Journal of Interdisciplinary Research in Accounting and Finance
ISSN: 2837-1895| Impact Factor : 5.8
Volume.9, Number 1; January-March, 2022;
Published By: Scientific and Academic Development Institute (SADI)
8933 Willis Ave Los Angeles, California
https://sadipub.com/Journals/index.php/jiraf | editorial@sadipub.com

ANALYSING THE BANKRUPTCY PREDICTION INDICATORS FOR CZECH COMPANIES

Dana Kubickova and Vladimir Nulicek
Department of Business Management, University of Finance and Administration, Prague, Czech Republic

Abstract: The aim of this paper is to prepare the bankruptcy model construction. In the first part, multivariate discriminant analysis and its possibilities in deriving predictive models are characterized. The second part defines the possible indicators/predictors of financial distress of companies, which could be included in the new bankruptcy model. The model itself compares different views of factors that affect the company's financial situation and contrasts the indicators that were constructed in the model in previous works (with special regard to the models in the transition economics). The result is the collection of 39 indicators to be verified in the next stage of the research project employing the multiple discriminant analysis methods to specify which of them to be included in the new model.

1.INTRODUCTION

In the contemporary dynamic economic environment, the prediction of the future development and the early detection of possible failure are very important for all stakeholders. The research project is aimed to verify the prediction models in various times. National conditions have brought an important finding, that is, the reliability and accuracy of the models decrease if they are used in an environment and time other than in which they were originally developed. It became an incentive to the research projects aimed to develop new models, appropriate for the time and the environment in which they are to be used. The result is a series of new models or new versions of the older models that were created for a specific locale. As presents Čámská (2012), in Polish, Slovak, Lithuanian environment constructed national models reflecting the conditions in transition economics. Zhang et al. (2010) present new Altman model for the UK, Ohlson model for Iran, China, etc. In this context, the attention of researchers was turned to the methodology of constructing default models.

The aim of this paper is to suggest and define proper indicators which are able to detect the signs of the failure in Czech companies at present conditions and that would have to be included in the intended predictive/bankruptcy model. The second aim is to characterize the method based on the verification of these indicators, including its assumptions and limitations. This paper is the first output of an internal research project, the aim of which is to suggest and verify new bankruptcy model. We would like to discuss our proposed set of indicators to get feedback for improvement.

The structure of the paper is as follows: proceeding part gives a review of existing literature, which follows up with the methodology used to analyze this work. Next part contains characterization of the MDA method and the results obtained. A brief overview of the factors influencing the financial failure follows up in the next section. Lastly, we compare the indicators of the structure of the models which were used in the Czech

Republic and other CEE countries. As a result of our elaboration, we suggest a set of possible indicators for failure detection. The paper wraps up with concluding remarks, which has formulated questions for further research.

2.METHODOLOGY

The construction of a bankruptcy model involves many issues and sub-issues, which has to solve many questions. The primary problems may be questions as following: when the company has fallen into the failure? What are the factors and the signs of failure (legal regulation, real practice)? When is the firm forced to close their activities? Other questions which are in common with the aim to predict the failure: what factors influence the firm activities and cause the firm failure? What phenomena accompany this development a year or two (or more) years before? The character of these factors can be financial and non-financial, quantitative and qualitative, external and internal. Data source is another area of concern, which, in turn, can provide all the appropriate data describing the firm's activities. The most common source of data for this purpose is the accounting and financial statements. But this provides only financial data, which is also influenced by the accounting methods. The sources of other data, non-financial and qualitative, are highly differentiated. A particular area is then a question concerning mathematical methods which can be used for deriving predictive models. Their classification is very varied. Dluhošová and Zmeškal (2011) distinguished GLM models (generalized linear models) and Merton model (2011), discriminant analysis and logistic regression. Klieštikand Birtus (2012) and also Darmovzal (2015) suggest using neural networks methods. Regarding the choice of methods to derive the model, the character of the method is decisive - parametric or non-parametric or combination of parametric and non-parametric. Karas and Režňáková (2014) pointed out that the choice of methods can affect the resulting reliability of the model. Till now the most often method used for construction bankruptcy models was the multivariate discriminant analysis (MDA). However, MDA has some limitations which have been found during the verification of the model and it still remains as the most commonly used method for deriving new models. Though, this model is assumed to be used in our project.

At the very first step, we described the possibilities and limitations of the multivariate discriminant analysis. To define a set of indicators that will be tested in our project, we used the method of comparison of selected bankruptcy models that have been designed for testing the companies´ failure. We took into consideration the models created in the past that are often used in the practice, i.e. Altman model designed for the non-listed companies and Beaver and Taffler´s model as a variant for the UK SMEs. Other models included in the comparison were those, which were created in the conditions of transition economies, namely in the Czech Republic, Slovak Republic and Poland: IN05 (CR), CH-index (SR), Gurčík index (SR) Holda index (PL)Gajdka and Stoda model (PL), Prusak model (PL), Maślanka model (PL),Model of Poznań (PL). The characteristics of these models are distinguished in their studies Čámská (2012) and Andrzejewski and Maślanka (2015). Within this comparison, those indicators that are the most often occurring in the models will be identified. Then they will be compared with the signs defined in the economic literature as the future bankruptcy symptoms.

3.RESULTS

3.1. Multivariate Discriminant Analysis and its limitation

The multivariate discriminant analysis (MDA) is one method of multivariate statistical analysis (MSA). The purpose of MDA is to differentiate (discriminate) objects into several classes (categories) based on the analysis of some indicators of compliance with the objects belonging to a training set. As a training set we mean in accordance with Härdle and Simar (2007) a subset of all the objects that have been in the past explicitly included in any of the categories surveyed. From the other point of view, discriminant function analysis is a statistical method determining which variables discriminate between two or more naturally occurring groups. Discriminant analysis is a statistical analysis to predict a categorical dependent variable (called a grouping variable) by one or more continuous or binary independent variables (called predictor variables).

Discriminant analysis is used when groups are known as a priori. As it is defined in the study of Bökeoglu and Büyüköztürk (2008), each case must have a score on one or more quantitative predictor measures, and a score on a group measure. Discriminant function analysis is a classification - the act of distributing things into groups, classes or categories of the same type. Hebák et al. (2005) note that computationally, discriminant function analysis is very similar to analysis of variance (ANOVA). The basic idea underlying discriminant function analysis is to determine whether groups differ with regard to the mean of a variable, and then to use that variable to predict group membership (e.g., of new cases). In the case of a single variable, the final significance test of whether or not a variable discriminates between groups is the F-test.

Usually, one includes several variables in a study to see which one(s) contribute to the discrimination between groups. In that case, we have a matrix of total variances and covariances; likewise, we have a matrix of pooled within-group variances and covariances. We can compare those two matrices via multivariate F-tests to determine whether or not there are any significant differences (concerning all variables) between groups. Huberty and Olejnik (2006) have stated that this procedure is identical to multivariate analysis of variance (MANOVA). As in MANOVA, one could first perform the multivariate test, and, if statistically significant, proceed to see which of the variables have significantly different means across the groups.

Discriminant analysis has very broad areas of application in science, business, education and economic studies. MDA is often used in sociology to split researched set of people into different groups. This method is also often used in biology for identifying different species of plants or animals and for their inclusion in certain categories, or in medicine for determining risk patients to certain diseases. In the banking sector, MDA is used to classify clients who ask for a loan to various classes regarding their credit risk. In economics, the MDA method is used for many years to construct bankruptcy models.

Let us concentrate on the computational approach to MDA. Huberty (1994) defines the aim of discriminant analysis to establish a parametric based procedure, known as a linear discriminant function, with which membership of any object to one of the groups surveyed can be assessed. For discriminant function modelling, a number of methods have been established, among which Jiang et al. (2001) assigns: (Bayesian) Quadratic discriminant analysis (QDA), (Bayesian) Linear discriminant analysis (LDA), Fisher linear discriminant analysis (FLDA), Discriminant partial least squares (DPLS), Soft independent modeling of class analogies (SIMCA) and Artificial neural networks (ANN).

In the two-group case, discriminant function analysis can also be thought of as (and is analogous to) multiple regression; the two-group discriminant analysis is also called Fisher linear discriminant analysis (computationally all of these approaches are similar). If we code the two groups in the analysis as 1 and 2, and use that variable as the dependent variable in a multiple regression analysis, then we would get results that are analogous to those we would obtain via Discriminant Analysis. In general, in the two-group case we fit a linear equation of the type:

$= + \quad * + \quad * + \ldots + \quad *$ (1)

Where: is a constant and $b_1$through are regression coefficients.

The interpretation of the results of a two-group problem is straightforward and closely follows the logic of the multiple regression. As proved Mardia et al. (1979), those variables with the largest (standardized) regression coefficients are the ones that contribute most to the prediction of group membership.

When there are more than two groups, the problem is more complex as we can estimate more than one discriminant function, like the one presented above. For example, when there are three groups, we could estimate a function for discriminating between group 1 and groups 2 and 3 combined, and another function for discriminating between group 2 and group 3. When interpreting multiple discriminant functions, which arise from analyses with more than two groups and more than one variable, one would first test the different functions for statistical significance, and only consider the significant functions for further examination.

Next, we would look at the standardized b coefficients for each variable and each significant function. The larger the standardized b coefficient, the larger is the respective variable's unique contribution to the discrimination specified by the respective discriminant function. To derive substantive, "meaningful" labels for the discriminant functions, one can also examine the factor structure matrix with the correlations between the variables and the discriminant functions. Finally, we would look at the means for the significant discriminant functions to determine between which groups the respective functions seem to discriminate. As ezanková (1řř7) states, many of analytical tools mentioned above are included in the statistical software for Sociological calculations SPSS (Statistical Package for the Social Sciences). Therefore, we assume to use this tool for the analysis of the topic of our research.

3.2. Indicators - predictors of the companies´ failure

The choice of indicators that indicate the future company bankrupt should be based on fundamental factors which weaken the financial position and which may lead to a situation where a company has to close down. These factors take quite specific forms in different companies, branches, national economies, at different times. They can be divided into internal and external, financial and non-financial, qualitative and quantitative. In the economic literature the symptoms of future bankruptcy are defined from various views. For example, Schönfeld (2011) defines the symptoms as following: a) a significant decline in sales, b) manufacturing to warehousing (increase in inventories of products), c) extending the period of payment of obligations, d) decreased liquidity, e) growth in the volume of overdue debts, f) unjustified increase in costs, g) decline in profitability, h) decrease of equity (loss), i) disturbances in cash flow. Also some non-financial manifestations of worsened situation are ranked: a) the departure of key executives, business partners, and employees, b) lack of innovation, c) unrealistic and unaffordable long-term strategy goals, d) increasing employee turnover, e) increased number of complaints, but also the f) lack of managerial skills, g) marketing unsystematic, h) insufficiently structured processes.

Another definition of symptoms of the future financial distress symptoms that Hálek (2013) carried out, focused on the cash flows and its role in the financial distress. As proved by Dluhošová (2010), the factors influencing the financial situation and future financial distress can be based on the pyramidal decomposition of return on equity indicator as well. In this decomposition three main aspects of the financial situation are distinguished: financial structure (the share of liabilities, degree of indebtedness), the intensity of resource exploitation (the turnover of assets) and market assessment (the profit margin, return on sales). All these factors can be measured by the various indicators based on accounting data.

Table 1: The frequency of indicators in the compared models

Indicator	No	Indicator	No
Efficiency	**13**	**Debt coverage**	**5**
Return on Assets:	9	- Equity / Liabilities	1
- EBIT / Assets	2	- EBIT / Interests	1
- EBITDA / Assets	1	- EBITDA / interests	1
- EAT / Assets	4	- EBT / Liabilities	1
- EBT / Assets	1	- (Operating Profit+Depreciation)/ Liabilities	1
- Operating profit /Assets	1	**Activity** (intensity of resources exploitation)	**7**
Return on Sales	4	- (ST Liabilities / Sales) x 365	1
- EBT / Sales	2	- Inventories / Revenues	1

- Operating profit / Sales	2	- (ST Liabilities / Cost on products)x360	2
Financial structure (indebtedness)	9	- Revenues / Assets	1
- Equity / Liabilities	1	- Sales / Assets	1
- Assets / Liabilities	1	- Operating costs / ST Liabilities	1
- ST Liabilities /Equity	1	Indicators based on CF	5
- ST Liabilities / Assets	1	- Cash flow / Assets	2
- Equity / Assets	1	- Cash flow / Liabilities	2
- Liabilities / Assets	3	- Operating Cash Flow / Sales	1
- ST Liabilities / Liabilities	1	Special indicators	6
Liquidity	5	- Accumulated Earnings / Assets	3
- Net working capital / Assets	2	- Operating cost (without Other operating costs) / ST Liabilities (without financial liabilities and special funds)	1
- ST Assets / ST Liabilities	2	- Value added / Assets	1
- (ST Assets–Inventories) / ST Liabilities	1	- Fixed capital / Assets	1

Source: Own elaboration

Note: ST = short term; EAT = earnings after taxes; EBT = earnings before taxes; EBIT = earnings before interests and taxes; EBITDA = earnings before interests, taxes, depreciation and amortization; CF = cash flow; ST assets = current assets;

Table 2: The bankruptcy model indicators and the symptoms of failure

Signs	Indicators in compared models	Suggested indicators
A significant decline in sales	Assets/sales (revenues); Revenues /Assets;	Assets/sales (revenues); Revenues /Assets;
Manufacturing to Warehouse (increase in inventories of products)	Inventories / Revenues;	Inventories / Revenues; Inventories / Current assets; Inventories / Assets;
Extending the period of payment of obligations	ST Liabilities / sales; ST Liabilities / Costs on Products; ST Liabilities/Costs on Inventories; EBIT / Interests; ST Liabilities / Costs of goods, products and materials sold; Operating costs /ST Liabilities;	ST Liabilities / Sales; ST Liabilities/Costs on production; Liabilities / EAT; Liabilities / Revenues; EBIT / Liabilities;

Decreased liquidity	Current assets/ ST liabilities; Current assets / Liabilities; (Current assets–inventories) / ST liabilities;	Current assets/ ST liabilities; Current assets / Liabilities; (Current assets–inventories) / ST liabilities; Receivables / Revenues; Receibables / Current Assets; ST Financial Assets / ST Liabilities; Current assets / Assets;
Growth in the volume of overdue debts	ST Liabilities /Assets; Liabilities /Assets; Liabilities / Equity; ST liabilities / Equity; Assets / Liabilities;	ST Liabilities /Assets; Liabilities /Assets; Liabilities / Equity; ST liabilities / Equity; Assets / Liabilities; Assets /Equity;
Unjustified increase in costs	EBT / Sales;	EBT / Sales; Operating costs / Sales;
The decline in profitability	EAT / Assets; EBIT /Assets; EBT/ Assets; EBT / Sales; Retained Earnings / Assets;	EAT / Assets; EBIT /Assets; EBT/ Assets; EBT / Sales; EAT / Equity;
Decreased equity (loss),	Equity / Assets; Equity / liabilities;	Retained Earnings / Assets; Retained Earnings/Liabilities; Equity / Assets; Equity / liabilities; Equity / Fixed Assets;
Disturbances in cash flow	Cash flow / Liabilities; ST Liabilitiesx365/Cash flow; Cash flow / Assets; (Operating profit+ depreciation) / Liabilities;	Cash flow / Liabilities; Cash flow / ST Liabilities; (ST Liabilitiesx365) / Cash flow; Cash flow / Assets;

Source: Own elaboration

To find what indicators are to be included in the bankruptcy models we compared twelve bankruptcy models which were derived and published in three countries: The Czech Republic, Poland, and Slovakia. Also, Altman model Z-score (model 1983) was included in this set of selected models. The structure of all these models (i.e. indicators included in the models) is listed in the Appendix. Table 1 presents, the frequency of indicators across the compared models. In compared models, the profitability indicators appeared most frequently. Profitability indicator was included in each of the models. In one model it was included in two forms. The most frequent form was the return on assets after tax (in four of twelve models). The debt indicators (indicators of financial structures) were the second largest group of indicators. Including the debt cover indicators, they were used fourteen times. The activity indicators (intensity of resources exploitation) were the third largest group. It is possible to conclude that this indicators´ frequency represents the areas which are the result of pyramidal decomposition of the return on equity indicator. The indicators describing these areas are profitability of sales, assets turnover and leverage. When these indicators are compared with the list of symptoms of the future company´s distress defined by Schönfeld (2010), we can conclude that only some symptoms are assessed (and some of them very poorly) - see Table 2.

In Table 2 symptoms of a deteriorating financial situation (as defined in the literature) are compared with indicators of the mentioned models. The appropriateness of these indicators for identifying the symptoms was the base, on which those indicators that will be used for verification in the project were defined. This choice was subsequently supplemented by additional indicators that offer financial analysis, and that extend the measurement of the symptoms. The criterion was the experience of using indicators in the analysis of the financial position of companies as well as the results of verification of the other models. The final set of indicators to verify in the project is included in the third column of the table.

4.DISCUSSION

The definition of a set of indicators has some limitations. The first one consists of the fact, that only financial data are presupposed for the indicators´ calculation. In the new variants of the elder models, the financial indicators are complemented by the other, both financial and non-financial indicators. The aim is to implement the broader conditions of firms´ activities into the assessment (size, inflation, development of conditions). The other limitation consists in the low accuracy of the accounting data in the financial statements (receivables, accounting items, etc.). On the other hand, the financial statements are published and easily accessible, they are in connection with the firms´ plans and need no other calculations. The other factor that influenced our indicators and data selection is based on requirements of the methods that will be used for the verification. MDA does not allow including into the assessment not only the financial data but also the other.

The method used to derive the set of indicators in this study (comparison of former models indicators), is only one of many others. It does not allow more preciously assess the ability of the indicators to detect the real companies´ conditions and symptoms of the failure. Analysis of the structure of previously developed models partially reproduces the conditions in which these models were derived. Which symptoms of bankruptcy and which indicators are the most sensitive to its detection is the theme of the next research studies. For our research project, we suppose that these indicators reflect the present conditions of the companies. The MDA method is just one of many multivariate statistical methods that can be used for the purpose of solving the problems of our research. We suppose that this method could be suitable for it.

5.CONCLUSION

The aim of this paper was to define a set of indicators, which would be able to identify the signs of financial distress of the firm. To verify the predictability of these indicators will be the starting point of the construction of a predictive model, coming from the actual Czech conditions, which is the aim of the internal research project funded at VSFS. The project aims to create a model that would help managers of the company as well as business partners and other users to identify the financial stability or instability of the company and to take timely preventive measures. We use the indicators based on commonly available financial data that should not require additional calculations or specific records and are in connection with the firms´ plans. The selection of indicators is determined and limited by the capabilities and limitations that bring multivariate discriminant analysis method, used for deriving default models. The main characteristics of this method were included in the paper.

ACKNOWLEDGEMENT

Authors acknowledge the support of Research project IGA VŠFS Prague No 7767 funded by the institutional support for the long-term strategic development of research organization, University of Finance and Administration, Prague, Czech Republic. Dana Kubíčková works as an assistant professor at the

Department of Business Management in the Faculty of Economic Science University of Finance and Administration, Prague. She specializes in financial reporting and assessment of the companies' performances. Her specific interest is the process of the implementation of International Financial Reporting Standards and effects of IFRS adoption on companies' efficiency assessment. Vladimír Nulíček works as an assistant professor at the Department of Computer Science and Mathematics in the Faculty of Economic Science of the University of Finance and Administration, Prague. His field of interest is algorithms of statistical and economic computations, the design of database systems and web design.

REFERENCES

Andrzejewski, M. and Maślanka, T. (2015). "Procedures of an audit in the prospective verification of the going-concern principle", In: IFRS - global rules and local use 2015, Proceedings of the 3rd international conference in Prague, AngloAmerican University, Prague, 2015. Available at: http://car.aauni.edu/conferences/ifrs-2015.conference, pp. 49-59. (Assessed 3 February 2016).

Bökeoglu, Ç. Ö. and Büyüköztürk, Ş. (200Ř). Discriminant function analysis: Concept and application. EğitimAraştırmalarıDergisi.

Čámská, D. (2012). "National view of bankruptcy models". In: International Days of Statistics and Economics, (MSED) Proceedings of the 6th international conference, Praha, September 2012. Praha: VŠE. Available at: http://msed.vse.cz/ msed_2012/ en/index, pp. 268-278

Darmovzal, J. (2015). Využitíneuronovýchsítí v konstrukcibonitních/bankrotníchmodelů. Disertation. Brno: MasarykovaUniversita.

Dluhošová, D. (2010). Finančnííízení a rozhodovánípodniku (3rd. ed.) Praha: Ekopress.

Dluhošová, D. and Zmeškal, Z. (2011). "Z-Metrics metodology and Altman rating models Evolution," In Financial management of firms and financial institutions, Ostrava, proceedings of international conference, Ostrava September 2011, Ostrava: VŠB-TU. Retrieved from http://www.ekf.vsb.cz/frpfi/cs/archiv/rocnik-2011/, pp. 88-98, (Assessed 12 February 2016)

Hálek, V. (2013). Predikcefinančnítísněpodnikunazákladěvlastníhobankrotníhomodelu CCB. Bratislava:

DonauMedia. Härdke, W. and SIMAR, L. (2007). Applied Multivariate Statistical Analysis. Berlin-Heidelberg: Springer Science & Business Media.

Hebák, P., Hustopecký, J., Jarošová, E. and Malá, I. (2005). Vícerozměrnéstatistickémetody (1st ed.). Praha: Informatorium (Vol. 3.).

Huberty, C. J. (1994). Applied discriminant analysis. New York: John Wiley and Sons.

Huberty, C. J. and Olejnik, S. (2006). Applied MANOVA and discriminant analysis. 2nd ed. Hoboken N. J.: WileyInterscience, CrossRef

Jiang Jian-hui, TśnkovaRoumiana and Ozaki, Yukihiro, (2001). "Principal Discriminant Variate Method for Classification of Multicollinear Data: Principle and Application." Analytical Sciences, Vol.17-Supplement (i471-i474).

Karas, M. (2013). Měeníúvěrovéhorizikapodnikůzpracovatelskéhoprůmyslu v Českérepublice. Disertačnípráce. Brno: VUT.

Karas, M. and Režňáková, M. (2013). "The Impact of Methodology on the Effectiveness of Bankruptcy Modeling." In: International Conference on Economics and Business Administration 2013 (EBA 2013), proceedings, pp. 99-102.

Karas, M. and Režňáková, M. (2014). "To what degree is the accuracy of a bankruptcy prediction model affected by the environment? The case of the Baltic States and the Czech Republic". Procedia - Social and Behavioral Sciences 156, pp. 564 – 568, CrossRef

Klieštik, T. and Birtus, M. (2012). "The aplication of neural networks in corporate governance", Acta oeconomicacassoviensia, Vol. 5, no.1, pp. 32-40.

Mardia, K., Kent, J. and Bibby, J. (1979). Multivariate Analysis. New York: Academic Press.

Neumaier, I. and Neumaierová, I. (2005). "Index IN 05". In: Conference Evropskéfinančnísystémy proceedings, Brno, Czech Republic, June 2005. Brno: Masaryk University, pp. 143–148.

ezanková, H. (1řř7). Analýzakategoriálníchdatpomocí SPSS, 1st ed. Praha: Vysokáškolaekonomická.

Schönfeld, J. (2011). Modernípohlednaoceňovánípohledávek. Praha: C. H. Beck.

Zdeněk, R. (2013). "Využitídiskriminačníanalýzy a logistickéregresevefinančníanalyse" In: international conference INPROFORUM 2013 proceedings,ČeskéBudějovice, Czech Republic November 2013. ČeskéBudějovice: University of South Bohemia, pp. 381-387.

Zhang, L., Altman, E. I. and YEN, J. (2010). "Corporate financial distress diagnosis model and application in credit rating for listing firms in China". Front Comput. Sci., Vol. 4, No 2, pp. 220-236, CrossRef

Appendix

Appendix A - Bankruptcy models compare

Indicator	Calculation	Indicator	Calculation
1. Z-score 1983		7. Gurčíkův index (SR)	
x1	Net Working Capital / Assets	x1	Retained Earnings / Assets
x2	Accumulated earnings / Assets	x2	EBT / Assets
x3	EBIT / Assets	x3	Cash flow / Assets
x4	Equity / Liabilities	x4	Inventories / Revenues
x5	Revenues / Assets		
2. IN05		8. Holda index (PL)	
x1	Assets / Liabilities	x1	Current Assets / ST Liabilities
x2	EBIT / Interests	x2	Liabilities / Assets (*100)
x3	EBIT / Assets	x3	EAT / Assets (*100)
x4	Revenues / Assets	x4	(ST Liabilities (average) *360) / Cost on products, goods and

			materials sold
x5	Current assets / ST liabilities	x5	Revenues / Assets (average)
3. Z-score – UK		9. Gajdka, Stoda model (PL)	
x1	Cash flow / Assets	x1	Sales / Assets
x2	EBITDA / Assets	x2	(ST Liabilities * 365) / Cost of production
x3	EBITDA / interests	x3	EAT / Assets
x4	Accumulated earnings / Assets	x4	EBIT / Sales
x5	ST Liabilities / equity	x5	Liabilities / Assets
+ Constant 4,28		Constant 0,7732059	
4. Taffler		10. Prusak model (PL)	
x1	EBT / ST Liabilities	x1	Operating profit / Assets
x2	Current assets (ST assets) / Liabilities	x2	Operating cost (less Other operating costs) / ST Liabilities (less financial liabilities and special funds)
x3	ST Liabilities / Assets	x3	Operating Assets / ST liabilities
x4	Sales / Assets	x4	Operating Profit / Sales
5. Beaver model		11. Maślanka model (PL)	
x1	Equity / Assets	x1	Net working capital / Assets
x2	Value Added / Assets	x2	Net operating Cash-flow / Sales
x3	Bank Loans / Liabilities	x3	(Operating profit+depreciation) / Liabilities
x4	Cash flow / Liabilities		
x5	Operating Capital / Assets		
6. CH-index (SR)		12. Model of Poznań (PL)	
x1	EAT / Assets	x1	EAT / Assets
x2	EAT / Sales (incl.Sales of assets)	x2	(Current Assets-Inventories) / ST Liabilities
x3	Cash flow / Liabilities	x3	Fixed capital / Assets
x4	(ST Liabilities * 365) / Sales (incl. sales of assets)	x4	Profit on sales (EBT) / Sales
x5	Liabilities / Assets		