USING DEA AS A USEFUL TOOL FOR BANKRUPTY ASSESSMENT IN ROMANIAN´S ENTERPRISES

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Abstract

Diagnosing the financial health of businesses is one of the relatively frequently discussed topics in management practice. Therefore, there are constant attempts to improve the diagnosis of the financial health of enterprises using modern quantitative methods, especially in recent years, the application of relatively non-standard methods, data envelopment analysis (DEA). Finance is a large area that uses economic tools, models, and processes to solve financial problems and benefit from new business opportunities. Finance also involves creating corporate strategies to maximize profits. Instead of maximizing profits, we can theoretically maximize the company's liabilities so that the company can go bankrupt. And it is the bankruptcy of companies that is the topic that we address in this research paper. DEA is a non-parametric method that measures the estimates of the classification function burden on the separation of failed and non-defaulted companies. We focus on DEA's ability to assess the bankruptcy of companies in Romania. The DEA method is unusual as there is no need to address many of the assumptions that must be followed with other methods. At the same time, it is not necessary to have a large sample to assess bankruptcy, making this method more attractive to the application of banker assessment. In the first part of the article, we deal with important theoretical aspects of the problem. At the same time, authors who dealt with a similar issue and in some way, helped to process the processing of the analytical part. Subsequently, we created a database and based our analysis of the financial health of Romanian companies on the negative DEA philosophy. We have constructed a threshold of financial distress, which is made up of businesses that are very likely to run into financial problems soon. This has made it relatively easy to classify the companies surveyed as those with a relatively low probability of financial failure and those with a probability of financial failure in the near future relatively high. DEA is not one of the most widely used tools for detecting financial health, and this was also the motive for choosing this model for the discussion of an article whose role was to assess the financial health of businesses through an innovative approach.

Keywords: prediction, data envelopment analysis, bankruptcy, financial analysis.

1 INTRODUCTION

To maintain the company's prosperity and competitiveness, it is essential for management and other stakeholders to know in detail what economic and financial situation their business is. The prerequisite for detailed knowledge of the financial situation is to pay sufficient attention to the diagnosis of the financial health of the company and to identify potential problems endangering its activities promptly. The need for early diagnosis of the economic difficulties of businesses has prompted the emergence of various diagnostic models based on financial indicators.

The possibility of predicting business failure is based on a results assessment achieved today and in the past, which is a prerequisite for further development (Hardingham, 2018, p. 13-18). To sum up, while ex-post analysis is past-oriented, it is at the same time the basis for ex-ante analysis that focuses on prediction for the future in horizon 2, a maximum of 5 years.

DEA is a non-parametric method of measuring the technical efficiency of homogeneous units, which belongs to a group of mathematical formulae based on linear programming procedures. The origins of the basic idea of assessing technical efficiency date back to the second half of the 20th century, when Farrell (1957, p. 253-281) proposed a procedure for analysing the technical efficiency of units, which allowed the acceptance of several input variables and provided a generally applicable and comprehensive measure of effectiveness. Farrell's approach (1957) was generalized several years later for multiple outputs and formulated as a problem of linear programming by authors (Simionescu, 2016, p. 46-60).

Performance is a phenomenon that predetermines the company's results (outputs), but at the same time, results in them and thus affects the market position. Nowadays, we can find more methods and ways to evaluate the financial performance of the company (Kliestikova, et al., 2017 p. 221-237). Some approaches focus on business performance by combining the three primary financial characteristics, namely the generated cash flows, the capital needed to make cash flows and the cost of capital invested (Kliestik, et al., 2018, p. 791-803). "Nowadays, a new approach based on analysing the company's performance through the creation of shareholder value is beginning to be increasingly applied to assess the company's financial performance. The importance of the traditional profit-making business objective is diminishing and replaced by goals that relate profit to the cost of resources used (Vochozka et al., 2016, p. 57-62).

The dynamic progress of the world economy is increasingly linked to the concept of competitiveness. The competitive ability of a country reflects, to some extent, the competitiveness of its firms. This is influenced by several factors, not least the efficiency achieved by the company. Greater efficiency can enable a company to perform strategic activities better, cheaper than the competition, which will, in turn, lead to a competitive advantage. This implies that for a successful business, measuring and monitoring the achievement of efficiency and finding the causes of its potential inefficiency are essential, as it means better in this case. In scientific studies, pay particular attention to the application of variant tools to the construction of diagnostic models. The most widely used tools currently include discriminant analysis, logistic regression, decision trees, and various types of neural networks. However, the need to meet several statistical assumptions or the relatively strict data set size requirements of these traditional tools has become an incentive to develop new approaches.

Effectiveness can generally be expressed as a ratio of the desired outputs that the rated entity produces and the inputs it consumes in that production. Each unit is, therefore characterized by a set of input and output variables that affect the unit's efficiency under assessment.

At present, there is a wide range of methods and procedures by which we can measure the efficiency of production units. Each of these methods has its positives and negatives. The leader among the methods is the methods we know under the single title data packaging analysis.

One of the critical terms in DEA is the Production Possibility Frontier (PPF), the creation of which is the basic principle of DEA. The set of those units, re-considered to be the most effective within the Production Possibility Set (PPS), creates PPF. If a unit is outside PPF, it is deemed to be ineffective. DEA models can be classified according to the orientation of the model into input-oriented, output-oriented, and non-oriented models. When queried about the extent to which inputs should be reduced without changing the output level, input-oriented models answer and vice versa.

DEA models have a non-parametric character of DEA, and no assumption of functional form between inputs and outputs is required. Still, since no production, cost, or profit function is estimated from the data, boundary products, partial elasticity, boundary costs, or flexibility of substitution cannot be evaluated.

2 METHODOLOGY

In processing the stated objective, namely the evaluation of the financial health of Romanian companies, we chose the procedure from Mendelova and Bielikova (2017, p. 26-44), which in addition to a detailed proposal for the procedure also provide a practical example for the implementation of the selected model. The database created consists of 600 enterprises that have been analysed according to this methodology and the results have been interpreted in Table 1.

Data packaging models are used to assess the technical efficiency of production units based on inputs and outputs. Thus, DEA models are looking for individual weights for each unit evaluated. These scales sought to maximize unit efficiency.

When analysing the efficiency of units (DMUs), which are characterized by one input *x* and one output *y*, it can be assumed that for a given task there exists a theoretical set of permissible options, consisting of all possible (permissible) combinations of inputs and outputs (*x, y*). The collection of production possibilities is determined by the effective theoretical limit (Gavurova, 2017, p. 1156-1173).

Consider that we have a set of homogeneous decision units $U_1, U_2, \ldots, U_n$. When monitoring the efficiency of these units, we consider *r* outputs and *m* inputs.

Input matrix: $X = \{xij, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\}$.

Output matrix: $Y = \{yij, i = 1, 2, \ldots, r; j = 1, 2, \ldots, n\}$.

The inputs and outputs of the Uq include the q-th column of matrices Xq and Yq. The measure of technical efficiency of this unit can generally be expressed as a function where v_i, i = 1, 2, ..., m are weights assigned to the i-th input and u_k, k = 1,2, ..., *r* are weights assigned to k-th output. This is the weighted sum of the outputs divided by the weighted sum of the inputs of the Uq unit. To derive the form of an effective threshold and what a production possibility set looks like, it is necessary to assume the nature of the scale returns for the problem. Yields can be constant and variable, possibly increasing, decreasing, non-increasing, non-decreasing, etc.

The assumption of constant returns to scale (CRS) determines whether the combination of inputs and outputs (x, y) is an element of a set of production options, then the combination (αx, αy) is an element of that set (Mendelova and Bielikova, 2017, p. 26-44).

The assumption of variable returns to scale (VRS) leads to a modification of the effective limit. The effective boundary here is the data envelope, which is convex. Unlike in the previous case, where only one unit has been marked as effective, multiple units may be effective in the case of VRS. This is because there is no requirement that, in order to maintain efficiency, α-multiple inputs must be supplemented by the same multiple of outputs. The VRS results in the unit being effective, even if the relative increase in returns is lower or higher than the corresponding increase in inputs. Assuming VRS, the efficiency of the evaluated units is higher than for CRS (Valaskova, 2018, et al., p. 105-121).

3 RESULTS

When designing the diagnosis of the financial health of businesses, we will be based primarily on the negative DEA philosophy, and in the proposed approach we will construct the boundary of financial distress. This will be made up of companies with a high probability of financial difficulties soon, which will make it relatively easy to classify the companies surveyed as having a relatively low probability of financial failure and those with a probability of financial failure shortly. future relatively high.

First, it is necessary to identify the financial indicators of companies that have the good discriminatory capacity. This selection can be based on the expert knowledge of the model builder, or the values of financial ratios can be compared between a group of financially sound enterprises and a group of companies in financial distress (Mendelova and Bielikova, 2017, p. 26-44).

Inputs are defined as a financial indicator that represent the financial strength and solvency of the company, and on the other hand, outputs are chosen financial indicators that represent the financial instability and insolvency of the company. In this way, all semi-positive linear combinations of inputs and outputs of the evaluated enterprises will create a production possibility set which is encapsulated by a so-called. financial distress (Mendelova and Bielikova, 2017, p. 26-44).

In this way, the threshold of financial distress will be created by companies that achieve relatively low input values and at the same time relatively high output values; companies with a high probability of their financial problems in the future.

Subsequently, outliers were removed because otherwise, the proposed DEA approach would lose the ability to identify other vulnerable enterprises, as the financial distress threshold would be constructed based on outliers.

The threshold of financial distress is constructed based on a whole sample of n enterprises. In this way, we identify businesses that create the threshold of financial distress. These enterprises will be considered to have a relatively high probability of their future financial problems (Mendelova and Bielikova, 2017, p. 26-44).

Then, those businesses that formed the threshold of financial distress in the first step are omitted, and the next threshold of financial distress is constructed again on such a reduced dataset. This partially eliminates the negative impact of potential outliers. Businesses that create a financial distress line in this step are considered to also have some probability of their future financial problems, but this probability is relatively lower than those that formed the financial distress line in the first step. The principle of this procedure is illustrated in Figure 1.

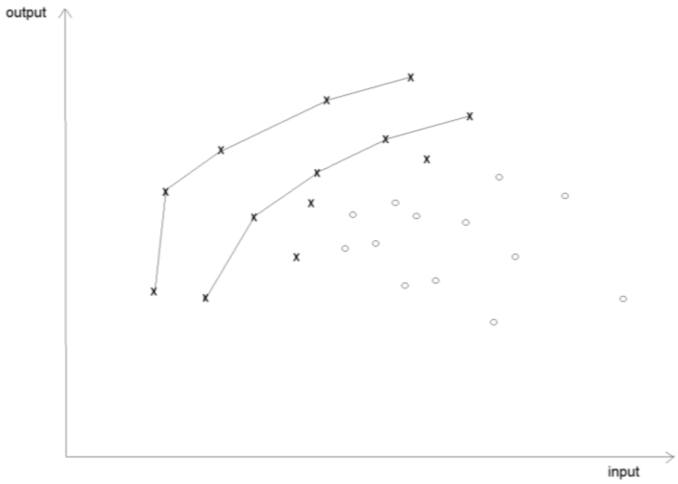

Fig. 1. The threshold of financial distress for one input and one output

The procedure for assessing the classification capability of the proposed DEA model for diagnosing the financial health of businesses is divided into six categories. Group A includes enterprises in financial distress classified in the financial distress zone, then group B comprises enterprises in financial distress classified in the grey zone, and group C includes enterprises in financial distress that are classified in the financial health zone. Group D includes financially healthy businesses in the financial distress zone, Group E includes financially healthy businesses in the grey zone, and Group F includes financially stable enterprises in the financial health zone.

This research paper aimed to assess the financial health of selected Romanian companies, namely 600 companies where the inputs were indicators of liquidity, cash flow, return on assets and the share of EBITDA in sales. Outputs were indicators of total indebtedness, duration of liabilities and long-term liabilities.

Table 1. Results of financial health of Romanian enterprises

	Financial distress zone	**Grey zone**	**Financial Health Zone**	**Total**
Enterprises in financial distress	23%	48%	29%	100% from 171
Financially sound businesses	12%	36%	52%	100% from 429

4 CONCLUSIONS

Analysis of the data packaging allows the output of the financial analysis, based on selected indicators, to determine the degree of efficiency achieved by the company in each year of the period while providing

ISBN: 978-605-82433-8-5

optimal solutions to improve (increase or decrease) these indicators necessary to achieve the desired efficiency of the company. The aim of this research paper was to assess the financial health of 600 Romanian companies using the DEA method. In the overall assessment, we can say that they are more or less balanced companies, some of which have problems in valorising the funds that need to be corrected and guarded. The importance of applying the DEA method in comparing the results of the analysis is in determining the target values of indicators that are important for the company in terms of increasing its efficiency and thus its competitiveness in the market.

5 ACKNOWLEDGEMENT

This research was financially supported by the project “Stabilization and development of SME in rural areas”, reg. No. TL01000349, the TACR Éta programme.

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