“Data envelopment analysis for measuring performance in a competitive market”

AUTHORS	Veronika Fenyves https://orcid.org/0000-0002-8737-0666 Tibor Tarnóczi https://orcid.org/0000-0002-5655-6871

ARTICLE INFO	Veronika Fenyves and Tibor Tarnóczi (2020). Data envelopment analysis for measuring performance in a competitive market. *Problems and Perspectives in Management*, *18*(1), 315-325. doi:10.21511/ppm.18(1).2020.27
DOI	http://dx.doi.org/10.21511/ppm.18(1).2020.27
RELEASED ON	Tuesday, 31 March 2020
RECEIVED ON	Sunday, 22 September 2019
ACCEPTED ON	Monday, 02 March 2020
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
35	2	6

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Veronika Fenyves (Hungary), **Tibor Tarnóczi** (Hungary)

DATA ENVELOPMENT ANALYSIS FOR MEASURING PERFORMANCE IN A COMPETITIVE MARKET

Abstract

In today's increasingly competitive markets, it is essential to be able to determine the position of a company as opposed to its competitors. Today the traditional financial ratios are most widely used to measure corporate performance, but more and more authors begin to criticize their use. It is difficult to use financial ratios as a complex measurement tool. It is crucial to use an appropriate method or tool to measure corporate performance, which can measure the company's performance in a complex way represented by one indicator. In this study, the Data Envelopment Analysis (DEA) method is used, which is one of the potential tools available. Several researchers have used the DEA method to measure corporate performance. Many authors consider DEA as a useful tool for measuring corporate performance, while others criticize it. The authors analyze the performance of retail food companies in Hungary's Northern Great Plain region. The companies analyzed were chosen from the region investigated, and they have "food retail grocery store" as their main activity, and they had six cleared annual reports in the period 2012–2017. There was a total of 887 companies in the region examined, and 563 (63.5%) met the conditions. The analysis was made using the time-series data of companies for 2012–2017 based on their financial reports, and the authors dealt with various possibilities for extending DEA, which can support its more accurate use. Based on evaluating the retail food companies' performance in the Northern Great Plain region, one can state that the efficiency of companies shows a very mixed picture over the years examined. The study suggests solutions to the indicated problem. The findings indicate that the application of extended DEA methods gives better results; that is, one can get better estimates of the efficiency of companies.

Received on: 22nd of September, 2019
Accepted on: 2nd of March, 2020
Published on: 31st of March, 2020

Veronika Fenyves, Ph.D., Associate Professor, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary. (Corresponding author)

Tibor Tarnóczi, Ph.D., Associate Professor, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary.

Keywords food retail, performance measurement, corporate efficiency, benchmarking, Data Envelopment Analysis (DEA)

JEL Classification C44, M20

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

In a globalized world in which companies have to compete with all operators in the market, both internal and external, comparison of the company's performance, i.e., benchmarking, is becoming more and more critical. Over recent decades, benchmarking has undergone a significant development due to advances in both methodology and information technology. For example, the Balanced Scorecard system (BSC) (Kaplan & Norton, 2004), Economic Value Added (EVA) (Ehrbar, 2000) or the Performance Prism (Neely, Adams, & Kennerley, 2004) have appeared as new frameworks and methods of performance measurement, which show an innovative approach and have provided an appropriate framework for measurement. Since more and more researchers dealt with corporate performance measurement in the middle of the 1990s, it has started to become a discipline within the new approach to management (Neely et al., 2004). The methods cited above have attempted to improve the performance measurement procedures, which dominated in previous years and were exclusively based on financial ratios. Many scholars have already offered descriptions of benchmarking, and, as a result, one can find a wide variety of definitions in the literature (Tehrani, Mehragan, & Golkani, 2012). Staplehurst (2009, pp. 3-6) presented various definitions of benchmarking in his book and gives the following definition as a conclusion, drawn from the definitions presented: “Benchmarking is a method of measuring and improving our organization using which we compare ourselves with the best” (Stapenhurst, 2009, p. 6). This definition is very brief, but it correctly represents the essence of benchmarking as the measurement of relative performance.

This study deals with the performance measurement of the companies chosen. The Data Envelopment Analysis (DEA) method, which has been chosen for measurement, has undergone significant development in the last 40 years. Many people have used this method in different areas of economy and society, and many criticisms have also been expressed regarding its applicability. These criticisms have assisted in the further development of the method.

One of the subjects of this study is to show how DEA can be utilized in measuring and comparing the performance of companies through the example of retail food companies in Hungary’s Northern Great Plain region. The article differs from what was described in the previous benchmarking definitions in that it examines not a chosen company, but compares companies in the region with each other and focuses to a significant extent on the method used and its application. One of the questions which one attempted to answer is whether the extension of the base method used in DEA can improve the possibility of using it and the results. One cannot present every extension within the framework of this study; a few of those were highlighted and considered as most important.

1. LITERATURE REVIEW

The corporate performance measurement means a necessary action for company survival in a contemporary changeable economic environment. Effectiveness and efficiency are the conceptions used in the framework of performance measurement (Farantos, 2015). There are different methods (Analytic Hierarchical Process, DEA, Fuzzy Logic, Financial Ratios, Mathematical Programming, and Hybrid Methods) to measure corporate performance, the efficiency of decision-making units (DMUs), which can be utilized in multi-attribute decision-making. Data Envelopment Analysis (DEA) focuses on measuring the efficiency of DMUs when there are multiple inputs and outputs. It measures the relative efficiency of similar units. The efficiency is defined as a ratio of the weighted sum of outputs to the weighted sum of inputs (Hamzeh & Xu, 2019). The study does not deal with the basis of the DEA method because it can be found in different books and articles (Charnes, Cooper, Lewin, & Seiford, 1994; Ramanathan, 2003; Ray, 2004; Cooper, Seiford, & Tone, 2007; Daraio & Simar, 2007). DEA was initially being developed to analyze the essential economic quantitative characteristics, such as capital, labour, etc.

This study uses several items of the financial statements of companies that are in a relationship with income generation. Some articles deal with the use of these accounting items in performance measurement (Thomas, Barr, William, Cron, & Slocum, 1998; Feroz, Kim, & Raab, 2003; Ablanedo-Rosas, Gao, Zheng, Alidaee, & Wang, 2010; Ko, Chang, Bae, & Kim, 2017; Stavárek & Řepková, 2012).

Combining financial ratios in DEA models, can cause biased results and lead to overestimated/underestimated efficiency scores, according to Halkosand Tzeremes (2012). Their study proves that traditional biases can be avoided with the application of bootstrap techniques in the case of related problems. Their research results showed that the efficiency values obtained applying the bootstrap techniques have been significantly improved.

There has been an ’exponential’ growth in the number of journal articles in recent four decades (1978–2016). Until the end of 2016, the total number of journal articles reaches 10,300, and the distinct authors reach 11,975 in total” (Emrouznejad & Yang, 2018, p. 7). The DEA method is very widely used; for example, Huang (2019) examined the Chinese mutual fund market using this method.

http://dx.doi.org/10.21511/ppm.18(1).2020.27

His results show that even so the development of the fund industry, only a small proportion of funds are entirely efficient. Figurek, Goncharuk, Shynkarenko, and Kovalenko (2019) applied DEA in higher education to measure its efficiency in Bosnia and Herzegovina. They found that the efficiency in higher education should take into consideration all the scientific fields and should take in academic and professional work and the quality of teaching and research.

Jordá, Cascajo, and Monzón (2012) worded the following advantages and disadvantages of DEA method:

- advantages: simultaneous analysis of outputs and inputs; not necessary to define the frontier form a priori; relative efficiency and compare to the best values;
- disadvantages: ignores the effect of exogenous variables on the operations; ignores statistical errors; does not say how to improve efficiency; difficult to perform statistical tests with the results.

There are two types of orientation using the DEA method, input, and output orientation, as well as one, can use the DEA method without orientation (input-output orientation). At input orientation, the basic DEA model assigns a value between 0 and 1, including the values 0 and 1, to every company, while a value of 1 or higher is assigned in the case of output orientation. The closer the value obtained from the DEA model is to 1, the more efficient a particular company is, and the better it utilizes its resources (Khezrimotlagh, Salleh, & Mohsenpour, 2014). It is essential to emphasize that the values calculated by DEA are valid only in the scope in which one used them, i.e., only for those companies which were involved in the examination. General inferences can be drawn from the results only to the extent to which the individuals examined cover the given area. There are limitations to using DEA. Shewell and Migiro (2016) wrote that the number of input and output variables related to the size of the population analyzed (number of DMUs) can limit the effectiveness of analysis. A further possible restriction of the DEA application is that there may be other performance indicators that can impact the performance of DMUs that are not included in the examination. This means that the results must be evaluated with due care. Nguyen, Vu, and Dinh (2019) remarked that the selection of input and output variables and the sampling method might restrict the significance of the results and the propositions of the research.

2. DATA AND METHODOLOGY

2.1. Examined population

The companies situated in the Northern Great Plain region were included in the database investigated, which indicated "food retail grocery store" as their main activity and were already existed in 2012 and had annual reports for six financial years (2012–2017). The enterprises have been selected from the OPTEN company database; the companies' annual reports have been downloaded from the Electronic Reporting Portal. Based on the conditions determined above, there were 887 enterprises in total in the examined region, 563 of which are part of the database under analysis. During the period examined, 96 of 887 enterprises went into liquidation or were wound up, another 238 enterprises produced no annual reports for several years during the period examined, or the rows of the annual report, which were important for the analysis, contained zero values. The number of enterprises involved in the analysis in the region, were, by county:

- Szabolcs-Szatmár-Bereg County – 131;
- Hajdú-Bihar County – 250;
- Jász-Nagykun-Szolnok County – 182;
- Northern Great Plain Region – 563.

The great majority of enterprises in the database prepared a simplified annual report, and so the analysis was built upon the data found in the simplified annual report.

2.2. The method used for analysis

DEA is essentially an optimization model for a frontier estimation that allows ranking the decision-making units (DMUs) involved in the examination by using different input and output characteristics. DEA models are nonparametric deterministic models, where the 'deterministic' expression can be applied only to the basic model and their extensions because it is also possible to create a stochastic DEA model (Huang & Li, 2011).

There was used the benchmarking package of the R statistical system (Bogetoft & Otto, 2015), which allows applying different return to scale (RTS) calculations. The RTSsof the benchmarking module differ both in their efficiency and the algorithm applied (Zhu, 2009). Working with RStudio or the Excel spreadsheet program eases the use of the system (Heiberger & Neuwirth, 2009). The RTSs can be defined in several ways, such as CRS (constant RTS), DRS (decreasing RTS), IRS(increasing RTS), VRS (variable RTS). Choosing between DRS and the IRS depends on the firms' production orientation. CRS can be a wrong method for most companies; nevertheless, in many cases, it shows efficiency in the best way, and it can also be needed for determination of the size efficiency. A detailed description of the methods can be found in the book by Bogetoft and Otto (2011) (Chapter 4). The R2WinBUGS module of the R system is also used. WinBugs (Bayesian Inference Using Gibbs Sampling) is a modelling system based on the Bayes statistics, using the Monte Carlo Markov chain simulation (Sturtz, Ligges, & Gelman, 2005).

After selecting the input- and output variables, one should decide about the orientation of the model: input or output efficiency (Farrell's efficiency). Farrell's efficiency shows how one can proportionately decrease the inputs to produce the same outputs by input orientation and to produce the maximum outputs with the given inputs by output orientation. Forsund and Hjalmarsson (2004) proposed that it would be expedient to combine the input and output orientations in some way to determine the optimum DEA values.

Considering the above, the calculation with a third solution was also performed, which is discussed in Bogetoft and Otto's book, chapter 2.5 (2011). The essence of this method is that it is combined with Farrell's input and output efficiency, which means that the inputs are decreased, and the outputs are increased simultaneously. The performance indicators of this method can take values between 0 and 1, including the values 0 and 1. The basic characteristics of the efficiency orientations can be presented using the formulae (1)-(3) (Bogetoft & Otto, 2011):

Input efficiency:

$$I = \min\left\{ I > 0 \,\middle|\, (Ix, y) \in T \right\}. \tag{1}$$

Output efficiency:

$$O = \max\left\{ O > 0 \,\middle|\, (x, Oy) \in T \right\}. \tag{2}$$

Input-output efficiency:

$$IO = \min\left\{ IO > 0 \,\middle|\, \left(IOx, \frac{1}{IO} y \right) \in T \right\}, \tag{3}$$

where x – input variables, y – output variables, T – input and output combinations, I, O, IO – orientations of efficiency calculations (input, output, and input-output).

The calculations by averages of the original values were performed as well. The means of years may cause a significant equalization, equalizing the environmental effects occurring each year, to a certain extent.

Before the calculations, it was tested whether it is better to use a CRS or VRS method. The "bootstrap" method and simulation were utilized to select between the two methods. A run of 500 was chosen in order that the running time of the procedure should not be too long. There can be raised a question of whether the "bootstrap" method can be used for testing the DEA efficiency values. Ferrier and Hirschberg (1999) point out that it is advisable to use the "bootstrap" method for this type of test. The DEA boot procedure of the benchmarking package is suitable for substantiating the decision between the two methods. For the decision, the following hypotheses were set up:

H0: The method to be used is CRS.

H1: The method to be used is VRS.

The efficiency calculation was performed with input- and input-output orientation by using the CRS and VRS methods as well, and then the efficiency values obtained by each other were divided:

$$EC = \frac{\sum_{k=1}^{n} E_k^{crs}}{\sum_{k=1}^{n} E_k^{vrs}}, \tag{4}$$

http://dx.doi.org/10.21511/ppm.18(1).2020.27

where E_k^{crs} – the efficiency of the k-th company according to CRS, E_k^{vrs} – the efficiency of the k-th company according to VRS, k – number of enterprises involved in the examination.

If the value of EC is greater than 1, it means to apply the VRS method is better than the CRS method; at the same time, this is not an exact statistical method. Therefore, the bootstrapping method is used.

The classic DEA has disregarded the occurrence of variables that can have both negative and positive values. However, the efficiency analysis and estimating the return to scale are the essential management activities for the performance evaluation. So, Allahyar and Rostamy-Malkhandalifeh (2015) introduced a non-oriented (input-output) model that tolerates that the inputs and outputs have both positive, negative, and zero values.

3. RESULTS

From the available data, the following were chosen for the performance evaluation:

- input variables;
- tangible assets, current assets, non-current liabilities, current liabilities, material expenses, personnel expenses, depreciation;
- output variables;
- net sales revenues, operating profit or loss, earnings after taxes.

In the selection of input variables, it was essential to have variables related to capital and labour, as well as the production. Presumably, these are the variables that most affect the development of corporate revenue.

First, a "normal" analysis was performed by the DEA model using the VRSmethod. The evaluations were realized for all six years and the average of years. The program could not determine the output efficiency in some cases (122 cases during the six years and 107 cases (19%) in the case of the average of years. This means that 107 companies were left out from the analysis of average of years.), which makes the use of output efficiency more dif-

Table 1. Main statistical characteristics of the efficiency analysis of the Northern Great Plain region's food trading companies

Source: Authors.

Years	Description of method	Minimum	1st quartile	Mean	Median	3rd quartile	Maximum	Standard deviation	Relative standard deviation
2009	Input efficiency	0.0004	0.2390	0.5214	0.4743	0.8181	1.0000	0.3169	61%
	Output efficiency	1.0000	1.2364	25.2713	1.8718	3.5529	5609.4669	281.8469	1115%
	Input-output efficiency	0.0086	0.4950	0.6780	0.6955	0.9050	1.0000	0.2555	38%
2010	Input efficiency	0.0006	0.0657	0.2919	0.1422	0.4045	1.0000	0.3180	109%
	Output efficiency	1.0000	2.2359	63.5136	6.1399	14.3244	8800.9875	547.0810	861%
	Input-output efficiency	0.0087	0.2339	0.4494	0.3631	0.6393	1.0000	0.2959	66%
2011	Input efficiency	0.0000	0.0068	0.0835	0.0151	0.0379	1.0000	0.2097	251%
	Output efficiency	1.0000	7.7375	120.7313	27.4015	66.9020	12491.2697	711.7104	589%
	Input-output efficiency	0.0004	0.0637	0.1899	0.1000	0.2204	1.0000	0.2384	126%
2012	Input efficiency	0.0003	0.0539	0.4011	0.2986	0.7227	1.0000	0.3600	90%
	Output efficiency	1.0000	1.2957	86.9510	2.6201	13.2506	12348.0000	815.4722	938%
	Input-output efficiency	0.0057	0.1000	0.5328	0.5575	0.8610	1.0000	0.3466	65%
2013	Input efficiency	0.0002	0.0272	0.2063	0.0634	0.1804	1.0000	0.3065	149%
	Output efficiency	1.0000	6.2961	313.9494	24.7787	78.8827	107392.0000	4632.7699	1476%
	Input-output efficiency	0.0113	0.0841	0.2764	0.1000	0.3894	1.0000	0.3057	111%
2014	Input efficiency	0.0001	0.0418	0.3161	0.1731	0.5080	1.0000	0.3409	108%
	Output efficiency	1.0000	1.5133	27.1091	2.7177	12.1855	4065.6618	204.8704	756%
	Input-output efficiency	0.0052	0.2051	0.5011	0.4943	0.7664	1.0000	0.3248	65%
Mean	Input efficiency	0.0468	0.2117	0.3034	0.2878	0.3833	0.7507	0.1286	42%
	Output efficiency	2.1109	11.9227	117.0460	22.3428	48.4507	17905.0636	870.6530	744%
	Input-output efficiency	0.1120	0.3556	0.4379	0.4321	0.5173	0.8320	0.1223	28%

Source: Authors.

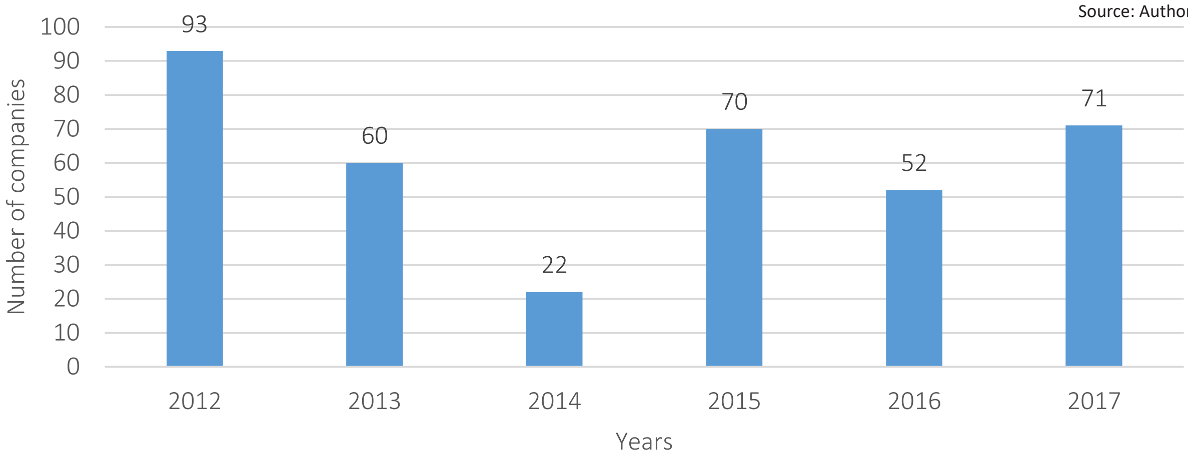

Figure 1. Number of companies with the input efficiency value of 1

ficult. Table 1 presents the statistical characteristics of the results of each year and the average efficiency values too.

Table 1 shows that the efficiencies of enterprises are very variable, which is also supported by the high relative standard deviation values of the years. Table 1 indicates that the input efficiency of the enterprises examined is quite low; that is, the companies should produce a much larger output using the given input. These values show that the companies performed their activities with bad output efficiency in the period examined.

The relative standard deviation of the input efficiency values was between 61% and 251% in the investigated period, and the means varied between 0.0835 and 0.6780. Considering the input efficiency, the number of enterprises reached a value of 1 in the different years can be seen in Figure 1. One can also see that these values change significantly; while around 17% of the enterprises had a good performance in the best year (2012), only about 4% of the businesses had the same values in the worst year. At the output-oriented examination, the situation is worse; the values of the relative standard deviation were between 589% and 1476%, which far exceed the input efficiency values.

The mean values were between 25.27 and 313.98exceed far from the input efficiency values. The number of enterprises that reached in the different years'value of 1 of output efficiency can be seen in Figure 2.

Table 1 also shows that the input-output efficiency values are higher on average than at input efficiency, and the relative standard deviation values are much smaller. By examining the efficiency values, one can observe that the value of input-out-

Source: Authors.

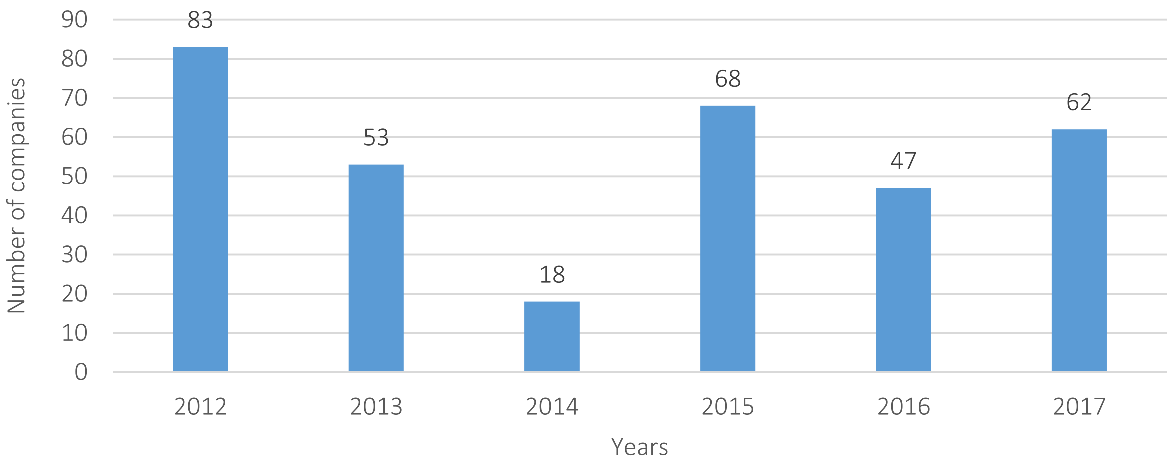

Figure 2. Number of companies with an output efficiency value of 1

http://dx.doi.org/10.21511/ppm.18(1).2020.27

Table 2. Main statistical characteristics of efficiency values based on the average of the years

Source: Authors.

Statistical characteristics	Input efficiency	Output efficiency	Input-output efficiency
Minimum	0.311	1.000	0.555
1st quartile	0.704	1.025	0.837
Mean	0.824	1.288	0.900
Median	0.850	1.187	0.920
3rd quartile	0.979	1.428	0.988
Maximum	1.000	3.092	1.000
Standard deviation	0.159	0.343	0.095
Relative standard deviation	19%	27%	11%

put efficiency was also 1 in all cases in which the input efficiency reached a value of 1. The number of times the value one was reached was the same as the number of 1 value for input efficiency each year; 2011 was the only exception when it was two more than this.

The calculations were performed by averages of the original values as well. The following result was obtained using formula (4):

- input efficiency EC = 0.9494;
- input-output efficiency EC = 0.9758.

Since the EC values are less than 1, the VRS method is better than the CRS method. Henceforth, the bootstrapping method is used. One can also see that the difference between the two methods is smaller using the input-output orientation.

The critical value was determined by the bootstrap method, which is 0.9849. Since the critical value is higher than the EC value, the null hypothesis is rejected; that is, the VRS method is better. This result applies to the average of years only. The presentation of these calculations is believed to be important because deciding which methods should be used from among the ones available generally represents a problem.

Table 2 contains the main statistical characteristics of the efficiency values based on calculations by the average of years. Table 2 shows that the 6-year average performance of companies was equalized on a significant level. The relative standard deviation has decreased at all three orientations; it is 27% for the output efficiency, and 11% for the input-output efficiency.

One can see in Table 3 that 21% of the companies reached an efficiency value of 1 by the input-output efficiency analysis. Almost 85% of the companies had an efficiency value of at least 0.8 by the input-output-oriented measurement. One can state that the performance of companies varies each year significantly, and very few enterprises can achieve consistent performance in the whole period.

Using the input-output orientation, the interval values of efficiency were calculated for the average of years using the R2WinBUGS module. For the calculation, there was utilized Pendharkar's

Table 3. Empirical distribution of input and input-output efficiency values based on the average of the years

Source: Authors.

Values		Input efficiency		Input-output efficiency	
		Number of companies	Distribution of companies	Number of companies	Distribution of companies
≥ 0.3	< 0.4	6	1.1%	–	–
≥ 0.4	< 0.5	15	2.7%	–	–
≥ 0.5	< 0.6	33	5.9%	5	0.9%
≥ 0.6	< 0.7	83	14.7%	15	2.7%
≥ 0.7	< 0.8	101	17.9%	68	12.1%
≥ 0.8	< 0.9	84	14.9%	171	30.4%
≥ 0.9	< 1.0	122	21.7%	186	33.0%
	= 1.0	119	21.1%	118	21.0%
Total element number		563	100.0%	563	100.0%

and Pai's (2013) article, in which they describe the procedure for this calculation. The 95 per cent confidence interval was 0.1602, which cannot be considered too wide. In the literature, one can find confidence intervals where the lower limit is negative. Probably if one had calculated the confidence intervals for the annual input- or output-oriented efficiency indicators, the lower limit of the intervals would have been negative in several cases as well. The upper values of the confidence intervals exceed 1 in only 8 cases (Table 6). Table 5 shows the statistical characteristics of the confidence intervals.

Table 4. Empirical distribution of output efficiency values based on the average of the years

Source: Authors.

Values		Output efficiency	
		Number of companies	Distribution of companies
	= 1.0	117	20.8%
> 1.0	< 1.1	105	18.7%
≥ 1.1	< 1.2	67	11.9%
≥ 1.2	< 1.3	62	11.0%
≥ 1.3	< 1.5	99	17.6%
≥ 1.5	< 2.0	90	16.0%
≥ 0.9		23	4.1%
Total element number		563	100.0%

Table 5 shows that the relative standard deviation is low in this case too since the calculation was similarly performed by using the input-output efficiency indicators where the relative standard deviation was also low. Determining the confidence interval allows a more accurate evaluation than if we characterized the efficiency only with a sole value.

Table 5. Main statistical characteristics of the confidence interval of input-output-oriented efficiency values calculated from the average of the years

Source: Authors.

Statistical characteristics	Lower limit (2.5%)	Upper limit (97.5%)
Minimum	0.2778	0.3095
1st quartile	0.6483	0.7282
Mean	0.7104	0.8892
Median	0.7083	0.8425
3rd quartile	0.8028	0.9932
Maximum	0.9507	1.2833
Standard deviation	0.1194	0.1612
Relative standard deviation	17%	18%

4. DISCUSSION

Comparing Figures 1 and 2, one can see that the number of the enterprises, which reached a value of 1, differs only slightly in the case of the input and output efficiency, despite the big differences in standard deviations. Examining the efficiency values, it also turned out that the output efficiency of an enterprise whose input efficiency was one was also 1, while in some cases, the output efficiency could not be determined. Consequently, companies working with the maximum efficiency had a maximum performance in both orientations.

Table 6. Main statistical characteristics of confidence interval values of input-output-oriented efficiency values calculated from the average of the years

Source: Authors.

Results		Input-output efficiency			
		Lower limit		Upper limit	
		Number of companies	Distribution of companies	Number of companies	Distribution of companies
≥ 0.2	< 0.3	1	0.18%		
≥ 0.3	< 0.4	7	1.24%	4	0.71%
≥ 0.4	< 0.5	21	3.73%	12	2.13%
≥ 0.5	< 0.6	65	11.55%	38	6.75%
≥ 0.6	< 0.7	167	29.66%	63	11.19%
≥ 0.7	< 0.8	156	27.71%	95	16.87%
≥ 0.8	< 0.9	137	24.33%	78	13.85%
≥ 0.9	< 1.0	9	1.60%	265	47.07%
≥ 1.0		0	0.00%	8	1.42%
Total element number		563	100.00%	563	100.00%

http://dx.doi.org/10.21511/ppm.18(1).2020.27

During the examination of the average performance, a certain balance can be concurrently observed, which also turned out from Table 1, i.e., there were not enterprises that could reach an average value of 1 over the six years, for input or output efficiency. The maximum value was 0.7507 for input efficiency, and the minimum value was 2.1109 for output efficiency, so both values are far from the optimum value of 1. These values show that better enterprises cannot achieve maximum performance continuously either.

By examining the relative performance indicators, one can see that only one could achieve maximum performance through four consecutive years, while two companies could achieve it over three years. Twenty-three companies could perform their activities with maximum efficiency in two consecutive years. Five companies could reach a value of 1 in two consecutive years and a third year. Four enterprises achieved maximum performance in three different years, and 41 enterprises did so in two different years. The enterprises examined cannot achieve outstanding performance continuously, which may have external and internal causes, as well. Most probably, it is the rapidly changing and unpredictable economic environment, which may also be the cause of inadequate performance.

Based on the results, one can determine that the output-oriented calculation has given quite extreme values, indicating very low output efficiency in many cases. The input efficiency shows much more balanced values, but the relative standard deviation indicators are also quite high, which indicates large differences between the results. The input-output (combined) efficiency has provided the most balanced result, although there are high relative standard deviation values with this indicator as well. Based on the results, one can state that it may be expedient to use this method, but one should never ignore the objective of the analysis.

Considering the data of Tables 1-4, one can state that the performance of companies shows very significant differences in single years, and one can conclude that the performance of most companies is inappropriate.The results of Tables 2-4 prove that the performances achieved no longer show as negatively as appeared in the annual data. The input-output-oriented calculation should be highlighted because more than 95% of the companies reached an efficiency value of at least 0.7, which, although it is 30% less than the optimum value, cannot be considered poor on the whole. Consequently, averaging the values of the years has significantly improved the valuation.

CONCLUSION

Based on evaluating the performance of retail food companies in the Northern Great Plain region, we can state that the efficiency of companies shows a very mixed picture over the years examined. There were also observed the most significant differences that occurred with output efficiency, where huge relative standard deviation values arose, which also raises the issue of accessibility. Based on the analysis, it can be stated that the combined method produced the best results during a simultaneous application of the input and output orientation. The analyses also support the idea that it is advisable to use the input-output efficiency calculation because a much more balanced result can be obtained. When choosing the method to be applied, the bootstrap method can also be used, which can also provide statistical support for the decision. The analysis is complemented by the calculation of the confidence interval, which assists in determining interval conjunction with a particular probability that characterizes the given enterprise. Based on the analysis, one can state that the DEA method can be used for analyzing efficiency, and the additions shown can make the evaluation much more accurate. It should also be noted that the analysis needs to be refined further and to be made much more effective by further research.

Two issues may be raised based on the results presented earlier. On the one hand, should the outlier values not be filtered out? There are various opportunities in the R system, but companies have to compete in the existing environment, and this includes every competitor. On the other hand, should the companies not be grouped according to any criterion (criteria), and should the performance not be measured within groups? It would be worth dealing with this latter suggestion, but the breakdown into groups and the evaluation of the groups' performance would go beyond the framework of this study. This could be a valuable perspective to take during future research.

REFERENCES

1. Ablanedo-Rosas, J. H., Gao, H., Zheng, X., Alidaee, B., & Wang, H. (2010). A study of the relative efficiency of Chinese ports: a financial ratio-based data envelopment analysis approach. *Expert Systems, 27*(5). https://doi.org/10.1111/j.1468-0394.2010.00552.x
2. Allahyar, M., & Rostamy-Malkhalifeh, M. (2015). Negative data in data envelopment analysis: Efficiency analysis and estimating returns to scale. *Computers & Industrial Engineering, 82,* 78-81. https://doi.org/10.1016/j.cie.2015.01.022
3. Bogetoft, P., & Otto, L. (2011). *Benchmarking with DEA, SFA, and R*. Springer Science + Business Media, LLC. https://doi.org/10.1007/978-1-4419-7961-2
4. Bogetoft, P., & Otto, L. (2015). *Package 'Benchmarking', Benchmark and frontier analysis using DEA and SFA. Version: 0.27.* Retrieved from https://cran.r-project.org/web/packages/Benchmarking/Benchmarking.pdf (accessed on June 13, 2019).
5. Charnes, A., Cooper, W. W., Lewin, A. Y., & Seiford, L. M. (1994). *Data Envelopment Analysis: Theory, Methodology, and Application*. Springer Science + Business Media, LLC. https://doi.org/10.1007/978-94-011-0637-5
6. Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis. A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Springer Science + Business Media, LLC. https://doi.org/10.1007/978-0-387-45283-8
7. Daraio, C., & Simar, L. (2011). *Advanced robust and nonparametric methods in efficiency analysis. Methodology and applications.* Springer, New York.
8. Ehrbar, A. (2000). *EVA: Economic Value Added: Gazdasági hozzáadott érték: Kulcs az értékteremtéshez.* Panem-Wiley, Budapest.
9. Emrouznejad, A., & Yang, G-I. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences, 61.* https://doi.org/10.1016/j.seps.2017.01.008
10. Farantos, G. I. (2015). The Data Envelopment Analysis Method and the influence of a phenomenon in organizational Efficiency: A literature review and the Data Envelopment Contrast Analysis new application. *Data Envelopment Analysis and Decision Science, 2,* 101-117. https://doi.org/10.5899/2015/dea-00098
11. Feroz, E. H., Kim, S., & Raab, R. L. (2003). Financial Statement Analysis: A Data Envelopment Analysis Approach. *Journal of the Operational Research Society, 54*(1), 48-58. https://doi.org/10.1057/palgrave.jors.2601475
12. Ferrier, D. G., & Hirschberg, J. G. (1999). Can We Bootstrap DEA Scores? *Journal of Productivity Analysis, 11,* 81-92. https://doi.org/10.1023/A:1007787406099
13. Figurek, A., Goncharuk, A., Shynkarenko, L., & Kovalenko, O. (2019). Measuring the efficiency of higher education: case of Bosnia and Herzegovina. *Problems and Perspectives in Management, 17*(2), 177-192. https://doi.org/10.21511/ppm.17(2).2019.13
14. Forsund, F. R., & Hjalmarsson, L. (2004). Are all Scales Optimal in DEA? Theory and Empirical Evidence. *Journal of Productivity Analysis, 21,* 25-48. https://doi.org/10.1023/B:PROD.0000012451.84910.6e
15. Halkos, G. E., & Tzeremes, N. G (2012). Industry performance evaluation with the use of financial ratios: An application of bootstrapped DEA. *Expert Systems with Applications, 39*(5), 5872-5880. https://doi.org/10.1016/j.eswa.2011.11.080
16. Hamzeh, R., & Xu, X. (2019). Technology selection methods and applications in manufacturing: A review from 1990 to 2017. *Computers and Industrial Engineering, 138,* 1-12. https://doi.org/10.1016/j.cie.2019.106123
17. Heiberger, R. M., & Neuwirth, E. (2009). *R Through Excel. A Spreadsheet Interface for Statistics, Data Analysis, and Graphics.* Springer Science + Business Media, LLC. https://doi.org/10.1007/978-1-4419-0052-4
18. Huang, C. C. (2019). Does rapid market growth enhance efficiency? An evaluation of the Chinese mutual fund market. *Investment Management and Financial Innovations, 16*(2), 383-394. https://doi.org/10.21511/imfi.16(2).2019.32
19. Huang, Z., & Li, S. X. (2011). Stochastic DEA Models with Different Types of Input-Output Disturbances. *Journal of Productivity Analysis, 15,* 95-113. https://doi.org/10.1023/A:1007874304917
20. Jordá, P., Cascajo, R., & Monzón, A. (2012): Analysis of the Technical Efficiency of Urban Bus Services in Spain Based on SBM Models. *ISRN Civil Engineering,* 1-13. https://doi.org/10.5402/2012/984758
21. Kaplan, R. S., & Norton, D. P. (2004). *Balanced Scorecard.* Complex Kiadó. Budapest.
22. Khezrimotlagh, D., Salleh, S., & Mohsenpour, Z. (2014). A new method for evaluating decision making units in DEA. *Journal of the Operational Research Society, 65,* 694-707.

http://dx.doi.org/10.21511/ppm.18(1).2020.27

23. Ko, K., Chang, M., Bae, E.-S., & Kim, D. (2017). Efficiency Analysis of Retail Chain Stores in Korea. *Sustainability, 9*(9), 1629. https://doi.org/10.3390/su9091629

24. Neely, A., Adams, C., & Kennerley, M. (2004). *Teljesítményprizma: Az üzleti siker mérése és menedzselése*. Alinea Kiadó, Budapest.

25. Nguyen, N. T., Vu, L. T., & Dinh, L. H. (2019). Measuring banking efficiency in Vietnam: parametric and nonparametric methods. *Banks and Bank Systems, 14*(1). http://doi.org/10.21511/bbs.14(1).2019.06

26. Pendharkar, P. C., & Pai, D. R. (2013). A Bayesian Approach for Estimating Confidence Intervals for DEA Efficiency Scores under Certain Inefficiency Distribution Assumptions. In *Proceedings for the Northeast Region Decision Sciences Institute* (pp. 897-916). Retrieved from https://img1.wsimg.com/blobby/go/b9387c06-e09f-4bd2-8ad3-f01bb9ae4e0d/downloads/1btskgqem_401422.pdf?ver=1557238716474 (accessed on June 13, 2019).

27. Ramanathan, R. (2003). *An Introduction to Data Envelopment Analysis. A Tool for Performance Measurement*. Sage Publications India Pvt Ltd.

28. Ray, S. C. (2004). *Data Envelopment Analysis. Theory and Techniques for Economics and Operations Research*. New York: Cambridge University Press.

29. Shewell, P., & Migiro, S. (2016). Data envelopment analysis in performance measurement: a critical analysis of the literature. *Problems and Perspectives in Management, 14*(3-3), 705-713. https://doi.org/10.21511/ppm.14(3-3).2016.14

30. Stapenhurst, T. (2009). *The Benchmarking Book: A How-to-Guide to Best Practice for Managers and Practitioners*. Elsevier Ltd.

31. Stavárek, D., & Řepková, I. (2012). Efficiency in the Czech Banking Industry: A non-parametric approach. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, LX*(2), 357-366. https://doi.org/10.11118/actaun201260020357

32. Sturtz, S., Ligges, U., & Gelman, A. (2005). R2WinBUGS: A Package for Running WinBUGS from R. *Journal of Statistical Software, 12*(3), 1-16. https://doi.org/10.18637/jss.v012.i03

33. Tehrani, R., Mehragan, M. R., & Golkani, M. R. (2012). A Model for Evaluating Financial Performance of Companies by Data Envelopment Analysis. A Case Study of 36 Corporations Affiliated with a Private Organization. *International Business Research, 5*(8). http://doi.org/10.5539/ibr.v5n8p8

34. Thomas, R. R., Barr, R. S., William, L., Cron, W. L., & Slocum Jr., J. W. (1998). A process for evaluating retail store efficiency: a restricted DEA approach. *International Journal of Research in Marketing, 15*, 487-503. http://doi.org/10.1016/S0167-8116(98)00021

35. Zhu, J. (2009). *Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets*. Springer Science + Business Media, LLC. http://doi.org/10.1007/978-3-319-06647-9