

THE DEA METHOD IN MANAGING THE CREDIT RISK OF COMPANIES

Anna Feruś, PhD

Rzeszów University of Technology,
Faculty of Management and Marketing,
Department of Finance and Banking,
ul. Wincentego Pola, 2
35-959 Rzeszow, Poland
Phone: +48 17 865 19 14
E-mail: aniaferus@poczta.fm

The subject of the present paper is a new procedure of forecasting credit risk to companies in the Polish economic environment. What favors the suggested approach is the fact that in Poland, unlike in western countries, the DEA method has not yet been implemented in assessing credit risk faced by companies. The research described in the paper has been conducted on the basis of comparing the proposed DEA method with the currently used procedures, namely the point method, discriminative analysis and linear regression. To verify and compare the efficiency of various methods of company credit risk estimation, the efficiency of the classification of companies has also been examined. The study has involved an analysed sample (a teaching sample) as well as a test sample which was not taken in model building. To conclude, the DEA method facilitates forecasting financial problems, including bankruptcy of companies, in Polish economic conditions, and its efficiency is comparable to or even greater than that of the approaches implemented so far.

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

1. Introduction

Credit risk is inevitably linked with every bank's activities. It is one of the basic types of credit risk. It is understood mainly as the risk of default by a borrower with remaining interest rates and commissions. A 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. Credit-scoring methods are 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 the Basel Committee on Banking Supervision has published the guidelines of the 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:

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130, 150]. The procedure of using the DEA method for credit scoring suggested in the article may prove an effective tool in solving the problems of credit risk assessment in Polish banks.

2. Implementing DEA method in credit risk management

The DEA method was first introduced in 1978 by American economists Charnes, Cooper and Rhodes. Relying on the productivity concept formulated by G. Debreu (1951) and M.J. Farrell (1957), which defined efficiency measure as a 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 the DEA method, efficiency is defined as follows (Gospodarowicz, 2002: 56):

$$EFFICIENCY = \frac{\sum_{r=1}^s \mu_r OUTPUT_r}{\sum_{i=1}^m v_i INPUT_i}, \quad (1)$$

where:

s – amount of outputs,

m – amount of inputs,

μ_r – measure demonstrating of importance of each group of inputs,

v_i – measure demonstrating the importance of each group of outputs.

Using the DEA method, the efficiency of a variable is calculated in relation to other variables from a particular group. Effective variables within a particular group make the so-called efficiency curve (Figure 1). The efficiency of the other variables is calculated in relation to the curve defined through solving the issue of linear

programming (using the DEA method). The efficiency curve is defined by variables in the form of inputs and outputs in a particular study of a given variable. In the DEA method, no prior knowledge of measurements is required because through the whole study the measure of the maximum efficiency of each variable is constantly calculated.

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

The DEA analysis uses 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, Slocum, 1998: 489). These assumptions are illustrated in Figure 2.

For each production unit, the input and output variables are indicated as follows:

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

where $x > 0$ and $y > 0$.

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

The methodology of credit risk assessment the DEA method proposed in this article was prepared on the basis of litera-

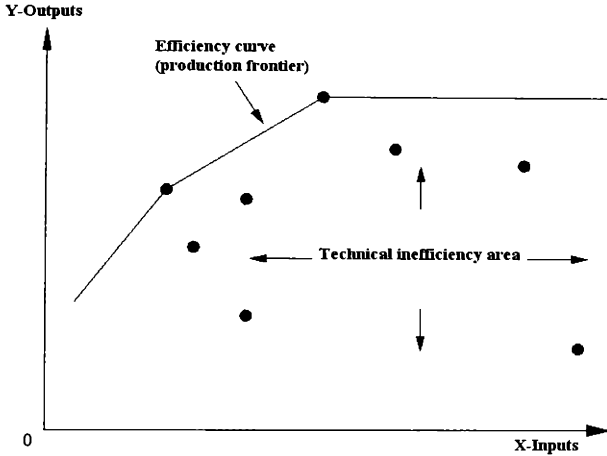


Figure 1. Efficiency curve

Source: Gospodarowicz M., 2000, p. 12.

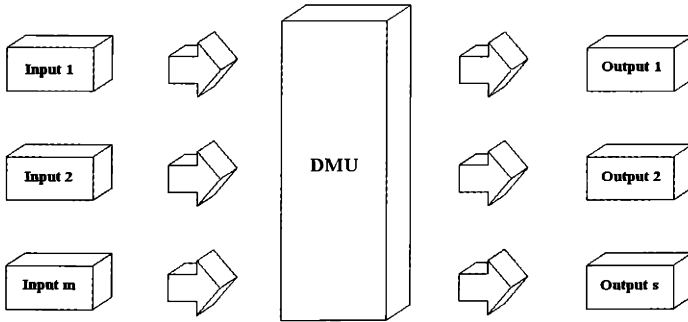


Figure 2. The DEA model outline

Source: Gospodarowicz A. (ed.), 2002, p. 57.

ture studies (Emel et al., 2003, p. 103–123; Simak, 2000, p. 1–189; Gospodarowicz, 2004, p. 119–129) as well as the author’s own research (Feruś, 2006a: 44–59, Feruś, 2006b: 263–269, Feruś, 2006c: 245–253; Feruś, 2007d: 225–233; Feruś, 2007e:

144–154). It consists of five stages presented in Figure 3.

Stage 1: Choosing a study sample

The base of the study was statistical material containing information provided by a bank on 100 construction companies

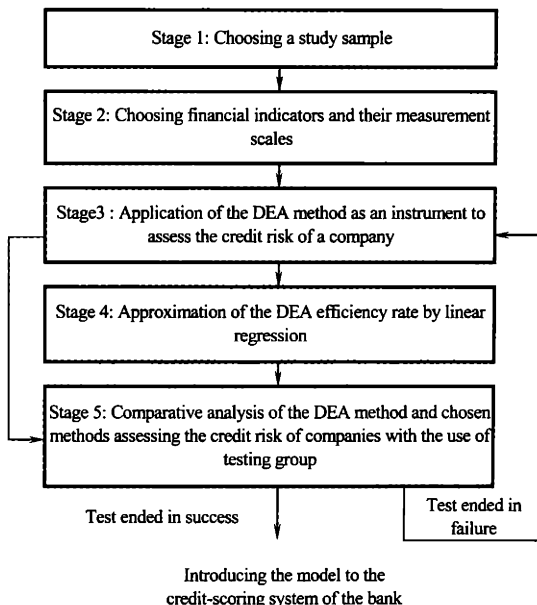


Figure 3. The proposed method of assessing credit risk of companies by the DEA method

Source: author's study.

that obtained a credit loan in the years 2001–2003. This study included the status of credit repayment history¹.

Stage 2: Choosing financial indicators and their measurement scales

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

financial indicators from this study, but at the same time were good representative indicators that were not chosen for the diagnosis².

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

A crucial problem in this stage is the choice of the right set of inputs and outputs used in firms' component. Assignment of individual financial indicators to groups of inputs and outputs depends mainly on

¹ Statistical material contained 50 solvable firms and 50 firms with delinquency risk.

² The chosen indicators were weakly correlated with each other and strongly correlated with the fluctuating alignment.

Table 1. Financial indicators used in the study

Indicator's symbol	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: author's study.

problem format. Often the scripts on the object under study 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 the DEA method depends on choosing the right DEA model. To classify a DEA model, two criteria must be present simultaneously: the type of the effect scale and the 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 the inputs are minimized or the outputs are maximized. Depending on the choice of the model orientation, either the technical efficiency of input or technical efficiency oriented to solution, or the so-called undirected models can be calculated.

Based on a thorough study of the literature (Emel et al., 2003, p. 108–121; Simak, 2000, p. 43–100; Gospodarowicz, 2004, p. 123–129), credit inspectors' interview and personal experiences (Feruś, 2006a, p. 53; Feruś, 2006b, p. 265; Feruś, 2006c, p. 248; Feruś, 2007d, p. 228; Feruś, 2007e, p. 147)

in that aspect, input and output classifications were compiled³:

- **inputs:** X_5 and X_6 ,
- **outputs:** X_1 , X_2 , X_3 and X_4 .

To calculate the technical efficiency indicator value of the firms, the CCR (constant scale effect) model was used. It was directed toward inputs with a search for the minimal value of the efficiency indicator that will possibly reduce the amount of input and result in an equal output of the study object. For this calculation, the optimal linear EMS⁴ program was used. The efficiency indicator values for each firm in the study ranged from 0 to 1. The value of the efficiency indicator equal to 1 demonstrates the firm being effective, whereas the efficiency indicator value lower than 1 demonstrates that the firm has a possibility to improve the input and output relations, i. e. indicates the efficiency loss level.

In this part of the study, research was also aimed at finding the base point (cutoff

³ The author used numerous studies examining the model effectiveness. The present paper gives the final model that proved to be the most effective in determining the firms' credit risk factor.

⁴ Dortmund University website sources: <http://wiso.unidortmund.de/LSFR/OR/scheel/ems>

Table 2. Evaluation of different methods of efficiency using 2001–2002 data⁵

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: author's study.

point) of the efficiency coefficient that will separate the solvent group of firms from the firms with a risk of delinquency.

A good concept allowing for setting the right base point value, but also considering an incorrect object classification, was a study of interdependence between the value of incorrect classification and the value of the base point. In this approach, the optimal base point regulates the minimal entire cost of incorrect classification. Moreover, this concept permits a multivariant analysis, the optimal base point change due to an incorrect classification to Type I or II.

⁵ S_2 – type II Efficiency – determines what percentage of solvable firms was correctly classified ($S_2 = \frac{P2}{P2 + NP2} * 100\%$, where $P2$ is the number of solvable firms classified as the solvable group, $NP2$ is the number of solvable firms classified as the delinquency risk group), S_1 – type I efficiency – determines what percentage of firms with delinquency risk was classified correctly ($S_1 = \frac{P1}{P1 + NP1} * 100\%$, where $P1$ is the number of firms with a risk of delinquency, classified as the delinquency risk group, $NP1$ is the number of firms with a risk of delinquency classified as solvable, S – general classification of efficiency – determines what percentage of all firms was correctly classified applying the $S = \frac{P1 + P2}{P1 + NP1 + P2 + NP2} * 100\%$. The base-point value in the discrimination analysis model and the regressive linear model was calculated as the average value from the average of the groups.

To show the entire cost of incorrect classification, the following formula was applied (Simak, 2000, pp. 94–95):

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

where C_1 is the loss indicator Type I error, C_2 is the loss indicator 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 $C2$ are equal to 0.6 and 0.03, respectively.

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

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

Based on the classification results shown in Table 2, we can conclude that the efficiency of classifications I and II with

Table 3. Selected properties of the regressive linear function YDEA

$R^2 = 67\%, F(6/93) = 31,46$						
Variables	X_5	X_6	X_7	X_2	X_1	X_4
$t(a_j)$	-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

the use of the DEA method is similar to that of the discriminating analysis and a linear regression.

Stage 4: Approximation of DEA efficiency rate by linear regression

The main purpose of this phase is an attempt to reduce the DEA method fallacy caused by the necessity of applying an optimal linear program for every study of a firm applying for a credit loan (Simak, 2000: 94–95). The suggested solution of this problem is the application of the regressive linear function which allows finding a correlation between the coefficient of the DEA method value and its effectiveness with defined inputs and outputs. In this case, the regressive linear function could be used as a linear estimation of the coefficient of the DEA method values, omitting an extensive process of the DEA method verification each time a new firm is applying for a credit. In other words, the regressive linear function could be used while determining the firm's credit risk level without going through the first three phases (Emel et al., 2003: 108–115). Accordingly, the regressive linear function was defined during the process of estimating the coefficient value of the DEA method efficiency. In the past, the coefficient values of the DEA method efficiency through a regressive linear function were treated as a dependent variable Y , and the defined input and output were noted as an operand X_i (independent variable). The regressive linear

function research was conducted employing the Statistica 6.0 program. When rating the value of the regressive linear function model, the level of significance $\alpha = 0.05$ was established.

The final linear regression model formula is as follows:

$$Y_{\text{DEA}_{2001-2002}} = -0.0006X_5 + 0.0010X_6 + 0.0826X_1 + 0.0126X_2 - 0.0003X_3 + 0.2831X_4 + 0.0564.$$

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 Student's t test is applied. The variable quantity determining the outcome in this 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 $t_\alpha = 1.6614$. 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 studying 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 justified on none of the levels and can be rejected.

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

Summarizing the results of the above study (Table 3 – test of essence: Student's t , F-Snedecora, determining the 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 the regressive linear function $Y_{DEA, 2001-2002}$ 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 a linear approximation of the coefficient of the DEA efficiency value.

Table 4. Comparison of the classification efficiency of the DEA method and the 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: author's study.

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

To check and verify the accuracy and efficiency of the prognostic qualities of the

above models, the statistical material (100 firms) was divided equally 1:1 in respect to two separate research samples: controlled and placebo groups. The efficiency rate of both groups' classification is presented in Table 5.

Table 5. Comparison 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: author's study.

The classification results presented in Table 5 imply that the DEA method has superior prognostic indicators. It best minimizes type I errors where the classification efficiency was higher than 12% two years before delinquency and higher than 16% one year before delinquency. However, the general classification efficiency of the DEA method is similar to that of the method discrimination and linear regression analysis.

3. Conclusions

The above analysis shows that a well reflected credit scoring model is reliable in differentiating a potentially high risk of default from a low risk of default clients. The DEA method correctly predicts the possible financial difficulties, including a company's bankruptcy risk, in the Polish economic situation. These results are com-

parable with or even superior to the results obtained by other methods presently employed.

The study has confirmed the universal value of the DEA method in analysing a large spectrum of credit risk uncertainty. It not only measures efficiency in respect to the use of financial risk indicators, but also facilitates an accurate credit risk classifica-

tion for corporations in the credit application process.

Due to the overall credit scoring success, it is safe to presume that this method will become a central tool in credit risk assessment for corporations and individual consumers. This credit scoring method is very dynamic, very promising, and continually developing.

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DEA (DUOMENŲ APGAUBIMO ANALIZĖS) METODAS VALDANT BENDROVIŲ KREDITO RIZIKĄ

Anna Feruś

S a n t r a u k a

Šio straipsnio tema yra naujas veikimo būdas, numatantis bendrovių kredito riziką Lenkijos ekonominiėje aplinkoje. Lenkijoje, kitaip nei kitose

Vakarų šalyse, DEA metodas dar nėra įgyvendintas, kad bendrovės galėtų išgyventi kredito riziką. Tyrimas, aprašytas straipsnyje, buvo vykdomas remian-

tis siūlomo DEA metodo palyginimu su dabartinėmis naudojamomis procedūromis (diferencijuota analizė, linijinė regresija ir t. t.). Siekiant patikrinti ir palyginti įvairių bendrovių kredito rizikos vertinimo metodų veiksmingumą, taip pat buvo tirtas bendrovių klasifikavimo efektyvumas. Remiantis tyrimu gali-

ma išvada, kad DEA metodas palengvina finansinių problemų prognozę, įskaitant bendrovių bankrotus Lenkijos ekonominėje situacijoje, o jo efektyvumas yra panašus arba net didesnis nei iki šiol naudotą metodą.