analysis and logistic regression were originally used for the models' construction. Most tested models use two or three zones (unhealthy, grey and healthy) for evaluation. Verified models were created in different political, economic and geographical environments.

The core of verified approaches is represented by the Czech models because of the paper focus. The Czech Republic is introduced by the family indices IN –

IN99, IN01 (Neumaierová and Neumaier, 2002) and IN05 (Neumaierová and Neumaier, 2005), followed by Grünwald Bonita Index (Grünwald, 2001) and Balance Analysis System by Rudolf Doucha (Doucha, 1996). Karas and Režňáková (2013) or Hálek (2013) have come up with new approaches during recent years. These approaches will unfortunately not be verified here because Hálek's approach is not a quick scoring model and Karas and Režňáková approach works successfully only for large entities and it requires accounting data expressed in euros, more detail in Čámská (2014). The developed economies are represented by Altman Z-Score (Altman, 1993), Bonita Index (in the German original Bonitätsanalyse, Wöber and Siebenlist, 2009) or Kralicek (Kralicek, 2007). These approaches are widely used in the Czech Republic (for example Klečka and Scholleová, 2010; Mičudová, 2012; or Čámská, 2015). Completely different historical and economic development of the developed economies makes the use of prediction models widely questionable in the Czech Republic and other transition economies. This is the main reason why the article uses plenty of approaches constructed in the transition countries such as Poland and Hungary as members of Visegrád Group and Baltic states (Latvia, Lithuania and Estonia). Polish models are Hadasik (Hamrol and Chodakowski, 2008), Holda (Pociecha, 2005 and Hamrol and Chodakowski, 2008), Gajdka and Stoda (Kisielinska and Waszkowski, 2010 and Hamrol and Chodakowski, 2008), Prusak (Kisielinska and Waszkowski, 2010), PAN-C, PAN-D, PAN-E, PAN-F, PAN-G, Wierzba, Poznanski, D1, D2, D3, D4 (all previously discussed in Kisielinska and Waszkowski, 2010), Apenzeller and Szarzec, Pogodzinska and Sojak, Sojak and Stawicki (all previously discussed by Hamrol and Chodakowski, 2008). The Hungarian models are created by Hajdu and Virág by the discriminant analysis as well as the logit model (Hajdu and Virág, 2001). The Baltic models are Šorins and Voronova (Jansone, Nespors and Voronova, 2010), Merkevicius (Merkevicius et al., 2006), two factor model (Koleda and Lace, 2009), Stoškus (Stoškus, Beržinskiene and Virbickaite, 2007), Genriha and Voronova (Genriha, Pettere and Voronova, 2011) and R model (Davidova, 1999). Due to paper page range the models' formulas cannot be displayed in this paper but they can be found in the relevant mentioned literature. According to literature review the formulas of some models are not uniform and therefore all known versions are verified.

2. Objectives and Methodology

This part is dedicated to the paper's objectives and used research methodology. The part consists of the subparts Paper's objectives, Research methods, Analyzed industry branch and Definition of surveyed entities. The subpart 2.1

Paper's objectives defines research questions. The subpart 2.2 Research methods is dedicated to the methods used for fulfilling the paper's objective. The final verification is applied to the chosen industry branch (subpart 2.3 Selected industry branch) from which the appropriate enterprises are selected (subpart 2.4 Definition of surveyed entities).

2.1. Paper's Objectives – Research Questions

The paper should solve several connected research questions. The first research question verifies the explanatory power or the accuracy of already existing models predicting financial distress. According to part 2 there are 40 different models' formulas. The research should provide an answer if models created in the past are still sufficient for today's decision making process. The second question stems from the first one. It is looking for models with the highest accuracy because these models should be recommended for practical use. The research is based on the models created in transition economies and verification is done on national data (Czech Republic) and therefore it opens a question if there are differences among the models created in developed countries, the Czech Republic and other transition economies. On the other hand this was not a primary research objective to evaluate national differences and therefore the national differences are not evaluated separately but they will come out as by-products of the primary objective.

2.2. Research Methods

This paper evaluates the explanatory power and performance of various prediction models. The models' quality and accuracy can be measured and compared by several metrics. Sobehart, Keenen and Stein (2000) mention the following tools: Cumulative Accuracy Profiles (CAPs); Accuracy Ratios (ARs); Conditional Information Entropy Ratio (CIER); Mutual Information Entropy (MIE). On the other hand the Basel Committee on Banking Supervison (2005) provides its list of tools according to their popularity in the financial industry: Cumulative Accuracy Profile (CAP) and its summary index, the Accuracy Ratio (AR); Receiver Operating Characteristic (ROC) and its summary indices, the ROC measure and the Pietra coefficient; Bayesian error rate; Conditional entropy, Kullback-Leibler distance, and Conditional Information Entropy Ratio (CIER); Information value (divergence, stability index); Kendall’s τ and Somers’ D (for shadow ratings); and Brier score.

The tools used for verification are described immediately. Specifically, the following methods are Type I Error, Type II Error, ROC curve and its coefficient AuROC. The usage of Type I Error and Type II Error is indispensable in this kind of research. The main advantage is simple calculation whose results are easily interpretable and transparent even for people lacking high mathematical and statistical education. Almost all papers working with creation or verification of prediction models use these measures (for example Altman, 1968; Agarwal and Tafler, 2007; Karas and Režňáková, 2013; Mičudová, 2012). The definition of Type I Error and Type II Error is displayed in Table 1.

T a b l e 1

Type I Error and Type II Error

		Estimated	
		Non-default	Default
Observed	Non-default Default	True Miss (Type I Error)	False alarm (Type II Error) True

Source: Fernandes (2005).

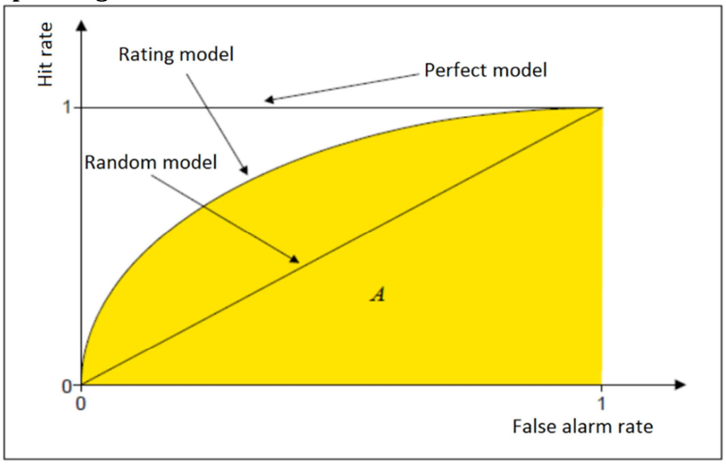
An example of Type I Error is when the model marks a defaulted enterprise as a non-defaulted enterprise. On the other hand when the model classifies a non--defaulted enterprise as a defaulted enterprise than it is a case of Type II Error. The results are also highly dependable on the sample size and therefore instead of absolute values it is better to prefer relative measures. The amount of all defaulted enterprises marked incorrectly is divided by the number of all defaulted enterprises (Type I Error). Vice versa, the number of all non-defaulted enterprises marked incorrectly is divided by the number of all non-defaulted enterprises (Type II Error). Models are generally only a simplification of reality and therefore they will never classify all cases correctly. There is a general consensus in the case of a high quality model which state that the error should not exceed 20% measured in a relative term.

Another approach is represented by the ROC curve (Receiver Operating Characteristic). This approach works as a graphical tool (Figure 1).

The ROC curve is shown by the Rating Model, Perfect Model represents a curve without any incorrect classification and the Random model can be introduced as a coin flip. The index indicator ROC (also called in the literature as A, AuROC or AUC) can be graphically shown as the area under the Rating Model. The explanatory power of the model is higher the greater the area under the Rating model is. This paper uses the ROC curve and its coefficient as an additional tool. Further information about construction and advantages of this tool can be found in Basel Committee on Banking Supervison (2005).

The paper first evaluates the models according to Type I and Type II Errors. Secondly the ROC curves are designed but only for models whose error rate did not exceed 20%. The main difference between error rates and ROC curves is the following. Error rates are based on original cut off points selected by models' authors but ROC curve does not use original cut off points. The ROC curve tries different cut off points for dividing entities into defaulted and non-defaulted groups.

Figure 1
Receiver Operating Characteristic Curves



Source: Basel Committee on Banking Supervison (2005), p. 38.

2.3. Selected Industry Branch

Enterprises belonging to different industries can differ in performance, financial results, composition of liabilities or assets because different activities induce specific requirements. Due to this fact it is common that verification of models predicting financial distress is done on one or more selected industry branches. It is recorded by researches carried out by Klečka and Scholleová (2010), Čámská (2015) and many others. This paper verifies models on the data sample consisting of enterprises belonging to the same industry branch. The selected industry branch is CZ-NACE 25, called Manufacture of fabricated metal products, except machinery and equipment. The Manufacturing, as well as its subpart CZ-NACE 25 has been highly negatively influenced by the last global economic crisis. The number of defaulted enterprises in this industry branch is one of the highest in the Czech Republic as proven by the following researches: Čámská (2013) or by Creditreform (2014).

2.4. Definition of Surveyed Entities

It is necessary to define which enterprises are used for models' verification in this paper because it carries serious consequences on obtained results. The bankruptcy models are designed with two data samples. One consists of enterprises classified as non-defaulted (in other words with low risk of bankruptcy, healthy). The other one contains enterprises classified as defaulted (in other words with high risk of bankruptcy, unhealthy, already bankrupt). Comparable approach is also applied in the case of models' testing.

Enterprises creating economic value added in all years 2010, 2011 and 2012 are defined as non-defaulted entities for paper purposes. Gradually increasing invested capital is one of the most important enterprise goals, emphasized by Synek and Kislingerová (2010) as well as by Veber and Srpová (2005). In spite of the computation of economic value added from financial accounting data (Jordan, Westerfield and Ross, 2011) the economic value added is one of the best indicators for measuring the main entrepreneurship goal.

According to literature review the definition of defaulted enterprises is not uniform. This paper is based only on publicly available data and therefore uses the definition of a legal term from Act No. 186/2006 Coll., Bankruptcy and Settlement (the Insolvency Act). As defaulted entities this paper defines enterprises to which the insolvency proposal was declared during 2012, 2013 and first months of 2014. The second assumption is the data availability. Although all Czech enterprises should regularly publish their financial data they break this legal requirement very often (CRIF – Czech Credit Bureau, 2013). The assumption of a compact annual data series at least three years before declared insolvency proposal is very strict which therefore significantly reduces the final data sample.

According to the aforementioned criteria the enterprises are extracted from the corporate database Albertina. The amount of enterprises is displayed in Table 2.

Table 2

Size of Data Sample – Number of Enterprises

	Data sample – original export	Final data sample – after clearing
Non-defaulted	4 599	390
Defaulted	74	40

Source: Author.

3. Results

The values of prediction models introduced in part 2 are computed for enterprises from the final data sample. The group of non-defaulted enterprises is evaluated based on annual financial statements covering the year 2012. The group of defaulted enterprises is evaluated on the basis of the annual financial statements which cover the first or second year before bankruptcy. Bankruptcy is expressed as the court has agreed to insolvency proposal. The initial step is calculating the Z-scores. The second step is evaluating enterprises according to the original cut off points. Most models use two or three zones (healthy, grey and unhealthy). But some models such as R model, Bonita index or Grünwald Bonita Index work with more than three zones. Enterprises are divided into scoring zones and these results are compared with real situation (healthy x unhealthy). Measures of Type I Error and Type II Error in a relative term are computed. The indicator reliability presents the number of entities classified correctly divided by all entities in the related sub-group /healthy x bankrupt). The sum of the ratio of Type I Error or Type II Error and the appropriate reliability indicator is not always equal to one. This is caused by models using grey zone and by the fact that some enterprises were not classified because of the non-availability of required data.

The results of the indicators Type I Error and Type II Error are displayed in Tables 3 and 4. Table 4 is determined for Polish models. All verified models except the Polish are included in Table 3. Dark coloured numbers indicate when error indicators are higher than 50% or reliability indicators ale lower than 50%. Light coloured numbers are used when it almost hits 50%.

T a b l e 3

Explaining Power of the Verified Models Except the Polish Models

	Defaulted entities		**Non-defaulted entities**	
Model	Reliability	Type I Error	Reliability	Type II Error
Altman	0.775	0	0.715	0.008
IN99	0.725	0.025	0.233	0.013
IN01	0.850	0.025	0.626	0.008
IN05	0.900	0.025	0.718	0.018
Doucha	0.675	0.075	*0.421*	0.144
Grünwald	0.625	0.050	0.644	0.013
Kralicek	0.850	0.050	0.782	0.046
Bonita index	0.775	0.050	0.818	0.000
Hajdu and Virág	0.075	0.900	0.979	0.021
Hajdu and Virág – logit	0.900	0.050	0.713	0.287
Šorins and Voronova	0.975	0	0.890	0.110
Merkevicius	0.975	0	0.721	0.279
2factor_1	0.100	0.875	0.982	0.015
2factor_2	0.600	0	0	0.969
2factor_3	0.025	0.950	1.000	0.000
Stoškus	0.350	0.600	0.426	0.574
Genriha and Voronova	0.300	0.700	0.997	0.000
R model	0.850	0.150	0.867	0.121

Source: Author.

Incorrect classification in case of defaulted companies is connected with the approaches of Hajdu and Virág, two factor model in versions 1 and 3, Stoškus, Genriha and Voronova (all previously mentioned included in Table 3), Holda in version 1 and 2, Gajdka and Stoda in both versions, PAN-C, PAN-D, Wierzba in both versions and Pogodzinka and Sojak (all previously mentioned included in Table 4). Low reliability in this sub-group is also connected with approaches by Appenzeller and Szarec and Sojak and Stawicki. A detailed analysis based on the ROC curves could be applied to the approaches by Altman, IN99, IN01, IN05, Doucha, Grünwald, Kralicek Quick Test, Bonita index, Hajdu and Virág in logit version, Šorins and Voronova, Merkevicius, two factor model in version 2, R model (all previously mentioned included in Table 3), Hadasik, Prusak in both versions, from the PAN family approaches E, F, G, Poznanski, D1, D2, D3 and D4 (all previously mentioned included in Table 4).

Incorrect classification in case of defaulted companies is connected with approaches of the two factor model in version 2, Stoškus (Table 3), D1 and D4 (Table 4). Low reliability in this sub-group is also connected with the approaches of IN99 and Doucha.

The results for both sub-groups can be summarized as follows. Further evaluation is appropriate for the approaches Altman, IN01, IN05, Kralicek Quick Test, Prusak in both versions, from the family PAN models PAN-E, PAN-F and PAN-G, Poznanski, D2, D3, Hajdu and Virág in logit version, Šorins and Voronova, Merkevicius, R model, Grünwald and Bonita index.

T a b l e 4

The Explaining Power of the Verified Polish Models

Model	Defaulted entities		Non-defaulted entities	
	Reliability	Type I Error	Reliability	Type II Error
Hadasik	0.750	0.200	0.895	0.105
Holda1	0	0.975	1.000	0
Holda2	0	0.975	1.000	0
Gajdka and Stoda 1	0.125	0.825	0.979	0.021
Gajdka and Stoda 2	0.050	0.500	0.874	0.095
Prusak 1	0.875	0.050	0.710	0.090
Prusak 2	0.950	0	0.651	0.118
PAN-C	0.350	0.525	0.985	0
PAN-D	0.300	0.6	0.985	0
PAN-E	0.800	0.125	0.974	0.010
PAN-F	0.875	0.100	0.982	0.018
PAN-G	0.850	0.125	0.967	0.033
Wierzba 1	0.400	0.550	1.000	0
Wierzba 2	0.325	0.625	1.000	0
Poznanski	0.825	0.125	0.938	0.062
D1	0.975	0.025	0.541	*0.459*
D2	0.850	0.100	0.838	0.162
D3	0.900	0.050	0.718	0.282
D4	0.900	0.050	*0.541*	*0.459*
Appenzeller and Szarzec	*0.500*	0.325	0.928	0.015
Pogodzinka and Sojak	0.100	0.675	1.000	0
Sojak and Stawicki	*0.550*	0.050	0.815	0.059

Source: Author.

The approaches predicting corporate financial distress chosen according to the results in Tables 3 and 4 are evaluated using the ROC Curve and its appropriate AuROC coefficient. The statistical program SPSS is used for this determination. The final results are shown in Table 5. The arrangement of the models is in the descending order: from the largest to the smallest area. All evaluated models provide better results than Random Model (coin flip) because the area is larger than 0.5. For all verified models the value of AuROC coefficient is higher than 0.8 and their explaining power is therefore high.

T a b l e 5
AuROC Values for Models with Low Type I and II Error

Results Models	Area	Std. error[a]	Asymptotic sig.[b]	95% Confidence interval	
				Lower	Upper
Merkevicius	0.994	0.004	0	0.985	1
PAN-E	0.989	0.007	0	0.974	1
Šorins	0.989	0.006	0	0.978	1
IN01	0.987	0.011	0	0.965	1
IN05	0.987	0.011	0	0.965	1
PAN-F	0.986	0.008	0	0.970	1
Grünwald	0.984	0.007	0	0.972	0.997
Prusak 2	0.982	0.012	0	0.959	1
Bonita	0.982	0.017	0	0.949	1
Altman	0.980	0.010	0	0.961	0.999
PAN-G	0.978	0.012	0	0.955	1
D3	0.974	0.009	0	0.957	0.991
Kralicek	0.969	0.016	0	0.937	1
Prusak 1	0.964	0.023	0	0.919	1
Poznanski	0.964	0.017	0	0.930	0.998
D2	0.953	0.017	0	0.919	0.986
R model	0.919	0.025	0	0.869	0.969
Doucha	0.848	0.050	0	0.751	0.945
Hajdu and Virág	0.839	0.020	0	0.800	0.878

Note: [a.] Under the nonparametric assumption; [b.] Null hypothesis: true area = 0.5.
Source: Author.

The used data samples are strictly polarized due to the definition of surveyed entities described in part 3.4. The critical value of any area under the ROC Curve is usually stated as 0.8 but according to the strict polarization the critical value should be moved. If it is shifted to 0.9 boundary then the models created by Doucha and Hajdu and Virág in logit version do not have enough explanatory power. The paper should have solved two connected research questions which can be answered right now.

The first question was focused on the verification of explanatory power or the accuracy of already existing models predicting financial distress. There were tested 40 different models' formulas. The research confirmed that there are some approaches predicting financial distress which can be used nowadays although they have been created in the past. These models are still sufficient for decision making and prediction. The question 2 stemmed from the first question. Its aim was to evaluate which models are the best or in other words which have the highest accuracy and therefore could be recommended for practical use. The approaches are displayed in Table 5 and we especially recommend approaches whose AuROC coefficient exceeds 0.9.

4. Discussion

This paper answered the research questions introduced in part 3.1. The first question was focused on the appropriate accuracy of prediction models. The part *Results* confirmed that there are many approaches used for predicting corporate financial distress which have enough explanatory power. This means that these approaches can be used nowadays for the decision making. These approaches are specifically Merkevicius, PAN-E, Šorins, IN01, IN05, PAN-F, Grünwald, Prusak 2, Bonita, Altman, PAN-G, D3, Kralicek, Prusak 1, Poznanski, D2 and R model. These mentioned models were not created in the same economic, political and geographical conditions. There are Czech approaches, as well as Polish or Baltic tools accompanied by models created in developed countries. This is the case of Bonita Index, Altman and Kralicek in this sample. It can be summarized that the country of origin does not determine the model's quality. The values of AuROC coefficient exceeded 0.9 in our data sample. These approaches predicting financial distress were able to explain at least 90% of studied entities. These results enable us to conclude a debate about the necessity of the new models' construction. There is no need of a new prediction model because there are plenty of models with high accuracy and explanatory power for our purposes.

In spite of answering the research question many other issues are opened. It is impossible to conclude the debate that there are no better approaches. Plenty of tools predicting distress were not published because of the institutions' know-how. There is a high probability that some models were not discovered although they were published, but in insignificant sources or national languages. The common critique is that models created in the developed countries should not be used for the Czech Republic and other transition countries because of different conditions. This paper reacts to this critique and verifies many approaches created in transition economies which have similar historical, economic and political development as the Czech Republic.

The models predicting financial distress can never function for all verified cases because they are not a physical law and they work on probabilistic roots. Still we would like to ask a question why some prediction approaches have significantly higher accuracy than others. It has been proven by the research on previous pages. The model's success or in more scientific words reliability and accuracy is set up already during the creation phase. The explanatory power of every analysis or created model generally depends on the data quality and quantity. It is almost impossible to construct a reliable model predicting financial distress using only 10 business cases and even from very different entrepreneurial branches. It is not usual that authors publish the samples size and many verified models above were not retaken from original sources. The used data should be representative in terms of size, industry branch, geographical area or ownership relationships of statistical units (in our case businesses). The models' construction methods should be used adequately. The researchers should respect limitations, statistical requirements etc. It is impossible to come to a conclusion if all these conditions were fully met during the creation phase. On the other hand a comparison of an applied statistical method will not bring serious differences because discriminant analysis and logit or probit are based on the same statistical assumptions and therefore they provide comparable results. The main difference between discriminant analysis and logit (probit) is just in user interpretation. Discriminant analysis is verified due to the evaluation table and logit is verified as a probability of occurring the state of the world. Last thinking could be about the models' variables. It may be surprising but the most reliable models are based on general financial ratios such as return on assets, total leverage or liquidity working with net working capital. On the other hand many Polish models use very specific ratios based on inventories and they fail for the Czech data. It can be caused by the non-representative data used for the model's creation, specifics of some industry branches or specific development of inventories management in the Polish enterprises. This paragraph has contained qualified considerations which can be further discussed and even published but with their verification based on data it will not be achievable.

Conclusion

This paper focused on the verification of approaches predicting corporate financial distress. The explanatory power (or accuracy) of these approaches was evaluated. Four dozens of these tools were verified in case of the industry branch CZ-NACE 25, Manufacture of fabricated metal products, except machinery and equipment. This industry branch had a significant number of enterprises under insolvency proposals during the last global economic crisis in the Czech Republic. Statistically significant data samples were tested by approaches as Type I Error, Type II Error, ROC Curves and their related AuROC coefficients. This paper confirms that there are models predicting financial distress which have high accuracy and their practical use is recommended. These approaches are specifically Merkevicius, PAN-E, Šorins, IN01, IN05, PAN-F, Grünwald, Prusak 2, Bonita, Altman, PAN-G, D3, Kralicek, Prusak 1, Poznanski, D2 and R model.

It is necessary to emphasize that the models predicting corporate financial distress should provide quick and inexpensive recommendations. On the one hand they can help in decision making and strategy creation but on the other hand they should not be used as the only tool. These models cannot operate at 100% because they are not a physical law. They will be always only a simplification of the reality.

References

AGARWAL, V. – TAFLER, R. J. (2007): Twenty-five Years of the Taffler z-score Model: Does it Really have Predictive Ability? Accounting and Business Research, *37*, No. 4, pp. 285 – 300.

ALTMAN, E. I. (1993): Corporate Financial Distress and Bankruptcy. NewYork: John Wiley & Sons.

ALTMAN, E. I. (1968): Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, *23*, No. 4, pp. 589 – 609.

BIS (2005): Studies on Validation of Internal Rating Systems. [Working Paper 14.] Basel: Basel Committee on Banking Supervison. Retriewed June 22, 2014 from <www.bis.org>.

BEAVER, W. (1966): Financial Ratios as Predictors of Failure. Journal of Accounting Research, *4*, No. 3, pp. 71 – 111.

CREDITREFORM (2014): Tisková informace: Vývoj insolvencí v České republice v roce 2013 a 2014. Výzkum insolvence. Retriewed May 16, 2014 from: <http://www.vyzkuminsolvence.cz/data/files/zpravodajstvi/creditreform-2013-celek-vyvoj-insolvenci-v-cr-2013.doc>.

CRIF – Czech Credit Bureau (2013): Účetní závěrku za rok 2011 nezveřejnilo v řádném termínu 79 % firem. CRIF – Czech Credit Bureau. Retriewed March 16, 2014, from: <http://www.crif.cz/Novinky/Novinky/Pages/%C3%9A%C4%8Detn%C3%ADz%C3%A1v%C4%9Brku-za-rok-2011-nezve%C5%99ejnilo-v-%C5%99%C3%A1dn%C3%A9m-term%C3%ADnu-79--firem.aspx>.

ČÁMSKÁ, D. (2014): České modely predikce finanční tísně z pohledu uživatele. In: JEDLIČKA, P. (ed.): Hradecké ekonomické dny 2014. Ekonomický rozvoj a management regionů. [Sborník recenzovaných příspěvků z mezinárodní vědecké conference. Díl I, pp. 125 – 131.] Hradec Králové: Gaudeamus.

ČÁMSKÁ, D. (2015): Models Predicting Financial Distress and their Accuracy in the Case of Construction Industry in the Czech Republic. In: PASTUSZKOVÁ, E., CRHOVÁ, Z., VYCHYTILOVÁ, J., VYTRHLÍKOVÁ, B. and KNÁPKOVÁ, A. (eds): Finance and Performance of Firms in Science, Education and Practice. [Proceedings of the 7th International Scientific Conference, pp. 178 – 190.] Zlín: Tomas Bata University in Zlín.

ČÁMSKÁ, D. (2013): Základní charakteristiky podniků v insolvenci. In: JEDLIČKA, P. (ed.): Hradecké ekonomické dny 2013. Ekonomický rozvoj a management region. [Sborník recenzovaných příspěvků z mezinárodní konference. Díl I, pp. 83 – 88.] Hradec Králové: Gaudeamus.

DAVIDOVA, G. (1999): Quantity Method of Bankruptcy Risk Evaluation. Journal of Risk Management, No. *3*, pp. 13 – 20.

DOUCHA, R. (1996): Finanční analýza podniku: praktické aplikace. Praha: Vox Consult.

FERNANDES, J. E. (2005): Corporate Credit Risk Modelling: Quantitative Rating System and Probability of Default Estimation. Retriewed May 22, 2014. Available at: <images.to.camcom.it/f/tofinanza/I_/I_01.pdf>.

GENRIHA, I. – PETTERE, G. – VORONOVA, I. (2011): Entrepreneurship Insolvency Risk Management: Case Latvia. International Journal of Banking, Accounting and Finance (IJ BAAF), *3*, No. 1, pp. 31 – 46.

GRÜNWALD, R. (2001): Analýza finanční důvěryhodnosti podniku. Praha: Ekopress.

HAJDU, O. – VIRÁG, M. (2001): Hungarian Model for Predicting Financial Bankruptcy. Society and Economy in Central and Eastern Europe, *23*, No. 1 – 2, pp. 28 – 46.

HÁLEK, V. (2013): Predikce finanční tísně podniku na základě vlastního bankrotního modelu CCB. Hradec Králové: Gaudeamus.

HAMROL, M. – CHODAKOWSKI, J. (2008): Prognozowanie zagrożenia finansowego przedsiębiorstwa. Wartość predykcyjna polskich modeli analizy dyskryminacyjnej. Badania operacyjne i decyzje, No. *3*, pp. 17 – 32.

JANSONE, I. – NESPORS, V. – VORONOVA, I. (2010): Finanšu un ekonomisko risku ietekme uz Latvijas partikas mazumtirdzniecibas nozares attistibu. Scientific Journal of Riga Technical University Economics and Business Economy: Theory and Practice, *20*, pp. 59 – 64.

JORDAN, B. D. – WESTERFIELD, R. – ROSS, S. A. (2011): Corporate Finance Essentials. New York: McGraw-Hill.

KAPLINSKI, O. (2008): Usefulness and Credibility of Scoring Methods in Construction Industry. Journal of Civil Engineering and Management, *14*, No. 1, pp. 21 – 28.

KARAS, M. – REŽŇÁKOVÁ, M. (2013): Bankruptcy Prediction Model of Industrial Enterprises in the Czech Republic. International Journal of Mathematical Models and Methods in Applied Sciences, *7*, No. 5, pp. 519 – 531.

KISIELINSKA, J. – WASZKOWSKI, A. (2010): Polskie modele do prognozowania bankructwa przedsiębiorstw i ich weryfikacja. Ekonomika i organizacja gospodarki żywnościowej, No. *82*, pp. 17 – 31.

KLEČKA, J. – SCHOLLEOVÁ, H. (2010): Bankruptcy Models Enunciation for Czech Glass Making Firms. Economics and Management, No. *15*, pp. 954 – 959.

KOLEDA, N. – LACE, N. (2009): Development of Comparative-Quantitative Measures of Financial Stability for Latvian Enterprises. Economics & Management, No. *14*, pp. 78 – 84.

KRALICEK, P. (2007): Ertrags- und Vermögensanalyse (Quicktest). Retrieved April 20, 2014, from: <http://www.kralicek.at/pdf/qr_druck.pdf>.

MERKEVICIUS, E. – ERKEVICIUS, E. – GARŠVA, G – GIRDZIJAUSKAS, S. (2006): A Hybrid SOM-Altman Model for Bankruptcy Prediction. In: ALEXANDROV et al. (ed.): ICCS 2006. Part IV, LNCS 3994, pp. 364 – 371. Berlin – Heidelberg: Springer-Verlag.

MIČUDOVÁ, K. (2012): Úpadky podniků v Česká republice a možnosti jejich včasné predikce. [Dissertation Tthesis.] Plzeň: Západočeská univerzita v Plzni.

NEUMAIEROVA, I. – NEUMAIER, I. (2005): Index IN05. In: Evropské finanční systémy, pp. 143 – 148. Brno: Masarykova univerzita.

NEUMAIEROVA, I. – NEUMAIER, I. (2002): Výkonnost a tržní hodnota firmy. Praha: Grada.

POCIECHA, J. (2005): Discriminant Methods for Bankruptcy Prediction – Theory and Applications. Ekonomika, *72*, pp. 77 – 83.

PRUSAK, B. (2004): Jak rozpoznać potencjalnego bankruta. Retriewed April 20, 2014, from: <http://www.zie.pg.gda.pl/~pb/jrpb.pdf>.

SOBERHART, J. R. – KEENAN, S. C. – STEIN, R. M. (2000): Benchmarking Quantitative Default Risk Models: A Validation Methodology. New York: Moody's Investor Service. Retriewed June 22, 2014, from: <http://www.rogermstein.com/wp-content/uploads/53621.pdf>.

STOŠKUS, S. – BERŽINSKIENE, D. – VIRBICKAITE, R. (2007): Theoretical and Practical Decision of Bankruptcy as one of Dynamic Alternatives in Company's Performance. Engineering Economics, *2*, No. 52, pp. 26 – 33.

SYNEK, M. – KISLINGEROVÁ, E. et al. (2010): Podniková ekonomika. Praha: C. H. Beck.

VEBER, J. – SRPOVÁ, J. et al. (2005): Podnikání malé a střední firmy. Praha: Grada.

WÖBER, A. – SIEBENLIST, O. (2009): Sanierungsberatung für Mittel- und Kleinbetriebe, Erfolgreiches Consolting in der Unternehmenkrise. Berlin: Erich Schmidt Verlag GmbH.