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Benchmarking—A Way of Finding Risk Factors in Business Performance

Jarmila Horváthová, Martina Mokrišová * and Mária Vrábliková

Faculty of Management, University of Prešov, Konštantínova 16, 080 01 Prešov, Slovakia; jarmila.horvathova@unipo.sk (J.H.); maria.vrablikova@smail.unipo.sk (M.V.)
* Correspondence: martina.mokrisova@unipo.sk

Abstract: The purpose of this study was to emphasize that the Data Envelopment Analysis (DEA) method is an important benchmarking tool which provides necessary information for improving business performance. To fulfil the abovementioned goal, we used a sample of 48 Slovak companies involved in the field of heat supply. As their position in the economic and social environment of the country is essential, considerable attention should be paid to improving their performance. In addition to the DEA method, we applied the Best Value Method (BVM). We found that DEA is a highly important benchmarking tool, as it provides benchmarks for units that have problems with performance and helps us to reveal risk performance factors. The DEA method also allows us to determine target values of indicators. The originality of this paper is in its comparison of the results of the BVM and the DEA methods.

Keywords: benchmarking; best value; business; data envelopment analysis (DEA); performance; risk factors

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1. Introduction

In the current turbulent period, it is necessary for every company to monitor market changes, not only in the areas of marketing and innovation, but also in the field of business performance and the application of financial indicators in its measurement. Businesses are looking for different ways to increase their performance and achieve a competitive advantage over their competitors. Therefore, they use different methods, techniques and indicators. One of the methods than can be applied in this area is benchmarking. Benchmarking finds the best practices for knowledge and know-how by learning from other companies, competitors and industry leaders to gain a competitive advantage in global competition (Tian and Ketsaraporn 2013).

Benchmarking is part of the concept of quality management. It is a method of analyzing and comparing practices and experiences in various areas of business operations (Kaczmarska 2010). This method was first used in the 1980s by the Xerox Corporation to improve its competitive position (Demjanová 2006). According to Veber (2000), benchmarking is based on two principles. The first is the principle of the Chinese general Sun-c (500 BC): "If you know the enemy and know yourself, you need not fear the result of a hundred battles." The second principle is being the best of the best.

The purpose of benchmarking is to be inspired by the best competitors (best practices). This, however, does not imply imitation. This is also confirmed by one of the definitions of benchmarking by R. C. Camp as "finding best practices in business that lead to excellent results" (Kiseľáková and Šofranková 2014). Benchmarking is currently one of the most widely used management tools, and it is applied in order to increase business performance (Bogetoft 2012). Benchmarking includes the benchmarking of products and services, business processes and performance measures (Maleyeff 2003).

Based on the above, we set the research problem and aim of the paper. The research problem is the following: Which benchmarking method is able to identify performance risk factors? The aim of the paper considers how to improve businesses' performances by applying selected benchmarking methods.

The next part of the text is structured as follows: The first section outlines the theoretical basis of benchmarking, performance benchmarking, performance benchmarking tools and performance risk factors. The second section describes the research sample and the methodology. The research problem and research questions are formulated in this part of the paper. When addressing the research problem, we made use of selected financial indicators, the BVM, the DEA and the Spearman's rank correlation coefficient. The third section includes results and a discussion of the results achieved. This section lists scores and rankings of companies obtained by the BVM and the DEA. The strength and association between rankings are determined by Spearman's rank correlation coefficient. A special part of this section is devoted to the calculation of target values—benchmarks for improving businesses' performances. The final part of the paper is the conclusion, which provides recommendations for improving business performance and the benefits of the DEA in terms of performance improvement. The process of the research is illustrated in Figure 1.

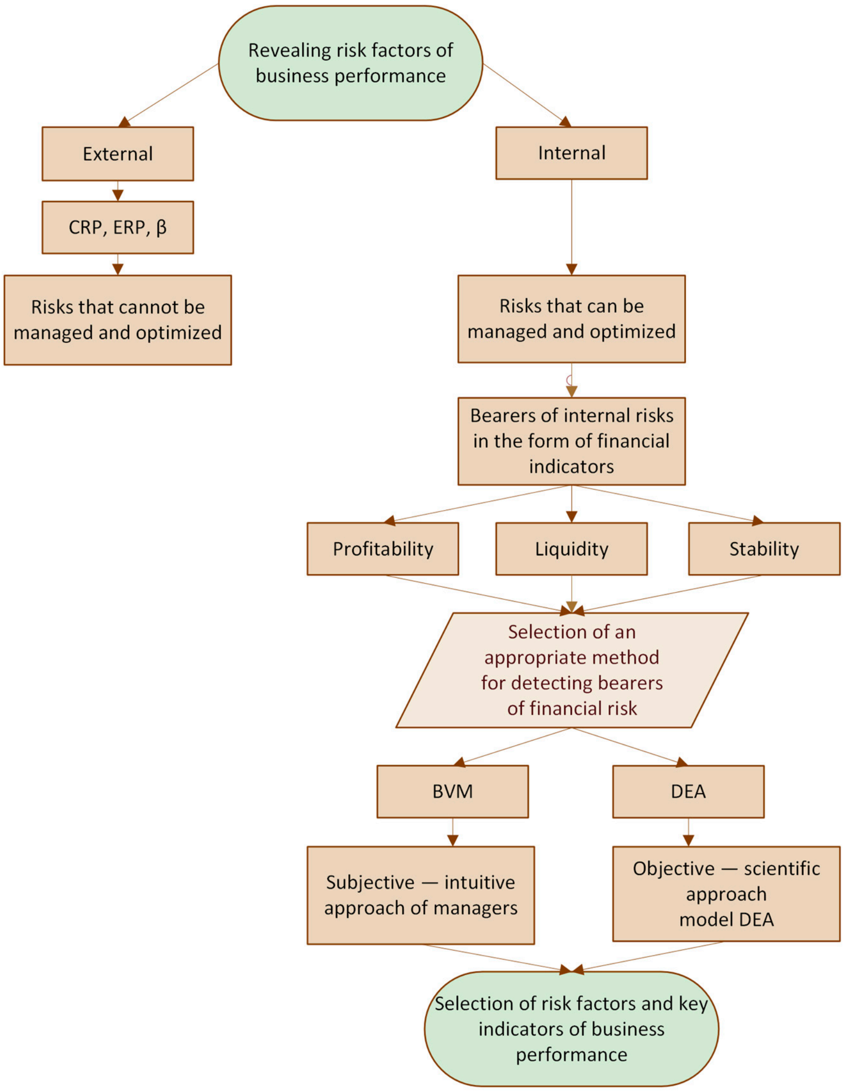

Figure 1. Flowchart of the research. Legend: CRP—Country Risk Premium, ERP—Equity Risk Premium, β—systematic risk.

2. Literature Review

Benchmarking studies can be divided according to the type of benchmarking into: process, functional and performance benchmarking studies (Nenadál et al. 2011). A similar classification is given by (Fong et al. 1998 in Anand and Kodali 2008), who divide benchmarking according to its content into process, functional, performance and strategic benchmarking. As part of our research, we focused on solving the issue of performance benchmarking, with the aim of increasing the performance of businesses.

Performance benchmarking is used by an organization to determine its market position compared to the performance characteristics of other organizations. To maintain ethical rules in the commercial environment, it is appropriate to use a third party for this type of benchmarking. It is the most common type and will probably be the starting point for any procedures aiming at the overall operation of an organization (Pogranová et al. 2011).

Performance benchmarking is a combination of two methodologies: benchmarking and performance management. According to Camp (1995, p. 16), the aim of benchmarking performance measures is to set and validate goals for several vital performance measures which guide an organization. Benchmarking is imperative for performance (Krishnamoorthy and DLima 2014). Many organizations include benchmarking as a component of their performance management system (Maleyeff 2003).

Benchmarking is also an important tool for identifying key performance indicators (Ho et al. 2000). Well-known key performance indicators are related to financial analysis (Bogetoft 2012). If we, during a performance measurement, find out which key financial indicators are lagging behind our competitors, it is advantageous for us to improve their values while preventing other indicators from creating an imbalance. Conversely, if we find out in which aspects we are significantly better than our competitors, and this indicator does not have a negative impact on other financial objectives, we can present this as a competitive advantage. Benchmarking is not only a measurement tool but a process of identifying gaps in performance, while the elimination of gaps and continuous improvement can bring the company closer to its competitors (Zairi and Leonard 1996).

When comparing businesses' performances, it is possible to apply different indicators (Štefko et al. 2012). Bogetoft (2012) states ROA, gross margin, debt ratio and price/book (stock capitalization/book values) are important performance indicators. According to Štefko et al. (2021), these measures include selected indicators of liquidity, profitability, capital structure and activity. According to Wood and McConney (2018), important performance indicators include, for example, return on assets (ROA), return on equity (ROE), return on capital employed (ROCE) and net interest margin (NIM). Additionally, according to Bărbuţă-Misu et al. (2019), the most used performance measures include ROA and ROE, but they mention also liquidity, leverage, productivity, solvency and assets turnover. One of the modern benchmarking models of enterprise performance evaluation is the Creditworthy Model (CWM), which is the most suitable model for the comparison of financial performance between two or more enterprises (Kisel'áková et al. 2018).

The selection of indicators must be based on the definition of performance. Business performance is understood by most authors as the ability of a business to value the investment invested in its business activities in the best way (Johnson and Kevan 2000). Therefore, the most commonly used performance measurement indicators are financial indicators based on the primary objective of business—to maximize profits. We talk about financial indicators (profitability, liquidity, indebtedness, activity and market value), but new indicators are being added, such as EVA (economic value added), MVA (market value added), CVA (cash value added), WACC (weighted average costs of capital), RONA (return on net assets) and the like (Neumaierová and Neumaier 2002; Ittner et al. 2003; Frost 2005; Šulák and Vacík 2005; Petřík 2009; Kislingerová et al. 2011).

Accounting measures of performance have been the traditional mainstay of quantitative approaches to organizational performance measurement. However, over the past two decades, a great deal of attention has been paid to the development and use of non-financial measures (customer loyalty, customer satisfaction, capacity utilization and prevention of heat losses, renewal of production facilities, employee satisfaction, employee qualification, water protection, waste reduction, employee environmental awareness) of performance (Neely 2002; Otley 1999).

When solving the given problem, various methods from the area of performance benchmarking were applied in individual studies. For example, in the gas industry, the following methods were applied: Agrell and Bogetoft (2007) estimated the efficiency of gas distribution in Germany by applying a method of the Ordinary least squares, the Stochastic frontier analysis and the DEA; Rossi (2001) estimated the efficiency of the gas distribution sector in Argentina, and he used the Stochastic frontier and Malmquist index; Farsi et al. (2007) estimated the economic efficiency of the gas distribution sector in Switzerland by applying SFA; Erbetta and Rappuoli (2003) estimated the optimal scale and technical efficiency of the Italian gas distribution industry with the use of the DEA (Goncharuk 2008).

Significant methods that can be applied in the field of evaluation, and improvements in business performance include multidimensional benchmarking analyses based on the measurement of a number of criteria. These methods include, e.g., network charts, AHP maturity index and Z charts (Vochozka et al. 2017). Multidimensional methods also include the BVM method. It is possible to mention the following studies of authors who applied the BVM method in the field of performance benchmarking. Magd and Curry (2003) focused on the application of this method in the public sector. The Best Practice methodology was also applied in an article by Asrofah et al. (2010), in terms of increasing the efficiency of the manufacturing industry. The interconnection of DEA and BVM methods was realized in an article by the authors Yang et al. (2016), who, using the given methods, searched for winners in the field of supply and provided for their needs. A more detailed description of the BVM method is given in the section Data and Methodology.

An effort in the application of benchmarking methods in business performance improvement has been to develop benchmarking models that are able to perform multidimensional measurement (Vochozka et al. 2017). Benchmarking can be seen as a process of determining valid measurements for comparing the performance of comparable units in order to determine their relative positions and thus set the standard for highest quality. In this regard, the DEA method can be considered as a multidimensional benchmarking tool. This quantitative analysis method for evaluating the relative efficiency of a set of comparable, homogenous decision-making units (DMUs) has been often used as a practical benchmarking tool in management (An et al. 2021). The foundations of the DEA method were laid by Farrell (1957). At that time, this researcher thought methods such as measuring labor productivity or capital productivity were restrictive, as they did not cover the possibility of combining multiple input measurements, and were thus insufficient for expressing the overall efficiency of the company. These shortcomings have resulted in a more relevant approach applicable to any company, leading to a broader concept of productivity and a more general concept of efficiency. He was inspired by the work of Vilfred Paret, who, in his welfare theory, considered, in addition to increases and decreases, their importance, and assigned them some weights—this principle is now known as the Pareto criterion. Farrell is considered to be the father of the DEA, as DEA is based on the principles of linear programming. The basic task of DEA models is to compare DMUs within a group of units with the same or similar units. The definition of DMU is relatively flexible. DMU is the entity responsible for converting inputs to outputs, the effectiveness of which needs to be evaluated (Cooper et al. 2007; Cooper et al. 2011; Hatami-Marbini 2019; Ruiz and Sirvent 2019).

Klieštik (2009) explains that input-oriented approaches measure efficiency based on input variables and, in order to improve efficiency, a company should reduce the volume of inputs. Opposite these are output-oriented approaches that recommend increasing outputs to improve efficiency. Another criterion for the breakdown of DEA models is the return on scale. Constant returns to scale (CRS) occur when a 1% increase in input yields a 1% increase in output (CCR models). Variable returns to scale (VRS) occur when output increases by 1% or output changes by less than or more than 1% (BCC models).

The disadvantage of CCR and BCC models, the need to choose whether we are input or output oriented, has been overcome by the SBM model (Slack-Based Measure) by Tone (2001). The model works well for complicated tasks where it is not possible to determine whether a DMU should minimize inputs or maximize outputs; therefore, it is necessary to combine these requirements (Zimková 2015).

Measuring business efficiency using DEA models also has various advantages and disadvantages. The advantages, according to Majorová (2007) and Kliečtik (2009), include working with multiple inputs and outputs at the same time, not requiring the normality of data distribution and quick identification of inefficient companies (companies below the efficiency limit), a comparison of such companies with efficient companies or objective measuring.

Another advantage of the DEA method is that it provides a more scientific basis for setting goals, and thus allows inefficient firms to find the easiest way to improve their performance. In 2008, Goncharuk applied three DEA models, as well as other performance benchmarking tools, to increase efficiency and effectiveness in the gas industry. The DEA method was used as a benchmarking method by Ruiz and Sirvent (2019), who applied it to improve business performance. Using the DEA for benchmarking ensures an evaluation in terms of targets that are attainable. Determining benchmarking information through closest efficient targets is one of the relevant topics in the recent DEA literature (Aparicio et al. 2014).

The above was confirmed also by Cooper et al. 2004, in Shewell and Migiro 2016, who state that studies of benchmarking practices using DEA have shown inefficiencies in some of the most profitable firms; therefore, DEA has been found to provide a better vehicle for establishing benchmarks than using profitability as a criterion. The DEA method was also used as a benchmarking method by Deville (2009), who compared branches and regional banks of a large French banking group. He applied DEA in the area of operational performance and, as a comparative variable, used the DEA score.

The benefits of the DEA method are also described in the work of Díaz et al. (2004). According to these authors, the DEA method can be used to assess and compare quantitative efficiencies and the weighting of any performance indicator, permitting managers to obtain a well-defined performance ranking.

The disadvantages of the DEA method include inefficiency deviations, which may be due to statistical distortion and a non-parametric approach that make it difficult to test hypotheses about inefficiency and the structure of the production function. DEA is non-statistical method; therefore, it does not yield estimates that can be easily validated with conventional statistical procedures (Banker 1990; Färe et al. 2001). Other disadvantages of the method concern its sensitivity to outliers (Coelli et al. 1998) and the fact that the method deals with relative efficiency (Farantos 2015). Another disadvantage of the DEA method is the sensitivity of its results to the selection of inputs and outputs, so their relative importance needs to be analyzed prior to the calculation. However, there is no way to test the appropriateness of inputs and outputs. Additionally, the number of DMUs on the frontier tends to increase with the number of inputs and outputs entering the model (Berg 2010; Zbranek 2013).

3. Data and Methodology

The research aimed at improving performance with the use of benchmarking methods was carried out on a sample of 48 Slovak companies in the field of heat supply. Companies in this sector use local district heating systems. Their sources and distribution of heat were built together with the development of urban agglomerations. Systems of these companies enable the efficient use of various energy sources produced in the city, including renewables, waste heat, etc. These systems are integrators of energy infrastructure, which can effectively link production and consumption and allow the storage of energy (in the form of heat) in times of surplus (Janiš 2018). The structure of these systems is provided by the climate and segmentation of the territory, historical development, demographic conditions, regional structure, the nature of residential, commercial and industrial construction, economic activity and the availability of fuel sources for heating (Antimonopoly Office of the Slovak Republic 2013). The analyzed industry is important from an economic as well as a social point of view, and plays an important role in the daily life of society and consumers. In this industry, a larger number of companies go bankrupt every year when compared to other Slovak industries. These companies have an important position in many Slovak districts. They are not subsidiaries of the parent company, but they are independent entities. They do not have interconnected management and each company represents a separate unit. In the area of fixed indicators and legislation, these companies have regulated heat prices. They are used to protect risk groups of the population from existential problems. Low energy prices have a positive effect on inflation, as well as on business development. However, on the other hand, heat management companies, in many cases, cannot adjust their variable and fixed costs to the level of regulated prices. Other important regulated indicators are indicators of environmental policy and environmental protection—emission limits for pollutants in the air, emission limits for pollutants in the water, wastewater limits or limits for waste reduction. The analyzed companies are not able to pay the costs and meet limits; therefore, they go bankrupt. However, they could be beneficial for the state and its people, as they provide alternative options for heat production and heat supply. Since they have an important position in many Slovak districts, in this paper, we focused on the evaluation, comparison and improvement of the performance and competitiveness of these companies. The data from the financial statements for the year 2016 were obtained from the Slovak analytical agency CRIF—Slovak Credit Bureau, s.r.o (CRIF 2016). The comparison of performance and subsequently competitiveness of these companies was realized with the use of two benchmarking methods—the BVM and the DEA.

In our research, we focused on the following 9 financial indicators which have a significant impact on the basic financial objectives of these companies. These indicators are the following: current ratio (CL) (1), average collection period (ACP) (2), creditors payment period (CPP) (3), return on assets (ROA) (4), return on equity (ROE) (5), return on sales (ROS) (6), equity ratio (ER) (7), interest coverage (IC) (8) and cost ratio (CR) (9).

Table 1 lists descriptive statistics for the analyzed businesses. The median of the current ratio indicates that half of the analyzed sample of businesses achieves a value of liquidity higher than 0.93, which can be considered appropriate in relation to the characteristics of the industry. The analyzed businesses have high creditors payment periods, the median of which is 183 days. They also achieve good results in profitability indicators in terms of both median and average. The capital structure of these companies is, on average, 30%: 70% in favor of debt, which may be the reason for the lower stability of these companies. From the point of view of interest coverage, the analyzed businesses are able to pay interest. The median of the cost ratio is 0.66.

Table 1. Descriptive statistics for the analyzed businesses.

Variable	Descriptive Statistics					
	Valid N	Mean	Median	Minimum	Maximum	Std. Dev.
Current ratio	48	2.5220	0.9337	0.032532	55.580	8.4011
Average collection period	48	61.6805	34.8444	5.028613	651.676	97.9389
Creditors payment period	48	297.3943	182.3338	2.176053	2941.961	473.0657
Return on assets	48	0.2332	0.1384	0.110630	2.071	0.3052
Return on equity	48	0.7502	0.5733	0.125611	6.227	0.9378
Return on sales	48	0.6160	0.2982	0.018377	7.215	1.4150
Equity ratio	48	0.3008	0.1814	0.054834	0.733	0.2190
Interest coverage	48	111.7940	5.1498	0.000000	2242.891	384.1357
Cost ratio	48	0.6862	0.6594	−0.251537	0.976	0.2139

As we stated in the Introduction, the research problem is as follows: Which benchmarking method is able not only to evaluate but also to improve business performance? In line with the research problem, we asked these research questions:

RQ1: What performance do individual companies achieve based on the BVM?
RQ2: What performance do individual companies achieve based on the results of an input-oriented DEA?
RQ3: What is the strength and direction of the association between the rankings achieved by the BVM and the DEA?

To analyze differences among businesses in space, we used a multidimensional map of objects, which uses an output of multidimensional scaling (MDS). Several authors (Rhee et al. 2009; Zema et al. 2020) used MDS as benchmarking technique. This map was also applied by Lukáčová et al. (2020) when analyzing and applying indicators in the field of tax harmonization and competitiveness. MDS allows us to test whether and how certain criteria by which one can distinguish among different objects of interest are mirrored in corresponding empirical differences of these objects (Borg and Groenen 1997). To express how well a data are represented by an MDS map, we applied Kruskal's *Stress*, which is the most widely used goodness-of-fit statistic. *Stress* is calculated according to Formula (1) (Kruskal 1964):

$$Stress = \sqrt{\frac{\sum_{k=1}^{m}\left(d_{ij} - \hat{d}_{ij}\right)^2}{\sum_{k=1}^{m} d_{ij}^2}} \quad (1)$$

where $\hat{d}_{ij}$ expresses the predicted distance between objects i and j, and d_{ij} is the actual distance between objects i and j.

The smaller the value of the *Stress*, the more the calculated and entered object coordinates fit. According to Kruskal (1964) *Stress* around 0.20 means insufficient overlap, while 0.10 is sufficient, 0.05 is good, 0.025 is excellent and 0.00 is a perfect fit. When applying MDS, an important task is to determine the total number of required dimensions. The goal is to keep the number of dimensions as small as possible (usually, we choose 2-dimensional; maximum is 3-dimensional space). The number of dimensions is chosen based on the lowest possible value of the *Stress* criterion.

To deal with the research problem, we applied two methods. Using the BVM method, we selected the companies that achieve the best values within the individual indicators. Subsequently, the sum of the final evaluation of individual indicators was processed to the final ranking of companies. The DEA method worked with an already created model, which processed all input values of indicators and created a ranking of companies in the field of performance, according to the achieved values of indicators.

In order to answer the research question 1 (RQ1), we used the benchmarking tool which we adopted from the product benchmarking methodology (Kovaľová and Nogová 2016; Vrábliková and Loučanová 2017). This method is used to determine innovative intention of a product, and consists of the following steps:

- Selection of subjects for comparison (48 companies operating in the heating industry);
- Selection of evaluation criteria (9 indicators);
- Determining the weight of the criteria by means of a paired comparison under the questionnaire survey (48 respondents—financial managers of surveyed companies). The weight of the criteria is determined as follows:
  - Average significance: $Øv_i$ = 100/number of criteria;
  - Significance coefficient: k_i = frequency of occurrence (based on pairwise comparison);
  - Average significance coefficient: $Øk_i = \sum k_i$/number of criteria;
  - Conversion using deviation: $D = (k_i - Øk_i) \times d$;
  - Deviation: $d = \sum v_i / \sum k_i$;
  - Real significance: $w = Øv_i + D$.

- the last phase is the BVM, which is based on the knowledge of the fair values of the benchmarking criteria and the real significance (w), resulting from the previous benchmarking steps. The tendency of the criterion (t) may increase or decrease depending on whether we want to maximize or minimize the criterion value. In order to identify the global benchmark, we proceed as follows:
  - The actual values of the criteria (x);
  - Transformed criterion values (a): if the criterion's tendency increases: a = actual value/highest value; if the criterion's tendency decreases: a = lowest value/actual value;
  - Point values for individual criteria (b): b = a × w;
  - Total score for the company (B): B = ∑b
  - Ranking of businesses according to their score.

The aim of the second step (RQ2) was to measure the performance of companies with the application of the input-oriented DEA CCR model. To solve this problem, we chose a model that was built as a dual task of linear programming, which uses the same data as the multiplicative model but reduces the number of model constraints (Kočišová 2012). Klieštik (2009) also considers it more advantageous and practical to work with a model that is a dual-model to the primary CCR model. In this case, the dual model will have $(m + s)$ constraints and $(n + m + s + 1)$ variables. Let us denote λj, $j = 1, 2, \ldots, n$, as dual variables belonging to the first set of constraints of the model, θ_o as scalar dual variable assigned to the next constraint and s_k^+, $k = 1, 2, \ldots, s$, and s_i^-, $i = 1, 2, \ldots, m$, as dual variables assigned to the lower limits for weights of outputs and inputs (slacks). A dual input-oriented CCR model can be written as follows (2):

$$\begin{aligned}&\text{Minimize } \theta_o - \varepsilon\left(\textstyle\sum_{i=1}^{m} s_i^- + \sum_{k=1}^{s} s_k^+\right)\\&\text{s. t. } \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta_o x_{io},\\&\quad\sum_{j=1}^{n} y_{kj}\lambda_j - s_k^+ = y_{ko},\\&\quad\lambda_j \geq 0, s_i^- \geq 0, s_k^+ \geq 0.\end{aligned} \tag{2}$$

Complementary variables are introduced in this model s_i^- and s_k^+ (3):

$$\begin{aligned}s_i^- &= \theta_o x_{io} - \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j,\\ s_k^+ &= \textstyle\sum_{j=1}^{n} y_{kj}\lambda_j - y_{ko}\end{aligned} \tag{3}$$

Slacks indicate how far the unit (DMU_o) is from the efficiency frontier. The variable s_i^- expresses excessive input consumption and s_k^+ expresses the lack of outputs. The unit that is effective in the CCR model has a value of the objective function $\theta_o = 1$, and values s_i^- and s_k^+ (slacks) equal to zero in every optimal solution.

The DEA model also provides information on how the DMU has to change its behavior to become efficient. The DMU, which is a projection of an inefficient unit on the efficiency frontier, is called a peer-unit. The inputs and outputs of this unit are target values of inputs x'_{io} and target values of outputs y'_{ko}, which can be calculated in two ways using optimal values of variables $\theta_o^*, \lambda_j^*, s_i^{*-}, s_k^{*+}$ and the following Formulas (4) and (5):

$$x'_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j^*,\ i = 1, 2, \ldots, m, y'_{ko} = \sum_{j=1}^{n} y_{kj}\lambda_j^*,\ k = 1, 2, \ldots, s. \tag{4}$$

$$x'_{io} = \theta_o^* x_{io} - s_i^{*-},\ i = 1, 2, \ldots, m, y'_{ko} = y_{ko} + s_k^{*+},\ k = 1, 2, \ldots, s. \tag{5}$$

The aim of the final step (RQ3) was to measure the strength and direction of association between the results achieved in the case of the BVM and the input-oriented DEA model.

We used Spearman's rank correlation coefficient to determine the correlation between the rankings of companies. We calculated the Spearman's correlation coefficient according to relationship (6) (Štiglic 2009), as there were several identical orders in the database of companies:

$$p = \frac{\frac{1}{6}\left(n^3-n\right)-\sum_1^n d_i^2 - T_x - T_y}{\sqrt{\left[\frac{1}{6}\left(n^3-n-2T_x\right)\right]*\left[\frac{1}{6}\left(n^3-n-2T_y\right)\right]}},$$
$$T_x = \sum_1^{S_x}\left(t_{i(x)}^3 - t_{i(x)}\right),$$
$$T_y = \sum_1^{S_y}\left(t_{i(y)}^3 - t_{i(y)}\right). \tag{6}$$

where T_x, T_y, for each repeated value in the group X, Y is the number of repetitions deducted from the third power of the repetition in question, and the results are summed as S_x, S_y, number of repetitions in the group X (Y), $t_{i(x)}$, $t_{i(y)}$ represents the number of repetition of the value X_j, Y_j in the group X (Y).

For larger sets ($n > 30$), the probability distribution can be approximated by a t-distribution with $(n-2)$ degrees of freedom. Then, the test statistic for the Spearman coefficient has the form (7):

$$t = p\sqrt{\frac{(n-2)}{(1-p^2)}} \tag{7}$$

We use this random variable even if the groups X and Y feature several repeated values. The null hypothesis H_0, which states that there is no statistically significant relationship at significance level $\alpha = 0.05$, is rejected (we accept alternative hypothesis H_1), assuming that $|t| \geq t_{1-\frac{\alpha}{2}}$ (for one-sided test); $|t| \geq t_{1-\alpha}$ (for two-sided test), $t_{1-\frac{\alpha}{2}}$; $(t_{1-\alpha})$ is the critical value of Student's t-distribution, with $(n-2)$ degrees of freedom. We chose the correlation coefficient based on the results of the normality tests and a two-dimensional point diagram with an ellipse of 95% constant probability density. This verification, as well as the calculations of test statistics and Spearman's coefficient, were performed using software Statistica.

4. Results and Discussion

The starting point for assessing the performance of the analyzed sample of businesses was the calculation of nine financial indicators listed in Data and Methodology.

As the next step, we performed an initial analysis of businesses in space with the use of an MDS map (Figure 2). We were looking for an optimal MDS solution for analyzed sample of businesses with the use of software Statistica. We applied three dimensions, since MDS with four and five dimensions provided the same results. The number of dimensions was chosen based on Kruskal's *Stress*. Value of *Stress* for the three-dimensional model achieved 0.003. Therefore, we can state that the fit of objects in the constructed MDS map is perfect. On the left side of Figure 2, we can see a cluster of businesses. The distances between these businesses and the values of their indicators are highly correlated. We can say that the distances represent the values of indicators well in a linear sense. The cluster marked in Figure 2 with a red circle is created by these businesses: 19, 20, 21, 22, 23, 26, 27, 28, 29, 31, 32, 33, 34, 35, 36, 38, 40, 41, 44, 45, 46, 48. They occur in the area of the negative values of dimension one and dimension two, but dimension three ranges from negative to positive values. These businesses have low liquidity, high indebtedness and are undercapitalized. According to the DEA, they achieved an efficiency score of 0.4–0.6. Business 48 is located near businesses 46, 40, 28, 35, 31 and 32; these businesses have a high creditors payment period, low interest coverage, insufficient liquidity and are undercapitalized. Business 43, which has a negative value of dimension three, is highly undercapitalized. Business 30 stands out from the cluster. It has a positive value in dimension one and negative values in dimensions two and three; the only indicator which achieved negative values is ROS. Business 13 has positive values in all dimensions, and all indicators achieve very good results. Business five also has positive values in all dimensions. It achieves a high average collection period and creditors payment period, but they are also balanced. Business two has negative values in dimensions one and two; it achieves a high creditors payment period and is undercapitalized.

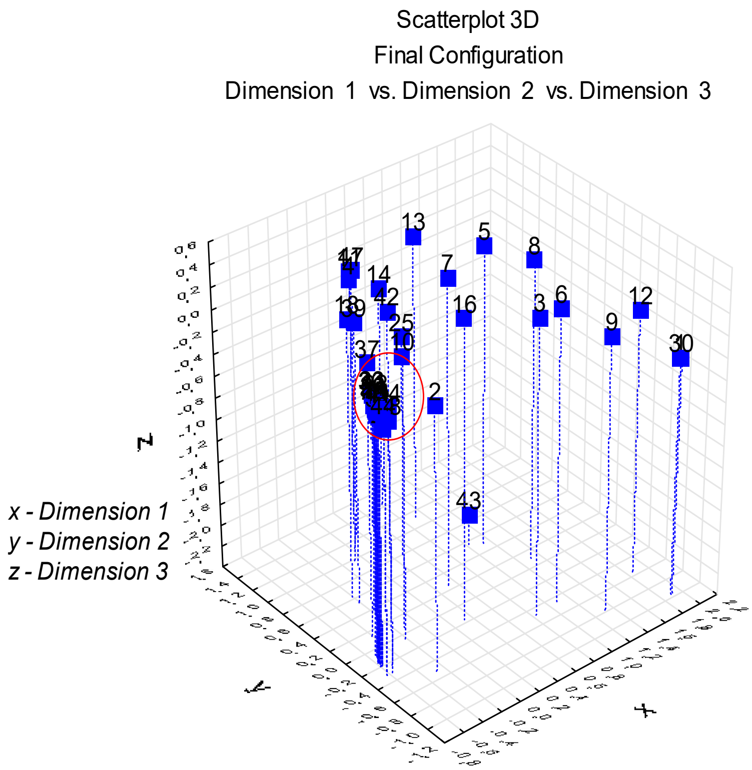

Figure 2. MDS map.

Depending on the tendency of the indicator (increasing or decreasing), we applied the BVM, which represents the final stage of benchmarking. We first found local benchmarks (LB 1–9) for each criterion and then the global benchmark (GB), which is DMU1. DMU1 is also a local benchmark, as it reaches the best values in ROA (4) and interest coverage (8). Overall, DMU2 finished in second place, and is a local benchmark in profitability indicators ROE (5) and ROS (6). DMU44 achieved the best values in terms of current liquidity (1) and the creditors payment period (3), and ended up in fourth place overall. The score (B) of all 48 companies is shown in Table 2.

Table 2. Score and ranking of DMUs in the research sample, according to the BVM.

DMU	Score (B)	Ranking	DMU	Score (B)	Ranking	DMU	Score (B)	Ranking
DMU1	42.27	1	DMU17	7.56	23	DMU33	2.95	39
DMU2	36.12	2	DMU18	3.07	36	DMU34	4.04	30
DMU3	15.20	5	DMU19	4.72	29	DMU35	9.89	16
DMU4	−45.14	48	DMU20	9.07	18	DMU36	2.92	41
DMU5	27.30	3	DMU21	2.96	38	DMU37	2.65	45
DMU6	13.62	7	DMU22	3.37	33	DMU38	8.12	21
DMU7	14.28	6	DMU23	2.80	42	DMU39	2.33	47
DMU8	11.45	11	DMU24	7.56	22	DMU40	5.34	28
DMU9	11.00	14	DMU25	3.14	35	DMU41	2.66	44
DMU10	9.78	17	DMU26	3.95	31	DMU42	5.37	27
DMU11	5.93	26	DMU27	3.06	37	DMU43	10.65	15
DMU12	11.57	10	DMU28	8.60	20	DMU44	19.99	4
DMU13	11.19	13	DMU29	3.34	34	DMU45	6.36	25
DMU14	12.67	8	DMU30	3.78	32	DMU46	2.53	46
DMU15	6.43	24	DMU31	11.39	12	DMU47	2.69	43
DMU16	8.75	19	DMU32	2.95	40	DMU48	12.60	9

LB4 = DMU1, LB5 = DMU2, LB6 = DMU2, LB7 = DMU35, LB9 = DMU6, LB1 = DMU44, LB2 = DMU5, LB3 = DMU44, LB8 = DMU1, GB = DMU1.

The results of input-oriented DEA (RQ2) shows that 12 companies achieved an efficiency score of "1" (DMU1, DMU2, DMU3, DMU6, DMU13, DMU19, DMU27, DMU30, DMU34, DMU43, DMU44 and DMU47). We can say that these companies use inputs efficiently, since they achieve zero slacks. The least efficient business is DMU36, which achieved a score of "0.23648". This company achieves very low liquidity, at the level of 0.07, a high creditors payment period of 2941 days, an equity ratio of 12% and is highly undercapitalized. The overall score and ranking of the companies' performances are shown in Table 3. The DEA model was processed in DEAFrontier (Zhu 2019).

Table 3. Score and ranking of DMUs in the research sample, according to the DEA.

DMU	Score (B)	Ranking	DMU	Score (B)	Ranking	DMU	Score (B)	Ranking
DMU1	1.00000	1	DMU17	0.27254	47	DMU33	0.62739	23
DMU2	1.00000	1	DMU18	0.32642	44	DMU34	1.00000	1
DMU3	1.00000	1	DMU19	1.00000	1	DMU35	0.36533	43
DMU4	0.29331	46	DMU20	0.39885	38	DMU36	0.23648	48
DMU5	0.71299	21	DMU21	0.42563	36	DMU37	0.62626	24
DMU6	1.00000	1	DMU22	0.56887	26	DMU38	0.39143	39
DMU7	0.69771	22	DMU23	0.79442	20	DMU39	0.56164	27
DMU8	0.79822	19	DMU24	0.45843	32	DMU40	0.43853	33
DMU9	0.88252	15	DMU25	0.31385	45	DMU41	0.81895	18
DMU10	0.50705	28	DMU26	0.39032	40	DMU42	0.91712	11
DMU11	0.84913	16	DMU27	1.00000	1	DMU43	1.00000	1
DMU12	0.90023	14	DMU28	0.41295	37	DMU44	1.00000	1
DMU13	1.00000	19	DMU29	0.45948	31	DMU45	0.43431	35
DMU14	0.83223	17	DMU30	1.00000	1	DMU46	0.48972	29
DMU15	0.47912	30	DMU31	0.36818	42	DMU47	1.00000	1
DMU16	0.61270	25	DMU32	0.37122	41	DMU48	0.43446	34

The DEA method allowed us to calculate target values-benchmarks for analyzed businesses, which were not efficient according to the DEA model. Since we used an input-oriented DEA model, we were able to calculate target values for inputs. Figure 3 shows current and target values of indicators ACP and CPP for inefficient businesses. The red line in the figure represents 90 days. Values of ACP and CPP above this line can be evaluated negatively. A majority of the businesses achieved current values of CPP above 90 days, and current values of ACP below 90 days. When calculating goal values, we can see a significant reduction in ACP and CPP. A majority of target values of these indicators are below 90 days.

We also calculated the target values of indicator CR for inefficient businesses with the use of the DEA. Figure 4 shows the comparison of current and target values of this indicator. The red line represents the value above which this indicator can be evaluated negatively. Despite the fact that all current values of CR are below the red line, businesses need to reduce them to target values in order to be efficient.

The third task of our research was to determine the strength and association between the abovementioned rankings (RQ3), where the first variable was the order of individual enterprises determined by the BVM and the second variable was the order of companies determined by the DEA.

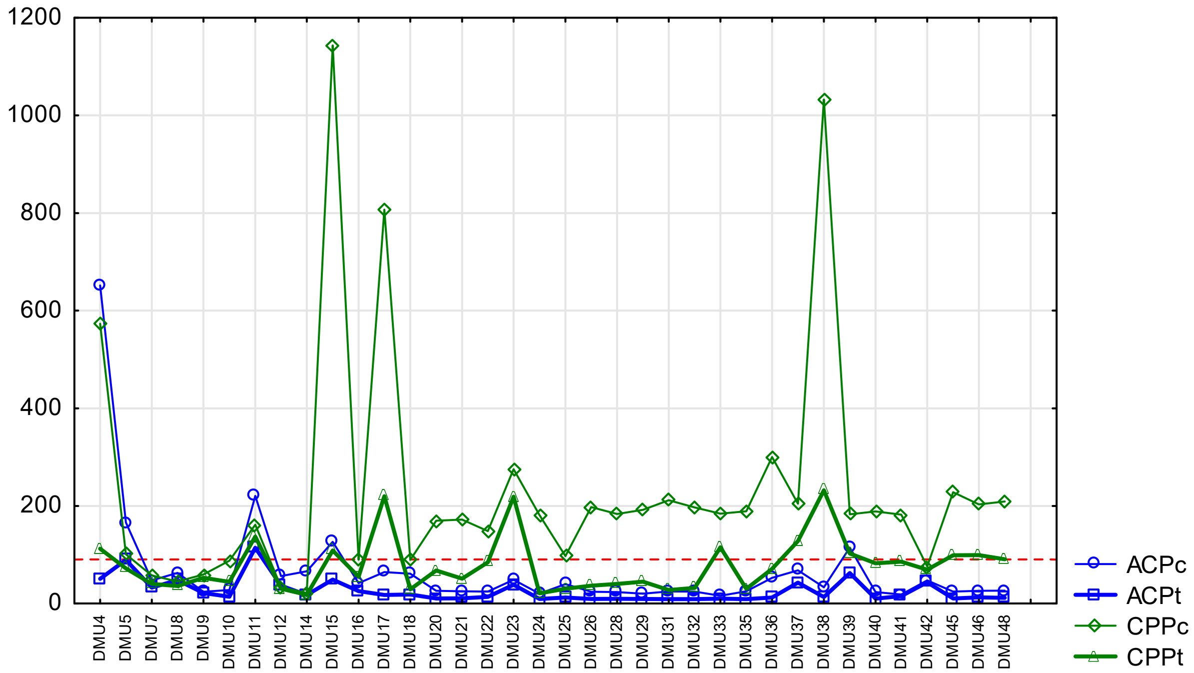

Figure 3. Comparison of current and target values of ACP and CPP (days). Legend: ACP_c—current Average collection period, ACP_t—target Average collection period, CPP_c—current Creditors payment period, CPP_t—target Creditors payment period.

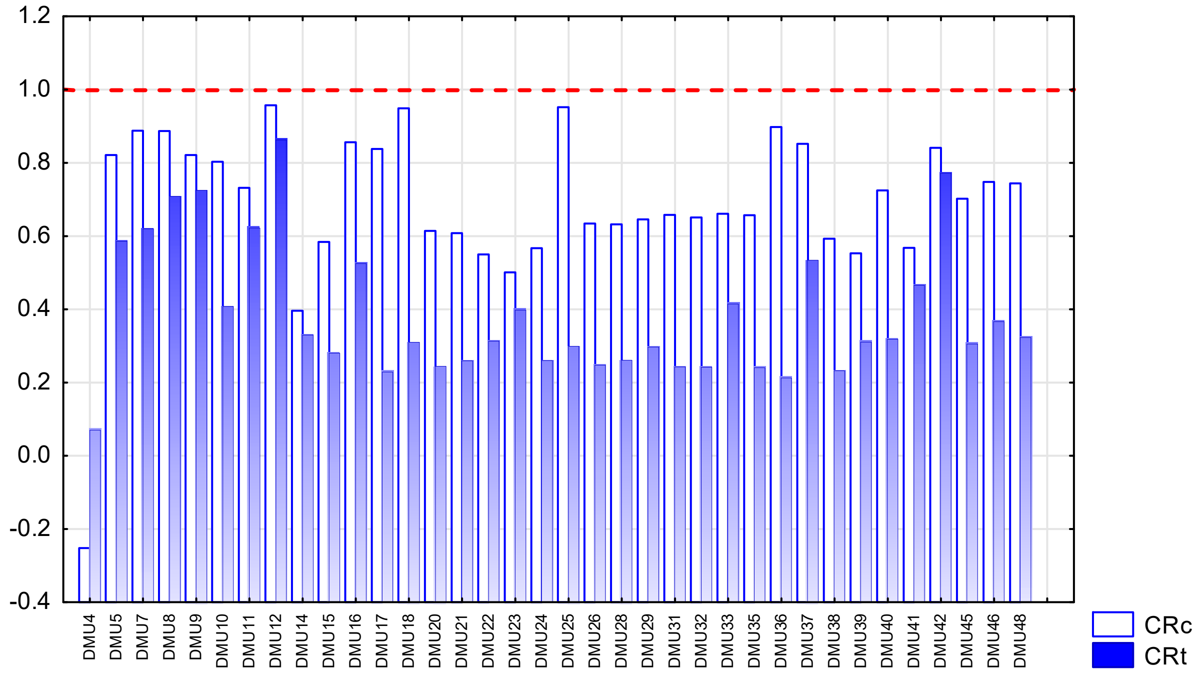

Figure 4. Comparison of current and target values of CR. Legend: CR_c—current Cost ratio, CR_t—target Cost ratio.

The Spearman's coefficient is 0.314965, i.e., 31.50%, which is a medium positive dependence. Table 4 shows the value of test statistic t ($n - 2$). The quantile of Student's distribution found in the statistical tables for reliability of 1-α and degrees of freedom ($n - 2$) is $t_{0.95}$ (45) = 1.671 (statistical tables). After determining the right-hand critical domain W $\leq$ 1.671, ∞), we found out that the test variable is located in the critical domain; therefore, we reject the null hypothesis and accept the alternative hypothesis of H_1. We conclude that there is statistically significant relationship between rankings achieved by the BVM and the DEA.

Table 4. Spearman's Rank Order Correlation.

Pair of Variables	Valid N	Spearman R	t ($n-2$)	p-Value
BVM ranking and DEA ranking	48	0.314965	2.250750	0.029224

Spearman's rank order correlations; marked correlations are significant at $p < 0.05000$.

The financial ratios used in this paper have an impact on the overall performance of the company. However, when applying benchmarking based on the BVM, weights are determined subjectively, according to a financial managers' preferences (pairwise comparison). With DEA, the measurement is more objective and accurate; however, it does not have to take into account a managers' preferences when making financial decisions. In order to determine the performance of a company in business environment, it is appropriate to combine these forms effectively.

5. Conclusions

In order to remain in a stable financial situation, a company must not only monitor the development of key financial indicators over time or in the future, but also analyze the status of the indicators in the industry with regard to its direct competition, and to be inspired by competition when solving financial problems (look for "best practices").

This research focused on measuring the financial performance of 48 Slovak companies in the field of heat supply. We calculated nine key financial indicators of analyzed companies and identified three research questions: determining the financial performance of the company through BVM, determining the financial performance of the company through DEA and analyzing the strength and direction of the association between the results achieved.

Benchmarking based on the BVM is one of the more subjective methods of measuring performance, as it uses a paired comparison method to determine the weights of indicators. This has to be carried out through a questionnaire survey. The advantage of using benchmarking is the motivation of financial managers to prioritize financial decision making. Financial managers evaluated the indicators as expected. The most important indicators are profitability indicators ROA, ROE and ROS, which were confirmed by several other authors (Wood and McConney 2018; Bărbută-Misu et al. 2019; Bogetoft 2012). These are important financial indicators which determine internal risk factors, such as business risk. The least preferred indicator is interest coverage. DMU1 became the benchmark, DMU2 came second, DMU5 was third, DMU44 was fourth and DMU3 was fifth. Compared to the BVM, the DEA is a benchmarking tool that offers more objective results, while inputs to the DEA model can be indicators expressing the preferences of managers. In our case, the input-oriented DEA CCR model was applied. Within the sample, there were 12 businesses that used their inputs efficiently (including DMU1, DMU2, DMU3 and DMU44).

Based on the Spearman's rank correlation coefficient, there is a 31.50% dependence among the companies' rankings. It is a positive dependence, and it is at a given level of significance. The value of the correlation coefficient may be lower due to the different nature of the methods and the fact that the BVM is a more subjective method than the DEA.

The originality of the paper is in its the use of a combination of DEA and BVM methods to improve performance. Both these methods are multidimensional ones. Both are also benchmarking methods, while each comes from a different set of benchmarking techniques which are used to improve performance. The contribution to the literature is that DEA can be considered a benchmarking tool and can be mentioned in the literature as a benchmarking technique for increasing business performance.

Some limitations of the research may be the smaller sample of companies or the subjective and benevolent attitude to managers when completing questionnaires. In our future research, we will improve these shortcomings.

For business practice, we recommend combining these methods, depending on whether the goal is to clarify priorities in terms of preference for financial ratios or to accurately determine financial performance. At the same time, DEA can be an important learning tool for managers to understand the importance of their decisions and their impact on business performance. It can motivate and stimulate them to focus on those indicators that are significant in terms of the financial situation of an enterprise. It can also be a tool to implement the need to identify key business performance indicators and performance risk factors.

Based on the obtained results, we can also generalize some recommendations for comparison, which could be useful for any company:

- To make a comparison with competitors as a multi-criteria comparison and not only on the basis of one criterion (for each indicator, the benchmark was also achieved by another company);
- To convert values of indicators into common unit;
- To involve managers in the selection of appropriate indicators and take into account their view on the significance of the applied indicators;
- To apply at least two evaluation methods when evaluating enterprises and compare their results;
- To monitor and optimize the profitability of the company, which has been confirmed as an important indicator of business performance.

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