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The Prediction Ability of New Bankruptcy Models in National Environment

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Abstract. The prediction of the firm´s future development and possible failure is one of the most important information needed for decision making by all stakeholders. Early detection of impending bankruptcy creates the possibility of adopting remedial measures that can, if they are effective, avert it. The crisis in recent years has raised the focus on predictive models and their reliability. In response to the experience with the elder models and their lower reliability the researches aimed to construct new versions of the older models as well as the new models based on the wider scale of variables. One of the stream of researches is aimed to construct specific models for the condition of emerging economies, i.e. Polish, Slovak, Lithuanian and Czech environment.

The aim of this paper is to compare the reliability of selected foreign bankruptcy models in the conditions of the Czech economy compared to the Czech model and to reveal if there are any differences in the prediction ability depending on the conditions under which they were compiled. We used a set of 80 Czech companies operating on the Czech market, in which insolvency was declared in 2017. Based on these data we compare the prediction ability of the selected models which were created in the foreign economies, both traditional economy and emerging. The results did not confirm the greater reliability of the model that was created in national conditions. The most reliable model has been identified the one created in terms of another transition economy.

Keywords: Bankruptcy Models, Prediction Accuracy, Transition Economy.

1. Introduction

In the contemporary dynamic economic environment, the prediction of the future development and an early identification of possible failure in the future is very important and usable information for all stakeholders. Consequently, many researchers are making considerable efforts, on the one hand, to create new, more advanced models to provide this information as reliably as possible, on the other hand they turn the attention to the models that have already been created and verify their prediction ability at present conditions and in different economies. The result of these studies is the finding that the reliability of predictions of individual models is lower if they are applied in a different environment and different time than they were created [9, 17, 4, 21, 15, 7, 14]. These findings stimulate further research activities aimed to develop new models, appropriate for the time and the conditions in which they are to be used. The result of these activities is a number of new models that are geared to the specific conditions of each economy or period, e.g. for Czech, Polish, Slovak, Lithuanian environment [5], or the new version of the former models, e.g. Altman's model for the UK, the version of the Ohlson´s model 2010 for China or 2011 for Iran [20, 23], etc. Their prediction ability has been tested, both in the conditions in which they originated and in the context of the other economies. Another problem is whether the models created within these conditions achieve higher reliability of prediction in terms of a transition economy compared to models created in traditional market economies. This became a research question in this study. The aim is to verify if the predictive ability of the models created under the conditions of transition economies is larger in the similar condition compared to the model created in the traditional market economy or to the model of domestic origin. It can be supposed, that the model derived from the condition of the transition economy can assess the situation of enterprises in the same condition more precisely and will show a hier reliability in prediction.

The structure of the paper is as follows: in the next chapter a literature review and the used method are described, in the third part the models and the set of firms are characterized, in the fourth part the results of all the models are presented and compared. In the last part the conclusion is presented and the questions for further research are formulated.

2. Previous Literature

The bankruptcy model and its construction involve many issues and sub-issues and many questions need to be solved before and during the process of its derivation. The primary question may be the ones as follows: when the moment is the company fall into the failure, what are the reasons and what are the signs of the failure (according the legal regulation and in real practice), when the firm is forced to close their activities. With the aim to predict the failure the other questions arise: what factors influence the firm activities and may be the cause the firm´s failure, what phenomena indicate the financial problems ahead of the year or two in advance. These factors can be both financial and non-financial, both external and internal, both quantitative and qualitative.

The other questions are focusing on the data source, which can provide a general statement about the company's processes and its financial situation and its ability to sufficiently reflect the future failure. The most common source of data appropriate for these purposes the financial statements have become. But the financial statements provide only financial data that is more or less influenced by the accounting methods. The other data sources, non-financial and qualitative, are highly differentiated.

In the process of the model creation the other specific question concerning the mathematical method used for deriving the predictive models is the key. The classification of these methods varied: the discriminatory models, discriminant analysis and logistic regression or GLM models and Merton model [22, 8] are most often distinguished. Some authors suggest using methods of neural networks as a new tool for model derivation [12, 6]. The choice of method is decisive for model derivation - it can determine its reliability and accuracy [10, 11]. Till now the most often method used for the bankruptcy model's construction was the multivariate discriminant analysis (MDA) although some weaknesses and limitations are known. Despite this, it remains the most commonly used method for construction of the new models.

At the first step the structure of models under investigation will be described. We chose models created in the United States, in Australia, in Poland, in the Czech Republic, and in Lithuania, which are often used in practice, namely: Altman model for nonlisted companies (1983), Ohlson´s model (2010), Gajdka and Stos 2 (1996), IN05 (2005), Hybrid SOM-Altman model (2006). Then we investigated whether the aforementioned models could indicate one or two or three years before the reported bankruptcy the future threat. The most reliable model then was identified, and the limitation of the findings will be discussed.

3. Data set and Methodology

The methodology of our research consists in the application of selected models on the set of Czech companies that got into serious financial difficulties in the year of 2017. As a moment of serious financial difficulties, the announcement of insolvency is considered in this study. The information about the firms with which the insolvency proceedings were commenced we gathered from the Insolvency register. Then we tried to find the financial statements of these companies from the Commercial Register. Even though the firms in the Czech Republic are obliged to publish their financial statements in the Commercial Register every year, this obligation is often not respected, even more by those companies that have been in a difficult situation. However, a group of 80 companies with financial statements available for all three years before the announcement of insolvency were found. The structure of companies in the set of firms according the SMEs parameters including the values of these parameters are shown in the Table 1.

Table 1. Structure of the set of 80 analyzed firms that have fallen into insolvency in 2017.

(in CZK)	Micro	Small	Medium	Large	Total
Total assets less than	9 mils.	100 mils.	500 mils.	More than 500 mils.	x
Turnover less than	18 mils.	200 mils.	1 000 mils.	More than 1 000 mils.	x
Employees less than	10	50	250	More than 250	x
Number of companies	53	26	1	0	80

The choice of the models for testing follows the intention to verify the prediction ability of the models created under different national conditions in conditions of the Czech Republic as a transition economy. The selected models were as follows:

- Altman Z-score for nonlisted companies – that is the original Altman model modified in 80th for non-listed companies. The original model was derived from US business data and US economic conditions in 70th. The adjustment consisted of the fourth indicator - after this adjustment, the calculation is based on this relationship (1):

$$Z' = 0.717*X1 + 0.847*X2 + 3.107*X3 + 0.420*X4 + 0.998*X5 \qquad (1)$$

where: X1 – net working capital/total assets; X2 – accumulated earnings/total assets; X3 – EBIT / total assets; X4 – equity / liabilities; X5 – sales / total assets.

Interpretation of the model results:

Z-score > 2.9 - not current threat of bankruptcy, ,

Z-score < 1.8 - serious financial difficulties,

Z-score in the interval of 1.8 to 2.9 - a grey zone, no prediction is possible.

- Model IN05 – this is a model created based on the conditions and accounting data of Czech firms at the beginning of the century. The authors used the experiences in creating the previous models. The calculation of this model is based on the following relationship (2):

$$IN05 = 0.15 \cdot X1 + 0.04 \cdot X2 + 3.97 \cdot X3 + 0.21 \cdot X4 + 0.09 \cdot X5 \tag{2}$$

where: X1 – total assets / liabilities; X2 – EBIT / interests; X3 – EBIT / total assets; X4 – sales / total assets; X5 – current assets / short-term liabilities.

Interpretation of the resulting values:

IN05 < 0.9 – companies are running for bankruptcy with a probability of 97% and with the probability of 76 per cent they will not generate the value,

0.9 <IN <1.6 – companies are with a probability of 50 per cent likely to fail and with the probability of 70 per cent they will not generate the value,

IN05 > 1.6 – companies are with the probability of 92 per cent in a good condition and with the probability of 95 per cent they are likely to generate the value.

- Ohlson's model 2010 – is the original Ohlosn´s model recalculated by economists at the Australian University of Queenslan with the aim of finding new weighting coefficients along with verification of some new indicators. This modified model was based on a much larger sample of companies and on the data from a relatively long period from 1980 to 2006. The calculation of this model is based on the formula (3):

$$Q = -0.17 \cdot X1 + 3.69 \cdot X2 - 1.87 \cdot X3 + 0 \cdot X4 - 0.54 \cdot X5 + 0.03 \cdot X6 - 0.06 \cdot X7 + 1.16 \cdot X8 - 1.02 \cdot X9 - 7.2 \tag{3}$$

The indicators $x_1, \ldots x_9$ included in the model are constructed as follows:

$X_1 = \log \frac{total\ assets}{GNP\ price-level\ index}$; $X_2 = \frac{total\ liabilities}{total\ assets}$;

$X_3 = \frac{working\ capital}{total\ assets}$; $X_4 = \frac{current\ liabilities}{current\ assets}$;

X_5 : $X5 = 1$, *if total liabilities > total assets* ; $X_6 = \frac{net\ income}{total\ assets}$;

$X5 = 0$, *if total liabilities < total assets*

$X_7 = \frac{funds\ provided\ by\ operations}{total\ liabilities}$

(where: funds provided by operations=net income+depreciations /amortizations);

X_8 : $X_8 = 1$, *if the sum of net income for the two previous periods is less than 0*

$X_8 = 0$, *if the sum of net income for the two previous periods is more than 0* ;

$X_9 = \frac{NI_t - NI_{t-1}}{|NI_t| - |NI_{t-1}|}$ *(where: NI_t is the net income for the current period and NI_{t-1} is the net income for the previous period, $|NI_t|$ and $|Ni_{t-1}|$ are the absolute values of the net income for current / previous period).*

Resulting variable Q is only an interim result that must be applied in the probability calculation relationship (see Formula (4)):

$$P = (1/(1 + e^{-Q}) \tag{4}$$

The resulting value (P) of the model describes the probability that bankruptcy for the company being analyzed occurs with a predetermined period of time (i.e. one year, two years, or five years). It may have different values from the interval of $\langle 0; 1 \rangle$. The probability calculation also suggests that the higher is the value Q, the higher is the propensity to bankruptcy; on the other hand, low Q values characterize stable situation:
- If $Q < 0$, then $P \to 0$ (P converges to 0);
- If $Q > 0$, then $P \to 1$ (P converges to 1);
- If $Q = 0$, then $P = 0.5$.

- Model Gajdka and Stos 2 – is the first model adapted to the conditions of the transition economy (in Poland), it was originally created by the authors in 1996. The reliability of the correct prediction for this model was verified in 82.5 per cent. The calculation is based on the following relationship:

$$PG = S - X1*0.0856425 + X2*0.000774 + X3*09.220985 + \\ + X4*0.6535995 - X5*0.594687 \tag{5}$$

where: S – constant value +0.7732059;
*X1 – sales / total assets; X2 – shortterm liabilities * 365 / operating costs;*
X3 – EAT / total assets; X4 – EBIT / sales; X5 – liabilities / total assets.

Interpretation of resulting values:
There is only one value (PG – Punct graniczny) of +0.45 to predict financial distress. If the resulting value PG is higher, the company is not going to bankruptcy, if it is lower it indicates the company's future financial distress.

- Hybrid SOM-Altman model - this is an exceptional model by linking Altman's original model and neural network mathematical model (more specifically the artifical neural network - self-organizing map). Application of neural networks to prediction models is often considered as the fourth developmental stage of the models. This model was created at the University of Lithuania in 2006 by E. G. Garšva and S. Girdzijauskas. The impetus to this step was the fact, that the predictive reliability of the Altman's Z-score for private unlisted enterprises in the condition of the Lithuanian market was very low. Therefore, they linked it with a neural network model tested on the NASDAQ list and a new Z-Score formula with modified weights was formed. It was proved as much more suitable for the conditions of the Lithuanian economy. The authors report a change in the prediction ability of the previous Altman model from 72.68 to 92.35 per cent. Its calculation is based on the formula (6):

$$Z' = 0.717*X1 + 0.843*X2 + 2.800*X3 + 0.440*X4 + 0.400*X5 \tag{6}$$

where: X1 – net working capital/total assets; X2 – accumulated earnings/total assets;
X3 – EBIT/total assets; X4 – market value of equity/liabilities;
X5 – sales/total assets.

Interpretation of the resulting values:

There is only one value for the final score of 1.8. When the firm´s resulting value is lower than 1.8 the bankruptcy can occur. If it is higher than 1.8 the company is assessed as seamless with a good financial condition. There is no interval of the grey zone where the prediction is not possible.

4. The Results and Interpretation

Based on the five models the final model values were calculated for all the firms in the set for three, two and one year before the initiation of insolvency proceedings. The results of bankruptcy predictions of all the models are presented in the Table 4. The number of firms were not the same in all the years due to the incompleteness of the data needed for the calculation.

Table 2. Results in bankruptcy prediction of analysed models.

Years before the bankruptcy	-3		-2		-1	
Model and its results	*abs*	*in per cent*	*abs.*	*in per cent*	*abs.*	*in per cent*
Altman´s model						
Number of firms in the set [1]	80	100	80	100	77	100
Threat of bankruptcy	33	41.25	30	37.50	37	48.05
Grey zone	28	35.00	26	32.50	16	20.78
Good condition	19	23.75	24	30.00	24	31.17
Model IN05						
Number of firms in the set	80	100	80	100	76	100
Threat of bankruptcy	43	53.75	40	50.00	42	55.26
Grey zone	18	22.50	18	22.50	21	27.63
Good condition	19	23.75	22	27.50	13	17.11
Ohlson´s model						
Number of firms in the set	79	100	79	100	75	100
Threat of bankruptcy	14	17.72	21	26.58	22	29.33
Good condition	65	82.28	58	73.42	53	70.67
Gajdka and Stos model						
Number of firms in the set	77	100	75	100	67	100
Threat of bankruptcy	57	74.03	58	77.33	52	77.61
Good condition	20	25.97	17	22.67	15	22.39
SOM-Altman model						
Number of firms in the set	80	100	80	100	77	100
Threat of bankruptcy	63	78.75	57	71.25	56	72.23
Good condition	17	21.25	23	28.75	21	27.27

The most reliable models in the prediction were Gajdka and Stos model and SOM-Altman model that predicted failure with an accuracy more than 75 per cent of companies in all the three years before the failure. The share of correct predictions slightly increased with the upcoming the year of failure. Z-score and IN05 models have shown relatively low reliability. Their forecast of the future failure was around 50 per cent. Significantly worse reliability was shown in case of the Ohlson's model which predicted the future problems only in 17-22 per cent of companies.

A comparison of the results of all analyzed models is present in Table 5 and shown in Figure 1.

Table 3. Comparison of the results in the bankruptcy prediction of all the models

Years before the bankruptcy	-3	-2	-1
The share of correct prediction	*in per cent*	*in per cent*	*in per cent*
Altman´s model	41.25	37.50	48.05
IN05	53.75	50.00	55.26
Ohlson´s model	17.72	26.58	29.33
Gajdka and Stos model	74.03	**77.33**	**77.61**
SOM-Altman model	**78.75**	71.25	72.23

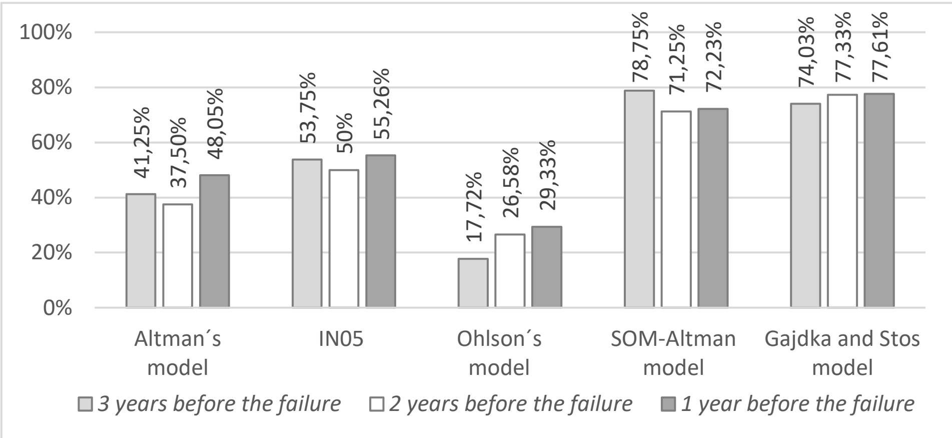

Fig. 1. Comparison of prediction ability of analysed models in the one, two and three years before the failure.

5. Discussion

Performed calculations and comparisons of the predictive reliability of the five selected models showed that the models quite significantly differ in the ability to predict the firms´ failure. Two models have proved to be significantly more sensitive and more reliable than three others. These models are the Gajdka and Stos model and the SOM-Altman model, i.e. Polish and Lithuanian models. Both the models were derived based on the data and conditions of the emerging economy, one of them with the new method use for its derivation. The success rate of the other models was relatively lower. Even in case of the IN05 model that has been derived from the Czech conditions as a transit economy and now was used in the same conditions. The share of its correct prediction was about 50 per cent. The lowest prediction ability was found in case of Ohlson´s model 2010.

These results arise a lot of questions however they can´t be answered based on the knowledge gained till now. Both the successful models were created under the conditions and for the conditions of transition economy. It can be considered as a reason of the higher reliability in the similar conditions of Czech firms. But one of these successful models was created using a new method, not yet used for predictive modeling (neural networks). And the share of correct predictions was the same as the other one based on the standard methods. This may lead to a simplified conclusion that the new method of model derivation is not a significant factor in the reliability of the prediction. But this finding cannot be unambiguously declared and must be verified in the next research in different conditions.

The explanation of the higher reliability in prediction of both the two models as well as the effects of the new method of derivation of the model will be also a question for further research. One of the reasons can be seen in the data and in the accounting standards which underlie the accounting data as a base for the model derivation and as a base for its application. The unambiguous conclusion the further follow-up research will allow.

The reliability of the two models´ predictions differed depending on the time before bankruptcy. It increases slightly with the approaching failure time for both models. But the increase was relatively slight. In case of SOM Altman model the highest rate of correct prediction was three years before the failure while the two years before it was lower and one year before failure it was slightly increasing. In case of the Gajdka and Stos model the highest rate of correct prediction was in the last year before the failure. To find out the reason could also bring subsequent research in the other conditions and different time.

6. Conclusions

The performed comparison of the ability of the selected models to recognize the upcoming financial problems in time turns the attention to the many areas of the predictive model construction: to the specific conditions of its derivation, to the methods used of its derivation, to the financial data as a base of its derivation as well as of its application as to the reason of the models´ reliability. As an important reason can be seen the specific economic conditions in which the model was derived. At the same time the results turn the attention to the time of the model creation: model IN05 even if it was derived in the Czech conditions, but the relatively long time ago and in the rapidly changing conditions of the transition economy may has already lost its distinctiveness. But this conclusion can be confirmed in the next research carried up in the other national conditions and using the other models.

The financial data which are the main source for both the derivation and the calculation of the models have its own national feature. The role of accounting data and accounting rules in the predictive ability and reliability of the models still remains in the background of the researchers´ attention. The accounting principles and methods affect the data across accounting statements. They are not only different in different national environments, but also within the national environment itself (as a result of options in the financial reporting regulation). The attitude to the information ability and usefulness of financial statement is the result of long time development and these historical roots affects the current access to the creation, quality and use of accounting data. It can be the reason of the different or the same prediction ability of the models originating from the different environments. These aspects may also be the subject of the following research.

Based on the results it can be concluded that the assumption of this research project has been confirmed, albeit only in part and not entirely unambiguously. The model derived from the same economic conditions (IN05) as the analyzed companies did not show a higher level of reliability compared to models derived from different economic conditions. The reasons may be in the time of its derivation, in the data used for its derivation etc. Striving for a more precise answer can be an incentive for further research projects.

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