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Financial Performance Evaluation of agricultural enterprises with DEA Method

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Abstract

The evaluation of performance is aiming to continuously monitor efficiency and economy of the company's operation and to provide information for corporate decisions. Benchmarking is one means of comparing corporate performance. Nowadays financial indicators are commonly used means in corporate performance analysis, but they can hardly be used as a complex tool of measurement. Adequate performance evaluation and comparability requires a method, a measuring tool, which can measure corporate performance in a complex way. A method is needed, which allows the use of both quantitative and qualitative characteristics; Data Envelopment Analysis (DEA) is a method like that. DEA may complete traditional indicator analysis, especially if the goal is to get more information regarding operational and technical efficiency. Based on the analysis of the chosen corporate data, DEA is presented to be suitable for the comparison and analysis of profit-making companies' performance. Variables included in the evaluation are selected by step-wise regression. Benchmarking module of R Statistics is used during the calculations.

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Keywords: performance analysis, benchmarking, financial ratios, Data Envelopment Analysis (DEA), scale efficiency

1. Introduction: performance evaluation, benchmarking

Performance evaluation and benchmarking are widely used methods regarding corporate process improvements (Bácsné-Nagy, 2014), which can be particularly important if there are no standards (benchmarks) available for the evaluation (Orbán, 2013). Generally speaking, benchmarking is a tool ensuring the comparison between decision-making units (DMU). DMUs can be companies, organizations, business

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units, projects, decision-making units or individuals.

In the last two decades a huge change occurred in performance evaluation. Nowadays, evaluation basically (critical success factors. Large number of inputs and outputs make the corporate performance evaluation more difficult (Herczeg, 2014). Traditionally, financial ratios calculated from accounting data were used for performance evaluation and it is still used today. The view was valid for a long time, that different accounting and financial indicators are the most appropriate for evaluation and comparison of corporate performance. From the 1980s the users of traditional methods have been facing growing number of problems, which led to the research of other performance evaluation options. As increasing number of people engaged in corporate performance evaluation from the middle of 1990s, it became a new management discipline. Performance evaluation – applied properly – provides opportunity for management to find out which corporate activity ensures more revenue than cost (Neely, 2004). Performance evaluation helps investors, especially private equity investors to measure the added value of their non-financial services (Becsky-Nagy – Fazekas, 2014). Frontier analysis methods used in performance evaluations can be parametric and non-parametric, deterministic and stochastic methods. Present article introduces a non-parametric method, DEA (Data Envelopment Analysis). The goal is to present how corporate performance can be measured – using DEA method – with determining a complex indicator.

2. Data envelopment analysis in performance evaluation

One of the biggest problems of financial indicators is dimensional evaluation, so they will not show a proper picture on corporate performance to the management and shareholders (Abdoli et al., 2011). At the same time a method, measuring tool would be crucial, that could measure corporate performance in a proper and complex way. The desirable method makes the use of both quantitative and qualitative characteristics possible. DEA is a method like this; it creates relative efficiency scores, considering more input and output at the same time. DEA usage does not require special functional relations between the input and output characteristics and it is not necessary to assign any statistical distribution to the error term. DEA denotes efficiency and inefficiency is denoted by values between 0 and 1 (Mohamad - Said, 2013). Nowadays DEA is not widespread in case of for-profit companies in Hungary. Related literature in Hungarian describes applications mostly in non-corporate sector; however there is an increasing trend of profit-oriented applications, still not in a huge amount. This article aims to present the combination of traditional financial indicators combined with DEA in performance evaluation.

DEA model was presented by Chames, Cooper and Rhodes in 1978 – based on Farell's (1957) former work (Charnes et al., 1978). Farell suggested a method for activity analysis to correct the traditional indicators' weaknesses. His main issue was to create an efficiency measuring tool for general use, which makes the measurement possible even with more input and output data (Farell, 1957). DEA creates a frontier based on the observed units' input and output data. All the coequal units of the examined set of data are compared to the frontier and it provides the basis of defining a relative performance point (Charnes et al., 1995). The detailed mathematical programming model can be found in all the referred literature. As for Cooper et al. (2007) DEA is a data-oriented approach of performance evaluation based on coequal characteristics forming DMU that calculates efficiency points. DEA is tending towards central tendency instead of extreme values. Researchers from various areas quickly recognized that DEA is an excellent method for modelling operative processes in any business area, both in for-profit and non-profit sectors (Cooper et al., 2007). In international literature – regarding from the born of the method in 1978 – DEA has a significant past. Tavares (2002) collected more than 3000 DEA related publications between 1978 and 2001, Emrouznejad et al. (2008) representing 30 year history of DEA mentioned more than 4000 publications. DEA related publications increased from year to year, in the beginning slightly, but after the mid '90s more than 200-250 article was published yearly, in 2004 this number nearly reached 400.

Benchmarking module of an open source, freely available R statistical system was used during my calculations, which provides the application of different DEA related methods (Figure 1). Methods shown in Figure 1 are different regarding their efficiency and applied algorithm, moreover their sequence implies a sort of rank (Zhu, 2009). As for the above-mentioned, DEA is a method based on linear programming so as the methods in Figure 1, except for the FDH (free disposability hull) and the FRH (free replicability hull) methods, use linear programming, while FDH and FRH use mixed integer programming.

DEA is different depending on the model supporting scale assumptions. Generally two scale assumptions are applied: constant return to scale (CRS) and variable return to scale (VRS). The latter one includes both increasing and decreasing return to scale. CRS assumes that the output changes with the same ratio as the input, while VRS assumes that the return to scale can be increasing, constant or decreasing. Regarding return to scale the following options are possible in terms of efficiency:

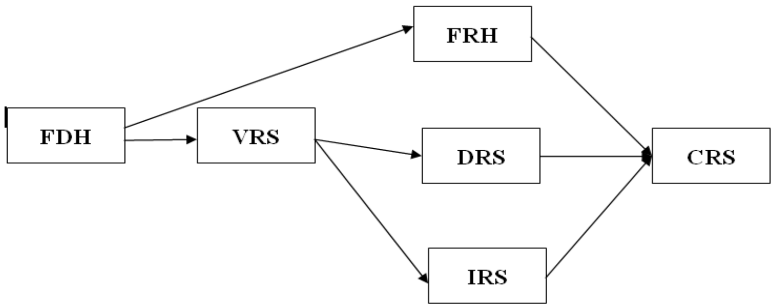

Fig. 1 Methods for calculating DEA in the Benchmarking module

- Changes occurred either in the input or in the output results a directly proportional change in the other. It is the constant return to scale, abridged CRS.
- Changes occurred in the input results in the larger scale of increase in the output. It is the increasing return to scale, abridged IRS.
- The increase of the input could also lead to proportionally lower increase of the output. It is the so called decreasing returns to scale, abridged DRS (Bogetoft – Otto, 2011).

The RS (return to scale) characteristics of an organization could depend on the nature of the industry, the size of the company, the way of operations and several other factors, which can limit the efficiency seeking strategies. For instance CRS assumption can only be used if the company's size is optimal and there is no perfect competition, there are no delivering, labour or financial, etc. limits. If the limits are existing, then applying VRS model scale efficiency and disturbing measurement problems can be avoided, which otherwise would lead to growth. Consequently, VRS model is the most popular type.

Using CRS (constant return to scale) could be considered a bad choice for most of the companies, at the same time this model shows the efficiency the best and this indicator is present in the numerator of the scale efficiency as well.

Different methods of DEA are applicable for scale efficiency analysis also. Scale efficiency can be determined with the help of the following formula:

$$SE = \frac{E(x^0, y^0; CRS)}{E(x^0, y^0; VRS)}$$

,where SE – scale efficiency

Scale efficiency ratio shows how close the current size of a company to the optimal size is. The closer SE ratio is to 1, the closer the company size is to the optimal size.

3. Application of DEA method in financial analysis

DEA can complete the traditional financial ratio analysis, especially if the aim is to gain more information on operational and technical efficiency. Feroz et al. (2003) in their article introduced the connection between financial indicators and DEA efficiency scores. According to their point of view financial indicators provides only an ad hoc and partial evaluation of corporate performance, while adding DEA could make more complex evaluation possible.

DEA provides modern opportunities for financial analysis by using financial data of DMUs as input or output and whereby the units' general financial performance can be evaluated using a complex indicator (score), which cannot be achieved by separate indicators gained from financial statements. During the analysis DEA creates a financial efficiency frontier and financial efficiency score is assigned to all the analysed DMU, which can be compared to the units present in the analysis. The advantage of this type of analysis is that the aspects of financial performance are studied not in a sequential, but in a simultaneous way. In my opinion, we can face two difficulties during the analysis. Firstly, choosing the input and output variables (financial indicators), secondly, the data gained from financial statements, which can include differences originated from the currently applied accounting practices. The first problem can be sold with the help of different statistical methods, while we have to concede the second one as a potentially distorting factor of the calculations. The analysed companies are selected out of the Hungarian agricultural companies whose main activity is denoted "Growing of cereals and other crops n.e.c". Selection of companies was taken place in OPTEN company information system, and the analysed data, data of the annual reports, were downloaded from the Electronic Annual Report's Portal (e-beszamolo). Data of the agricultural company's annual reports were collected in a period of 2008-2012. The analysed sample's scope was reduced based on two criteria: firstly, the amount of revenue, secondly, the number of employees. Accordingly, analysis only involved companies having revenue of 100 million HUF or more and at least employ 10 people. Out of the 230 annual reports 101 were subtracted from the sample, because they were abridged annual reports. Based on the data of the remaining 129 company financial ratios were calculated, then with the help of the boxplot diagram 47 companies having extreme data were also eliminated from the sample. This way the annual report of 82 companies provided the actually processed sample. I created 4 groups of financial indicators for my analysis as shown in Table 1. All the calculations were carried out in R Statistical System. Before using DEA, in order to choose the variables correctly, backward type multivariate linear stepwise regression was completed on yearly data, which revealed the connection between the applied indicators and helped picking the most influential explanatory variable.

Table 1. Indicators applied in the analysis

Name of indicators	**Name of ratios**
Liquidity ratios	Liquidity ratio
	Quick ratio
	Net working capital
Risk indicators	Liabilities / Balance sheet total
	Degree of operating leverage (DOL)
	Degree of financial leverage (DFL)
Grow opportunity indicators	Change in equity
	Change in Operating profit/loss
	Change in Net Sales
Asset management efficiency ratios	Inventory turnover
	Accounts receivables' turnover

Asset turnover

Stepwise regression helps choosing the explanatory variable, which influence outcome variable the most. Stepwise regression applies Akaike Information Criteria (AIC) for decisions regarding variables (Rawlings et al., 1998). During the calculation multivariate linear regression function is determined, and then stepwise regression is accomplished with the help of object including the outcome variable. The applied module (step) does not evaluate AIC for every potential model, rather uses a searching method, which compare the models (Varmuza-Filzmoser, 2009).

Return on Assets (ROA) was used as outcome variable and the rest of the indicators were used as independent variables during regression. Table 2. shows which variable were left in the model in different years (grey cells) and variables are separately marked (darker cells) that I suggest to be used in DEA model yearly. Only variables are considered, that appeared in case of stepwise regression model at least in 3 years. Determinant coefficients (R^2) show that the selection did not changes considerably the functions' explanatory nature.

Table 2. Results of stepwise regression[†]

Name / Year	2009	2010	2011	2012
Liquidity ratio				
Quick ratio				
Ratio of net working capital				
Liabilities / Balance sheet total				
Degree of operating leverage (DOL)				
Degree of financial leverage (DFL)				
Change in equity				
Change in Operating profit/loss				
Change in Net Sales				
Inventory turnover				
Accounts receivables' turnover				
Asset turnover				
R^2 – all variables	0,7678	0,6058	0,7126	0,5767
R^2 – var. remained after stepwise regression	0,7116	0,5012	0,6897	0,5507

Results of stepwise regression are used for DEA. Based on the abovementioned 5 input and 1 output variable will be presented in the model, whose result is included in Figure 2.

Input variables: liabilities/total assets; degree of operating leverage; degree of financial leverage; inventory turnover; asset turnover; Output variable: Return on assets; Summarizing the facts, according to my point of view stepwise regression helped to choose the input and output variables for DEA model, with which we gained a more utilizable performance measurement indicator. During the analysis efficiency scores were defined for the companies using every method.

† Data are represented only between 2009 and 2012 in Table 2 because both the data of the current and the previous year were neccessary, this way the following indicators data were not possible to determine: degree of operating leverage, degree of financial leverage, change in equity, change in operating profit/loss, change in net sales.

Table 3 details the main statistical characteristics of VRS efficiency ratio, which shows that the average efficiency of the companies decreases from 2009 to 2012 and rather have a value below 1. Simultaneously, Table 3 confirms, that the relative deviation of efficiency ratios is good, in two years it is under 10% and in the other two year it does not reach 15%. This table also demonstrated that the 3rd quartile values are relatively high and the values of the 1st quartile are not too low, which means that the analysed the companies' upper quartile (3rd quartile - maximum) accomplished a 0.1 higher performance compared to the median. The width of interquartile range (3rd quartile – 1st quartile) supports that the companies in the middle 50% are not differ significantly from each other considering efficiency.

Table 3. Statistical characteristics of yearly and average yearly VRS efficiency ratio

Statistical characteristics	2009	2010	2011	2012	Average
Average	0,9164	0,9108	0,8853	0,8377	0,8876
Standard deviation	0,0889	0,0771	0,1020	0,1207	0,0727
Relative deviation	9,70%	8,47%	11,52%	14,41%	8,19%
3rd quartile	1,0000	0,9938	0,9864	0,9397	0,9549
Median	0,9354	0,9076	0,8938	0,8358	0,8767
1st quartile	0,8780	0,8623	0,8082	0,7600	0,8384
Interquartile range	0,1220	0,1315	0,1782	0,1797	0,1165

Using Welch's two-sample t-test I have tested whether yearly data differ from each other, i.e. are there actual differences between the results of each year. After completing the tests, regarding VRS method, every year differ from the other in at least in level of 95% (Table 4). It means that the yearly reduction of efficiency can be determined in case of the analyzed agricultural companies and can be backed up statistically.

Table 4. p values of Welch's t-test using VRS efficiency method

Years	2009	2010	2011	2012
2009		0,0060	0,0491	0,0001
2010			0,0000	0,0000
2011				0,0422

In Table 5 the values of efficiency indicators are presented grouped by intervals, which lead us to the same conclusion as can be derived from the results of Table 3. Table 5 shows that the efficiency of the analysed agricultural company considered to be good in the first two years, but in the last two years deterioration was observed. The change can be likely related to the tendency of the economy's general status, the significant reduction of investments.

Table 5. Yearly distribution of VRS efficiency indicator values

Interval / Year	2009	2010	2011	2012	Average
0,5 – 0,6	1	0	0	2	0
0,6 – 0,7	1	1	3	9	0
0,7 – 0,8	5	5	15	22	9
0,8 – 0,9	24	31	25	22	36
0,9 – 1,0	51	45	39	27	37

In order to have a clear view, I determined the companies' average ranking for the first two and for the least two years, after comparing them, I got the following results: ranking worsened in case of 43 company (52,4%) and it improved regarding 39 companies (47,6%). The slightest deterioration was 3.5 and the greatest was ranked back by 51 places. As for the improving companies the slightest for ranking was 0.5 and the greatest was 60.5. These results show that there were significant changes in the efficiency ranking of the analysed companies in 2011-12 in comparison with 2009-10. There is only one company that showed no changes basically in four years, this company was ranked in the 1st place, except for 2010, when it earned the 2nd place. If we take a look at the four-year-average rank created on the basis of the yearly efficiency scales, then there is 13 point difference between the 1st and the 2nd place winner. Comparing the rank of 2009 to rank of 2012, it is evident, that there is an improve in 33 cases and a deterioration in 49 cases.

Finally, using the results of DEA model a scale efficiency analyses were completed, i.e. yearly SE ratio was calculated. Scale efficiency ratio was determined as the quotient of the efficiency values of CRS and VRS. Scale efficiency median of the analysed companies represented a quite low value in 2009-2010, later it began to increase and in 2012 is exceeded 0.7. Overall, it can be stated that the results of scale efficiency has worse results than the values of the general efficiency, in spite of general efficiency scale, efficiency showed continuous yearly increase in this case (Table 6).

Table 6. Statistical characteristics of yearly and average of years SE ratio

Statistical characteristics	2009	2010	2011	2012	Average
Average	0,4550	0,5014	0,5819	0,6390	*0,5443*
Standard deviation	0,3317	0,3552	0,3000	0,3303	0,2363
Relative deviation	72,90%	70,85%	51,56%	51,69%	43,41%
3rd quartile	0,6748	0,8089	0,8456	0,9186	0,7427
Median	0,9354	0,9076	0,8938	0,8358	0,8767
1st quartile	0,1583	0,1611	0,3536	0,4587	0,3648
Interquartile range	0,5165	0,6478	0,4920	0,4599	0,3779

The range of the upper 50% is continuously decreasing and in 2012 the upper 25% has a small range (standard deviation). At the same time, in order to see a clear picture, I consider important to introduce the interval distribution of scale efficiency (Table 7). Improvement is obvious, but it can be ascertained that considering scale efficiency the analysed companies are in a much worse situation than in case of general efficiency. Table 6 shows demonstrated that there is a growing tendency regarding the number of companies having 0.9, however the number of companies having 1 stagnate. The results support the high values of standard and relative deviation of the Table 7.

Table 7. Yearly values of Scale efficiency (SE)

Interval / **Year**	**2009**	**2010**	**2011**	**2012**	**Average**
0,0 – 0,1	15	16	5	11	3
0,1 – 0,2	9	8	6	3	4
0,2 – 0,3	6	6	5	2	11
0,3 – 0,4	8	6	9	3	6
0,4 – 0,5	6	5	8	5	10
0,5 – 0,6	10	9	6	8	6

0,6 – 0,7	9	4	11	7	19
0,7 – 0,8	2	7	10	11	10
0,8 – 0,9	4	3	6	10	11
0,9 – 1,0	13	18	16	22	2
from the previous = 1	10	12	9	10	

In order to have a clear view, I determined the companies' average ranking for the first two and for the least two years, after comparing them, I got the following results: ranking worsened in case of 43 company (52,4%) and it improved regarding 39 companies (47,6%). The slightest deterioration was 3.5 and the greatest was ranked back by 51 places. As for the improving companies the slightest for ranking was 0.5 and the greatest was 60.5. These results show that there were significant changes in the efficiency ranking of the analysed companies in 2011-12 in comparison with 2009-10. There is only one company that showed no changes basically in four years, this company was ranked in the 1st place, except for 2010, when it earned the 2nd place. If we take a look at the four-year-average rank created on the basis of the yearly efficiency scales, then there is 13 point difference between the 1st and the 2nd place winner. Comparing the rank of 2009 to rank of 2012, it is evident, that there is an improve in 33 cases and a deterioration in 49 cases.

It has been found that the general efficiency of the companies analysed is not diversified, not like scale efficiency. Companies should improve their general efficiency, because its value continuously decreased during the analysed period. The Scale efficiency ratio was improved year by year; the majority – regarding the selected businesses – need to take serious steps. Companies considered scale efficient nearly exceed the 10% of the analysed companies.

References

Abdoli, M., Garkaz, M., Golami, Y., Pourkazemi, A., 2011. The comparative study of ranking company's efficiency based on data envelopment analysis (DEA) and traditional methods (DuPont's method). International Conference on Economics and Finance Research, IPEDR vol.4, IACSIT Press, Singapore. 34.

É. Bácsné Bába – Z. I. Nagy (2014): The Organizational Adaptation of Football Enterprises. The Annals of the University of Oradea, Economic Sciences. Tom XXIII – 2014. Issue 1 (2014) Ed. A. Giurgiu University of Oradea. pp. 1173-1183.

Becsky-Nagy, P. – Fazekas, B. 2014. Returns of private equity: comparative analyses of the returns of venture capital and buyout funds in Europe and in the US Annals of the University of Oradea. Economic Science (ISSN: 1222-569X) (eISSN: 1582-5450) 2: (2) pp. 820-827.

Bogetoft, P., Otto, L., 2011. Benchmarking with DEA, SFA, and R. Springer, ISBN 978-1-4419-7960-5.

Charnes, A., Cooper, W. W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research, Vol. 2, p. 429–444, Elsevier Science Publishers B.V.

Charnes, A., Cooper, W.W., Lewin A.Y., Seiford, L.M., 1995. Data Envelopment Analysis: Theory, Methodology, and Application. Kluwer Academic Publishers, Boston, Dordrecht and London, ISBN 978-94-011-0637-5.

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, ISBN-13: 978-0387-45281-4.

Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Handbook on Data Envelopment Analysis. Springer Science+Business Media, LLC, ISBN: 978-1-4419-6151-8.

Emrouznejad, A., Parker, B. R., Tavares, G., 2008. Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. Journal of Socio-Economic Planning Sciences, Vol. 42, Issue 3, September 2008, p. 151–157.

Farrell, M., 1957. The measurement of productive efficiency. Journal of Royal Statistical Society, Series A, Vol. 120, No. 3., p. 253–281.

Feroz, E.H., Kim, S., Raab, R.L., 2003. Financial statement analysis: A data envelopment analysis approach. Journal of the Operational Research Society (2003) 54, p. 48–58, doi:10.1057/palgrave.jors.2601475.

Herczeg, A. 2014 Financing Aspects of the Hungarian general manufacturers in 2010-2012 The Annals of the University of Oradea. Economic Sciences, Tom XXIII -2014 Full Volume 1 st issue July 2014 p.905-911

Mohamad, N.H., Said, F., 2013. Profitability Performance of Selected Top Listed Malaysian GLCs and non-GLCs. International Journal of Trade, Economics and Finance, Vol. 4, No. 4, August 2013, pp. 177-181.

Neely, A. [ed.], 2004. Business performance measurement: Theory and practice. Cambridge University Press, ISBN 0-521-80342.

Rawlings, J.O., Pentula, S.G., Dickey, D.A., 1998. Applied regression analysis: a research tool. 2nd ed., Springer. ISBN 0-387-98454-2.

Tavares, G., 2002. A Bibliography of Data Envelopment Analysis (1978-2001). RUTCOR Research Report, Rutgers Center for Operations Research Rutgers University.

Orbán Mrs. Tamás Dékán, I. (2013): Reporting companies' performance – in respect of the International Financial Reporting Standards (IFRS), APSTRACT Vol. 7. Numbers 4-5. 2013. 107-112. p., Debrecen

Varmuza, K., Filzmoser, P., 2009. Introduction to multivariate statistical analysis in chemometrics. CRC Press Taylor & Francis Group. ISBN 978-1-4200-5947-2.

Zhu, J., 2009. Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets. Springer Science+Business Media, LLC, ISBN-13: 978-0-387-85981-1.