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The application of data envelopment analysis method in managing companies' credit risk

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The subject of the present article is a new procedure forecasting credit risk of companies in Polish economic environment. What favors the suggested approach is the fact that in Poland, unlike in western countries, DEA method has not yet been implemented in order to assess credit risk that companies face. The research described in the article has been conducted on the basis of comparison of suggested DEA method with currently used procedures, namely point method, discriminative analysis and linear regression. In order to verify and compare the efficiency of various methods of company credit risk estimation the efficiency of classification of companies has also been examined. The study has involved an analyzed sample (a teaching sample) as well as a test sample which was not taken in model building. Considering the research, it can be concluded that DEA method facilitates forecasting financial problems, including bankruptcy of companies in Polish economic conditions, and its efficiency is comparable or even greater than approaches implemented so far. The DEA methodology was found to be successful within the credit evaluation process, however it might not be used as a standalone tool for this purpose, but it can offer valuable insight to the loan officer or the analyst facing the credit approval decision.

JEL Classifications: C12, C30, C67

Keywords: Credit scoring, credit risk, creditworthiness, Data Envelopment Analysis, technical efficiency

Introduction

Competent credit risk management plays a major role in the process of bank administration. All operations undertaken by a bank, especially those involving loans are meant to reduce that risk. Using credit-scoring methods is believed to be one of the most accurate solutions, facilitating the process of credit risk management. It is worth mentioning that the procedure of credit - scoring has become more significant since Basel Committee on Banking Supervision published guidelines of New Basel Capital Accord, according to which credit - scoring is one of the possible tools of assessing credit risk within internal ratings (Iwanicz-Drozdowska, 2005, pp.130, 150). The procedure of using DEA model method for credit-scoring suggested in the article may prove an effective tool in solving the problems of credit risk assessment in Polish banks.

Use the method of DEA in credit risk management

DEA method was first introduced in 1978 by American economists Charnes, Cooper and Rhodes (1978). Relying on productivity concept, formulated by Debreu (1951) and Farrel

[1] The paper was reported at XVth ZAFIN Conference, "Financial Management - Theory and Practice", May 19-21, Wroclaw, Poland

(1957, pp.253-290), which defined efficiency measure as quotient of singular input and singular output, they used it for a multidimensional situation in which there was more than one input as well as more than one output. Applying this inference they were able to propose a very practical system to measure efficiency. In DEA method efficiency is defined as following (Gospodarowicz, 2002, pp.56; Charnes, Cooper, and Rhodes, 1978, pp.429-444; Banker, Charnes, and Cooper, 1984, pp.1078-1092; Banker, Cooper, Seiford, Thrall, Zhu, 2004, pp.345-362; Cook and Seiford, 2009, pp.1-17; Gattoufi, Oral, and Reisman, 2004, pp.141-58; Eemrouznejad and Thanassoulis, 1996, pp.1-21; Kao, Lu and Chiu, 2011, pp.310-317):

$$EFFICIENCY = \frac{\sum_{r=1}^{s} \mu_r OUTPUT_r}{\sum_{i=1}^{m} \nu_i INPUT_i} \tag{1}$$

Where:

s - amount of outputs,

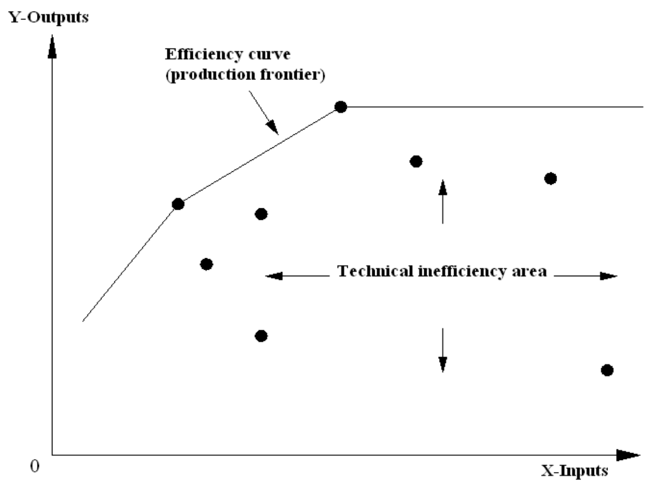
m - amount of inputs,

μ_r - measure demonstrating importance for each group of inputs,

μ_r, ν_i - measure demonstrating importance for each group of outputs.

Using DEA method, efficiency of a variable is calculated in relation to other variables from particular group. Effective variables within particular group make so-called efficiency curve (Figure 1). Efficiency of remaining variables is calculated in relation to the curve defined through solving the issue of linear programming (using DEA method). The efficiency curve is defined by variables in the form of inputs and outputs in particular study of given variable. In DEA method prior knowledge of measurements is not required because all through the study the measure of maximum efficiency of each variable is constantly calculated.

FIGURE 1. EFFICIENCY CURVE

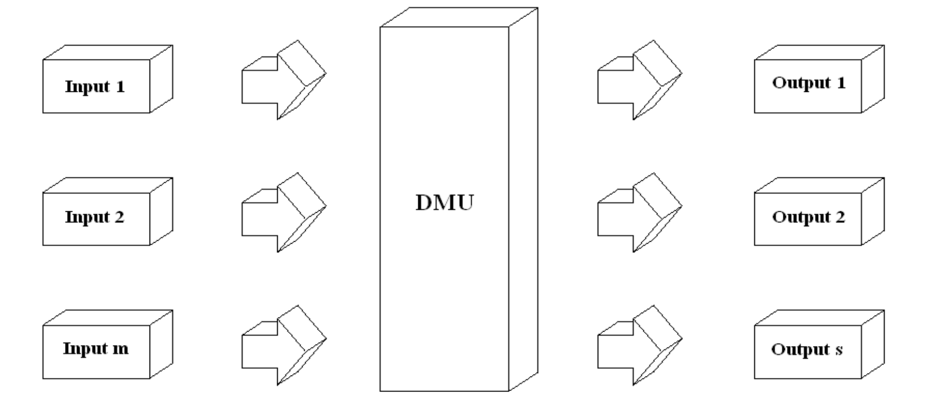


Source: Gospodarowicz (2000, p.12)

For the outcome where variables side with efficiency curve (Figure 1.) the coefficient is equal to 1. This demonstrates technical efficiency of those variables. Correspondingly, if variables descend below efficiency curve then its coefficient is less than 1. That is a sufficient indication of technical efficiency level.

The DEA method analysis use production units, called DMU (Decision Making Unit) as variables. DEA calculates a DMU's efficiency by determining the minimum possible inputs needed to capture a set of outputs or by determining the maximum possible outputs that can be generated from a given set of inputs. The efficient advertisers are set an efficiency score of one, while the inefficient advertisers' efficiency scores are less than one but greater than zero (Thomas, Barr, Cron, and Slocum, 1998, pp.489; Charnes et al., 1978, pp.431). These assumptions are illustrated in DEA model outline Figure 2.

FIGURE 2. DEA MODEL OUTLINE



Source: Gospodarowicz (2002, p.57)

For each production unit input and output variables are indicated as follow:

$$X_j = (x_{1j}, ..., x_{ij}, ..., x_{mj}) \text{ and } Y_j = (y_{1j}, ..., y_{rj}, ..., y_{sj})$$

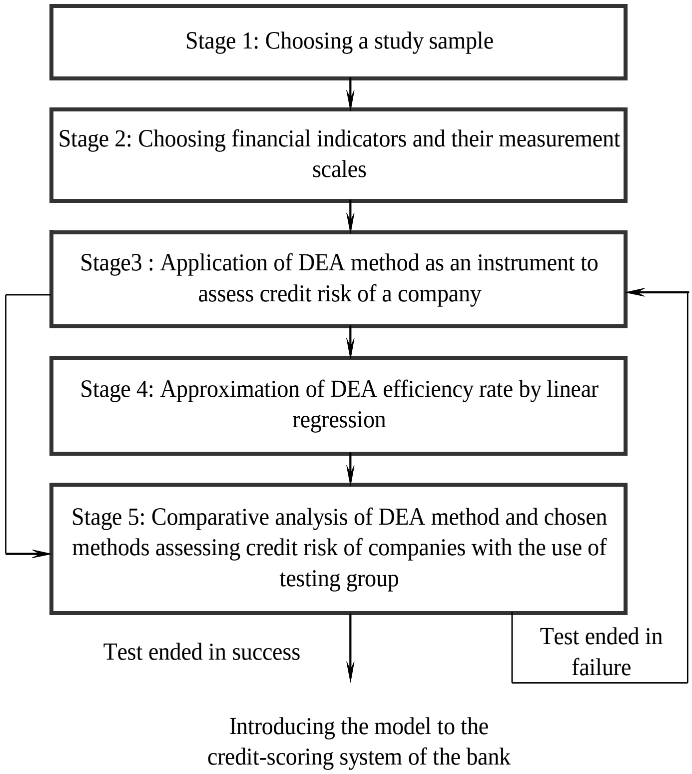
Where, $x > 0$ and $y > 0$.

It is assumed that each production unit contains at least one input and one output.

Today, various DEA efficiency models, such as the constant returns to scale (CRS) model, the variable-returns-to-scale (VRS) model, the additive model, the slacks-based measures and the free disposal hull (FDH) model, etc. are available for different types of measuring requirement. It also has been applied to various industrial and non-industrial contexts, such as banking, education, hospital, etc (Liu et al., 2013., pp.3-15).

Methodology of credit risk assessment with the use of DEA method proposed in this article was prepared on the basis of literature studies (Emel, Oral, Reisman, and Yolalan, 2003, pp.103-123; Simak, 2000, pp.1-189; Charnes et al., 1978, pp.429-444; Banker, Charnes, and Coper, 1984, pp.1078-1092; Banker et al., 2004, pp.345-362; Cook and Seiford, 2009, pp.1-17; Gattoufi, Oral, and Reisman, 2004, pp.141-58; Eemrouznejad and Thanassoulis, 1996, pp.1-21; Kao et al., 2011, pp.310-317; Gospodarowicz, 2004, pp.119-129) as well as the author's own research (Feruś, 2006(a), pp.44-59; Feruś, 2008(b), pp.109-118). It consists of five stages, as presented in Figure 3.

FIGURE 3. SUGGESTED METHOD OF ASSESSING CREDIT RISK OF COMPANIES, USING DEA METHOD



Source: Self-study

Stage 1: Choosing a study sample

The base of a study was statistical matter containing information provided by a bank on 100 construction companies that obtained a credit loan in the years 2001-2003. This study included the status of credit repayment history[1].

Stage 2: Choosing financial indicators and their measurement scales

The analysis was conducted for one year period as well as two years before considering the firms as bankrupt. The study used 22 financial indicators. Next, based on correlation assumption 6 indicators were chosen (table 1) that did not contain any information

[1] Statistical matter contained 50 solvable firms and 50 firms with delinquency risk

provided by other financial indicators from this study, but at the same time were good representative indicators that were not chosen for diagnosis[1].

TABLE1. FINANCIAL INDICATORS USED IN THE STUDY

Indicator's symbol	*1.1.1.1.1 Indicator's formula*
X_1	Net profit indicator = (financial result*100) / (profit from sales and equals + other operation profits + financial profits)
X_2	Asset return indicator (ROA net) = (financial result*100)/ total assets
X_3	Equity capital return indicator (ROE net) = (financial result *100*12/n) / equity capital n - number of days
X_4	Liquidity ratio = current assets / current liabilities
X_5	Daily return indicator = (total assets*number of days) / (profit from sales and equals+ other operation profits + financial profits)
X_6	Total liabilities indicator = (total liabilities * 100) / total assets

Source: Self-study

Stage 3: Application of DEA method as an instrument to assess credit risk of a company

A crucial problem in this stage is the choice of the right set inputs and outputs used in firms' component. Assignment of the individual financial indicators to groups of inputs and outputs depends mainly on problem format. Often the scripts on the studied object indicate five basic ways to define input and output: producer concept, financial agent concept, financial asset concept, summarized value concept and user expense concept. The solution of a given problem based on DEA method depends on choosing the right DEA model. To classify DEA model two criteria must be present simultaneously: type of effect scale and orientation of the model. The first criterion defines what theories were applied to effect scale in the model (variable (VRS), constant (CRS) or not rising (NIRS)). The second factor demonstrates whether inputs are minimized or outputs are maximized. Depending on the choice of the model orientation, either technical efficiency of input or technical efficiency oriented on solution or so called undirected models can be calculated.

Based on thorough literature study (Emel et al., 2003, pp.108-121; Simak, 2000, pp.43-100; Charnes et al., 1978, pp.429-444; Banker et al., 1984, pp.1078-1092; Banker et al., 2004, pp.345-362; Cook and Seiford, 2009, pp.1-17; Gattoufi et al., 2004, pp.141-58; Eemrouznejad and Thanassoulis, 1996, pp.1-21; Gospodarowicz, 2004, pp.123-129), credit inspectors' interview and personal experiences (Feruś, 2006 (a), pp.44-59; Feruś, 2008 (b), pp.109-118) in that aspect, input and output classifications were created[2]:

-inputs: X_5 and X_6

-outputs: X_1, X_2, X_3 and X_4

To calculate the technical efficiency indicator value of studied firms CCR (constant scale effect) model was used. This was directed toward inputs with search for minimal value of efficiency indicator that will possibly reduce the amount of input and result in equal output of the study object. For this calculation optimal linear program EMS[3] was used. The efficiency indicator results for each firm in the study ranged from 0 to 1. The value of efficiency indicator equal to 1 demonstrates the firm being effective whereas, the

[1] Chosen indicators were weakly correlated with each other and strongly correlated with fluctuating alignment.

[2] The author used numerous studies examining the model effectiveness. Present article gives the final model that proved to be the most effective in determining the firms' credit risk factor.

[3] Dortmund University website sources: http://wiso.unidortmund.de/LSFR/OR/scheel/ems

efficiency indicator value lower than 1 demonstrates the firm has an opportunity to improve the relations of input and output - indicates efficiency loss level.

In this part of the study research was also carried out aiming at finding the base point (cut off point) of efficiency coefficient that will separate the solvent group of firms from the firms with the risk of delinquency.

A good concept, allowing for setting the right base point value, but also considering incorrect object classification, was a study of interdependency between the value of incorrect classification and the value of base point. In this approach, optimal base point regulates minimal entire cost of incorrect classification. Moreover, this concept permits multi variant analysis, the optimal base point change due to incorrect classification Type I or II. To show entire cost of incorrect classification the following formula was applied (Simak P.C., 2000, pp.94-95):

$$TC = i(p) \cdot C_1 + j(p) \cdot C_2 \qquad (2)$$

Where: C_1 - loss indicator Type I error, C_2 - loss indictor Type II error, $i(p)$ - is the number of Type I errors, $j(p)$ - is the number of Type II errors.

For the purpose of this study, C1 and C2 is equal to 0.6 and 0.03 respectively.

TABLE 2. EVALUATION FOR DIFFERENT METHODS OF EFFICIENCY USING 2001-2002 DATA[1].

Method		MP		AD		RL		DEA
Base point		-		0		0,5		0,4
2001	S_2	100%	S_2	96%	S_2	96%	S_2	90%
	S_1	58%	S_1	80%	S_1	80%	S_1	72%
	S	79%	S	88%	S	88%	S	81%
2002	S_2	100%	S_2	90%	S_2	90%	S_2	80%
	S_1	70%	S_1	86%	S_1	86%	S_1	84%
	S	85%	S	88%	S	88%	S	82%

Source: Self-study

For the above mentioned CCR model (constant scale effect) concentrated on inputs, efficiency coefficient base value was verified for a year as well as two years before delinquency below 0.40. This indicates the 0.40 or lower rank implies a high risk of defaulting. Furthermore, 0.40 or higher rank implies a low risk of defaulting.

[1] S_2 –Type II Efficiency - determines what percentage of solvable firms was correctly classified ($S_2 = \frac{P2}{P2+NP2} * 100\%$; where *P2* – number of solvable firms classified as solvable group, *NP2*– number of solvable firms classified as delinquency risk group), S_1- Type I Efficiency – determines what percentage of firms with delinquency risk was correctly classified ($S_1 = \frac{P1}{P1+NP1} * 100\%$; where *P1* – number of firms with risk of delinquency classified as delinquency risk group, *NP1*– number of firms with risk of delinquency classified as solvable, *S*- General Classification of Efficiency – determines what percentage of all firms was correctly classified with application of the ($S = \frac{P1+P2}{P1+NP1+P2+NP2} * 100\%$). The base point value in the discrimination analysis model and regressive linear model was calculated as average value from average of the groups.

The DEA method classification efficiency is illustrated in Table 2. In addition, the DEA method results (table 2) were compared with point method (MP) results as well as with regressive linear (RL) results. Using the same material, the author was able to complete a credible comparative analysis using statistical data.

Based on the classification results shown in Table 2 it could be concluded that efficiency of I and II classification with the use of DEA method is similar to discriminating analysis and regressive linear regression.

Stage 4: Approximation of DEA efficiency rate by linear regression

The main purpose of this phase is an attempt at reducing the DEA method fallacy caused by a necessity of applying an optimal linear program for every study of a firm applying for a credit loan (Simak, 2000, pp.94-95). The suggested solution to this problem is the application of regressive linear function that allows for finding a correlation between the coefficient DEA method value and its effectiveness with defined inputs and outputs. In this case, regressive linear function could be used as linear estimation of coefficient DEA method values without the need of extensive process of DEA method verification each time a new firm is applying for a credit. In other words, regressive linear function could be used while determining the studied firm's credit risk level without going through the first three phases (Emel et al., 2003, pp.108-115). Accordingly, the regressive linear function was defined during the process of estimating the coefficient value of DEA method efficiency. Past coefficient DEA method of efficiency values through regressive linear function were treated as a dependent variable Y (dependent variable), and defined input and output were noted as an operand X_i (independent variables). The regressive linear function research was conducted through Statistica 6.0 program. When rating the value of regressive linear function model the level of significance $\alpha = 0.05$ was established.

This is the final linear regression model formula:

$$Y_{\mathrm{DEA\_2001\text{-}2002}}=-0.0006X_5+0.0010X_6+0.0826X_1+0.0126X_2-0.0003X_3+0.2831X_4+0.0564$$

TABLE 3. SELECTED PROPERTIES OF REGRESSIVE LINEAR FUNCTION Y_{DEA}

R^2 = 67%, F(6/93) = 31,46						
Variables	X_5	X_6	X_1	X_2	X_3	X_4
$t(a_i)$	-4.82	2.32	3.64	2.62	-2.13	6.57
Empirical level of essence p	0.0000	0.0227	0.0004	0.0102	0.0354	0.0000

Source: Self-study

In general, the right model is not the one perfectly coordinated with empirical data, but the one where all the variables of independent X_i and dependent Y are integrated.

To evaluate the effect of these variables a parametric *t-Student* test is applied. The variable quantity determining outcome in *t-Student* test is shown in Table 3. In this instance the statistical quantity that relates to t takes into consideration the level of $\alpha = 0.05$ with 93 degree where $t_{\square}$ = 1.6614. The overall parametrical quantity is satisfied in $|t| \geq t_{\alpha}$ representation where X_5, X_1 and X_4 variables are imperative at the level of $\alpha = 0.01$ or lower.

On the other hand, the parametrical *F-Snedecora* test is relevant for the study of the financial indicator X_i defined by its choice of changing variables. In reference to Table 3 the statistical *F-Snedecora* result is equal to 31.46. The critical value of F^* for the $\alpha = 0.05$

level for 6 and 93 degrees is $F^* = 2.197$. Based on $F = 31.46 > F^* = 2.197$ the H_0 theory is not justified on none of the levels and can be rejected.

Determining coefficient R^2 indicates the correct application of regressive linear function Y_{DEA}. In above analysis the R^2 coefficient equals to 67% (Table 3). This indicates that regressive linear Y_{DEA} model has a 67% correlation with X_i changing variables.

Summarizing the results of above study (table 3 - test of essence: *t-Student*, *F-Snedecora*, determining coefficient R^2) one can recognize that the choice of dependent variables in the regressive linear function Y_{DEA} is accurate. Furthermore, all the regressive linear function Y_{DEA} properties were statistically significant.

The efficient classification results in Table 4 in regressive linear function $Y_{DEA\_2001\text{-}2002}$ do not differ considerably from the DEA method results shown in Stage 3 of this study, which means that equalization of the linear regression could be treated as linear approximation of the coefficient DEA efficiency value.

TABLE 4. COMPARING THE CLASSIFICATION EFFICIENCY OF DEA METHOD WITH REGRESSIVE LINEAR FUNCTION Y_{DEA}

	Base point = 0,40			
	DEA		Y_{DEA}	
	2002	2001	2002	2001
S_2	80%	90%	86%	86%
S_1	84%	72%	86%	76%
S	82%	81%	86%	81%

Source: Self-study

Stage 5: Comparative analysis of DEA method and chosen methods assessing credit risk of companies with the use of testing group

To check and verify the accuracy and efficiency of prognostic qualities of above studied models, the statistic matter (100 firms) was divided equally 1:1 in respect to two separate research samples: controlled and placebo group. The efficiency rate of both groups' classification is presented in Table 5.

TABLE 5. COMPARING THE EFFICIENCY OF VARIOUS METHODS FOR THE PLACEBO SAMPLE GROUP USING 2001-2002 DATA

Method	AD		RL		DEA	
Base point	0		0,5		0,5	
2001	S_2	96%	S_2	96%	S_2	88%
	S_1	68%	S_1	68%	S_1	80%
	S	82%	S	82%	S	84%
2002	S_2	88%	S_2	88%	S_2	84%
	S_1	80%	S_1	80%	S_1	96%
	S	84%	S	84%	S	90%

Source: Self-study

Based on above classification results in Table 5 it can be determined that DEA method has superior prognostic indicators. It best minimizes type I errors where classification efficiency was higher than 12% two years before delinquency and higher than 16% one year before delinquency. However, general classification efficiency of DEA method is similar to general classification for methods: discrimination and linear regression analysis.

Conclusion

Based on the analysis in this article it would be justified to say that a well reflected credit scoring model is reliable in differentiating potential high risk of default from low risk of default clients. Founded by the study, it can be concluded that DEA method correctly predicts possible financial difficulties including a company's bankruptcy risk in Polish economic situation. These results are comparable or even superior to other methods presently employed.

This study signifies the universal application of DEA method in analyzing large spectrum of credit risk uncertainty. It not only measures efficiency in respect to the use of financial risk indicators, but it facilitates accurate credit risk classification for corporations in credit application process.

Due to overall credit scoring proven success and its great application it is safe to presume this method will become a central tool in credit risk assessment for corporations as well as individual consumer. This credit scoring method is very dynamic, very promising, and continually developing. Further research should focus on selecting the right industry specific indicators that allow for the identification of corporate similarities, with an increased number of firms in the analysis.

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