

PERFORMANCE ANALYSIS OF THE ROMANIAN AND HUNGARIAN AGRICULTURAL COMPANIES

Eva IEREMIAS¹, Tibor TARNÓCZI²

¹Károly Ihrig Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary

²Institute of Accounting and Finance, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary

evi.ieremias@yahoo.com

tibor.tarnoczi@econ.unideb.hu

Abstract: *Performance measurement is essential in all sectors of the national economies. Still, it is especially true for agriculture, as more efficient farming is becoming increasingly important to provide the population with adequate food.*

The study examines the performance of Hungarian agricultural companies in Romania. There were selected a total of 5,390 companies for the analysis database, of which 3,789 were from Romania and 1,601 from Hungary. In the performance analysis, the efficiency of companies was examined between 2018 and 2020 using the Data Envelopment Analysis method.

Based on the results, it can be concluded that Romanian agricultural companies operate with statistically significantly lower efficiency. However, it can also be seen that the average efficiency of businesses is very low considering both countries.

Low performance is also observed considering the averages of the sub-sector efficiency coefficients. There is not a single year in which the average efficiency coefficient in any sector exceeds 50%. On the other hand, the Oilseed and Grain Farming sub-sector analysis shows that the proportion of companies with an efficiency coefficient below 50% is very high, especially in Romania. Similar findings can be made for the Poultry and Egg Production subsector.

Further research is needed to explore the causes of low efficiencies of agriculture companies more accurately.

Keywords: *agriculture; efficiency; Data Envelopment Analysis, Romania and Hungary*

JEL Classification: *Q10; R15; C14; C44*

1. Introduction

Competition between economic operators has intensified because of the globalization of markets and the spread of free trade agreements. As a result, the focus has been on achieving the most efficient production possible. The importance of accounting records has changed accordingly over the years. As a result, there has been a growing demand for information from companies to support management decision-making, which must be provided in sufficient quantity and outstanding quality.

There is possible to find a lot of data in the obligatory annual financial statements. Still, they do not always contain information valuable for decision-makers. For example, from which they can be concluded the companies' current financial position, their performance compared to their competitors, or what would make it easier to develop a micro-environmental action plan. However, data from accounting reports can provide an excellent basis for a more in-depth financial analysis of businesses if they are processed. The most appropriate processing method is to calculate the proportions of the various items and develop different financial ratios. By examining the change in the indicators produced in this way over time, we can get the most helpful information.

The key to a business's success is continuous control over the performance and systematic feedback to managers, for which financial analysis is essential. Consequently, the study aimed to use one of the most widely used methods, the Data Envelopment Analysis, to measure and compare the efficiency of Romanian and Hungarian agricultural enterprises.

2. Performance evaluation

2.1. Importance of performance evaluation in agriculture

One of the biggest problems with financial ratios is dimensional valuation because they do not provide an adequate and complex picture of corporate performance for management and shareholders (Abdoli et al., 2011). Therefore, it became necessary to develop an appropriate method to measure efficiency and effectiveness. Globalization and the ever-accelerating market competition pressure every organization, demanding more flexibility and more performance awareness, which essentially requires identifying inefficiencies. The performance evaluation aims to continuously monitor the efficiency and economy of the company's operation and provide information for corporate decisions (Fenyves et al., 2015).

Agriculture and arable farming are becoming more mechanized today and require significant energy inputs at certain stages of the production cycle to achieve optimal yields. Therefore, it would be essential to know which minimal inputs give the highest outcomes determined by various performance and efficiency measurements (Moitzi et al., 2019). The Data Envelopment Analysis (DEA) method can support this activity and measure efficiency in an acceptable and complex way. This method provides opportunities to apply both quantitative and qualitative characteristics. Furthermore, it generates relative efficiency scores, taking multiple inputs and outputs simultaneously into account.

Agricultural activities, particularly soil tillage, have significantly impacted increases in atmospheric CO₂ and greenhouse gases in the last few decades (Lal, 1997; Tilmann et al., 2002). In this respect, mechanization and production intensity play essential roles in energy consumption (Hernanz et al., 1995). For example, in conventional plowing tillage cultivation systems, over 50% of the total fuel consumption is usually only required for soil preparation and sowing (Moitzi et al., 2015). Another example is that Pittelkow et al. (2015) performed 5463 paired

observations using 610 studies that compared non-tillage and traditional tillage practices with 48 crops and 63 countries. They showed that the non-tillage cultivation method reduces yields compared to conventional tillage systems in humid climates.

In contrast, in regions with a dry climate, the yield of a non-tillage cultivation method may be equal to or higher compared to conventional tillage systems. These findings suggest that direct tillage cultivation may become an important strategy for adapting to climate change in the drier regions of the world. However, inefficient production has also led to problems such as the abandonment of arable land. Accordingly, Terres et al. (2015) identified areas at higher risk of abandonment at the EU-27 level in Portugal, Spain, Italy, Greece, Romania, Slovenia, the three Baltic States, Finland, Sweden, and Ireland. The composite indicator at the Member State level shows significant differences in the risk of leaving agricultural areas between regions within a country. The most frequent farm types at risk identified in these regions are 'special permanent grazing livestock', 'special field crops', and 'special permanent crops'. All three types use large shares of land, mainly in an extensive way. Lack of good management in such areas may negatively affect landscape and biodiversity maintenance.

These studies and their results provide critical information for the management of companies to enable them to produce more efficiently. The previous also confirms that it is essential to examine the relationships between input resources and outputs considering corporate efficiency.

2.2. Data Envelopment Analysis

The DEA is a widely used method to analyze several sectors' performance, namely agriculture, using different inputs and outputs. The DEA model was developed by Charnes, Cooper, and Rhodes in 1978 - based on the previous work of Farrell (1957) (Charnes et al., 1978). The primary purpose of developing DEA was to establish a measure based on multiple input and output data. The DEA method does not require special functional relationships between input and output data, and it denotes efficiency by values between 0 (totally inefficient) and 1 (totally efficient). DEA creates a frontier line based on the observed units' (decision-making units) input and output data. All the co-equal units of the examined dataset are benchmarked against the frontier, and it provides a basis to define a relative performance score (Charnes et al., 1995). The DEA is a non-parametric model, so defining any function is unnecessary. DEA models can be input-oriented (objective: minimizing inputs while maintaining the same level of outputs) or output-oriented (objective: increasing outputs with the same level of inputs) (Malana and Malano, 2006).

The DEA has a long history in international literature since its birth in 1978. Tavares (2002) collected more than 3,000 DEA-related publications between 1978 and 2001. Emrouznejad et al. (2008) had been presented in their article on the 30-year history of DEA, and they are listed in more than 4,000 publications. The number of publications related to the DEA has increased year by year.

The selection of inputs is crucial as outputs (production value, labor productivity, etc.) depend on these input uses. Therefore, if an area can reach the current level of outcomes with lower expenditures, it can be assumed that sustainable development of the sector examined will take place (Dalgaard, 2001).

Toma et al. (2015) examined the efficiency of agriculture in Romania using the DEA model. Their results confirmed the usefulness of applying DEA models to judge agriculture areas with similar geographical patterns. Their analysis showed that only 14 counties (5 lowlands, 5 hilly, and 4 mountainous) achieved total DEA efficiency and operated at optimal scales. The other counties could need to change their input mix to achieve greater efficiency or increase output levels through better use of fixed capital and higher returns.

3. Data and methodology

3.1. Data

The data used for the analysis were downloaded from the EMIS database system. The database consists of the data of the financial statements of Romanian and Hungarian agricultural enterprises for three years (2018-2020). Only companies with financial reports for all three years were included in the database and had total revenues of over 50,000 euros. After filtering the data, 3,789 Romanian and 1,601 Hungarian, a total of 5390 companies remained in the database. The distribution of the companies in the database by subsector is shown in Table 1. The study used the NAICS American activity classification system to group the companies by subsector in the two countries. Table 1 shows that twice as many companies are on the Romanian side as the Hungarian one in the database. However, there are significant differences in the number of companies between the two countries for some subsectors.

Table 1: Distribution of the examined agricultural companies by subsector and country

Sector codes	Sector names	Hungary	Romania
1111	Oilseed and Grain Farming	834	2462
1112	Vegetable and Melon Farming	47	71
1113	Fruit and Tree Nut Farming	42	106
1114	Greenhouse, Nursery, and Floriculture Production	21	18
1119	Other Crop Farming	73	277
1121	Cattle Ranching and Farming	141	141
1122	Hog and Pig Farming	105	160
1123	Poultry and Egg Production	163	186
1124	Sheep and Goat Farming	4	29
1125	Aquaculture	7	60

1129	Other Animal Production	11	14
1151	Support Activities for Crop Production	144	253
1152	Support Activities for Animal Production	9	12
Total		1601	3789

Source: edited by authors

3.2 Methodology

The analyses were performed by the R statistical system using from the Microsoft Excel spreadsheet. The R statistical system has been chosen as an analytical tool because it is a widely used system and has been helping analysts for nearly twenty years. In addition, the R system is an open-source system and can be used and developed for free.

In the analysis, the decision-making units of the DEA were the 5,390 agricultural companies included in the database, of which efficiencies were compared with each other. It is important to emphasize that the efficiency scores are only valid for the firms examined.

For the DEA-based performance evaluation, there were selected the following variables to evaluate the efficiency of the agricultural companies selected.

Input variables:

- Material costs
- Employee costs
- Other costs
- Fixed assets

Output variables:

- Total revenue
- Operating profit

The input orientation model of DEA was used, which looks for the answer to how it is possible to reduce inputs proportionately while retaining the amount of outputs. Its mathematical form can be expressed as the quotient of input and output. The operating profit was used as one of the output variables because two countries are compared, and different interest rates and taxes can affect net profit.

4. Results and discussion

The DEA method was applied to all companies in the database annually. This complex comparison allows companies in the two countries to be comparable.

Table 2 shows that the efficiency of agricultural enterprises is very low in both countries. Decision-making units with an efficiency coefficient above 0.7 are generally considered acceptable efficiencies. 7.37%, 6.25%, and 5.12% of Hungarian companies fall into this category each year, while in the case of Romanian companies, these counts are 3.4%, 3.43%, and 2.53%. It can also be seen that the proportion of Hungarian companies in the category is almost twice that of Romanians. Based on the t-test, it can also be stated that Hungarian companies

perform significantly better than Romanians, still at this low level. The efficiency of Hungarian companies decreased by almost 30% from 2018 to 2020, which was 26.5% for Romanian companies.

Table 2: Efficiency scores of agricultural enterprises by countries between 2018 and 2020

Efficiency coefficient intervals		Hungary			Romania		
		2018	2019	2020	2018	2019	2020
	=1.0	48	39	35	48	57	43
>= 0.9	< 1.0	22	20	10	18	21	11
>= 0.8	< 0.9	17	16	12	24	21	14
>= 0.7	< 0.8	31	25	25	39	31	28
>= 0.6	< 0.7	49	38	27	56	61	39
>= 0.5	< 0.6	84	68	53	88	94	49
>= 0.4	< 0.5	154	88	95	130	122	63
>= 0.3	< 0.4	269	142	138	283	214	127
>= 0.2	< 0.3	400	283	230	640	430	219
>= 0.1	< 0.2	416	557	415	1496	1284	597
>= 0.0	< 0.1	111	325	561	967	1454	2599
Átlag		0.3213	0.2590	0.2253	0.2099	0.1905	0.1282

Source: created by authors

In order to have a more accurate picture of the performance of agricultural enterprises, the efficiency of enterprises by sub-sector with larger size is also examined (Table 3). Table 3 shows that companies in the Support Activities for Crop Production sub-sector have the highest average efficiency in Hungary and the Poultry and Egg Production sub-sector in Romania every year. On the other hand, the lowest average efficiency coefficients for the Fruit and Tree Nut Farming sub-sector are found in Hungary and Romania every year. This is probably because the natural exposure to fruit production can be relatively high in both countries.

Table 3: Average efficiencies of larger sub-sectors per year and by country

Sector code	Sector	Hungary			Romania		
		2018	2019	2020	2018	2019	2020
11	Agriculture	0.3213	0.2590	0.2253	0.2099	0.1905	0.1282
111	Crop production	0.3121	0.2448	0.2124	0.1940	0.1698	0.1112
1111	Oilseed and Grain Farming	0.3143	0.2419	0.2090	0.1918	0.1661	0.1075
1112	Vegetable and Melon Farming	0.3614	0.2998	0.2682	0.2774	0.2450	0.1569
1113	Fruit and Tree Nut Farming	0.2012	0.1334	0.0912	0.1703	0.1436	0.1057
112	Animal husbandry	0.3024	0.2580	0.2201	0.2742	0.2589	0.1945

1121	Cattle Ranching and Farming	0.2328	0.2055	0.1931	0.2103	0.1908	0.1319
1122	Hog and Pig Farming	0.2557	0.2583	0.2424	0.2451	0.2583	0.1887
1123	Poultry and Egg Production	0.4008	0.3138	0.2419	0.3213	0.2923	0.2390
115	Support Activities	0.4355	0.3555	0.3250	0.2431	0.2672	0.1695
1151	Support Activities for Crop Production	0.4376	0.3559	0.3292	0.2359	0.2594	0.1624

Source: created by authors

Due to size constraints, only two sub-sectors can be presented in more detail. Therefore, the sub-sectors with the largest number of companies in the database examined are presented. Thus, the first sub-sector presented is the Oilseed and Grain Farming, which includes the highest number of Hungary companies (834) and Romania (2,462).

In Figure 1, the bars relate to the left-side and the line to the right-side frequency values. The figure shows no significant differences in frequency values in the first three categories. However, there are 834 companies in the sub-sector in Hungary and almost three times as many in Romania (2,462). However, there are big differences in the lowest category, showing the difference in efficiency between the two countries. Romanian efficiency values are around 50-60% of Hungarian values. The average efficiency coefficients of the sub-sector are lower each year than those of the whole sector, and the differences are 3-6% in Hungary and 8-13% in Romania. In this sub-sector, Hungarian companies are statistically significantly better than Romanians.

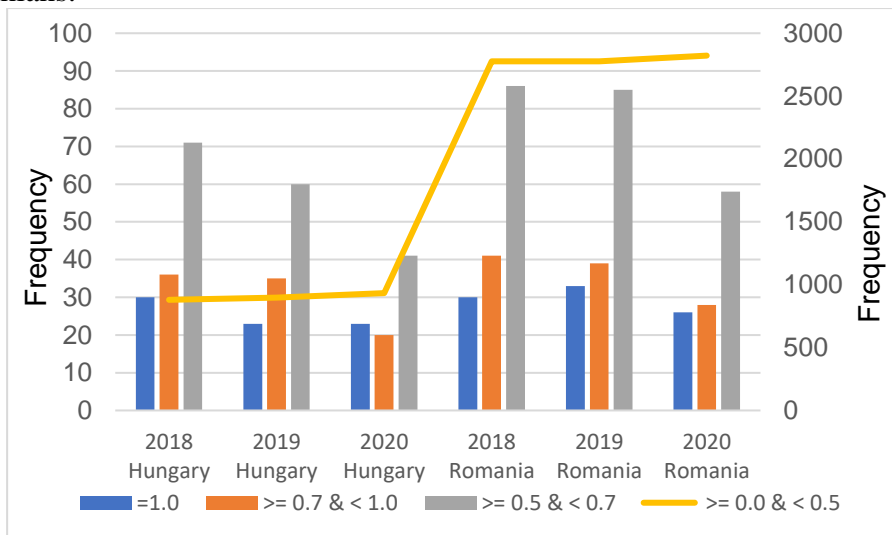


Figure 1: Distribution of efficiency scores in the case of the Oilseed and Grain Farming subsector

Source: created by authors

The second sub-sector to be examined in more detail was the Poultry and Egg Production sub-sector, the main characteristics shown in Figure 2. The number of

companies in this subsector is much lower than in the Oilseed and Grain Farming subsector. At the same time, most of the companies in the livestock sub-sectors are in this sub-sector (163 in Hungary and 186 in Romania). The figure shows that the number of companies with an efficiency coefficient above 50% is relatively low. The Romanian average values in this sub-sector are also worse than the Hungarian ones, although this sub-sector has the highest efficiency coefficients in Romania.

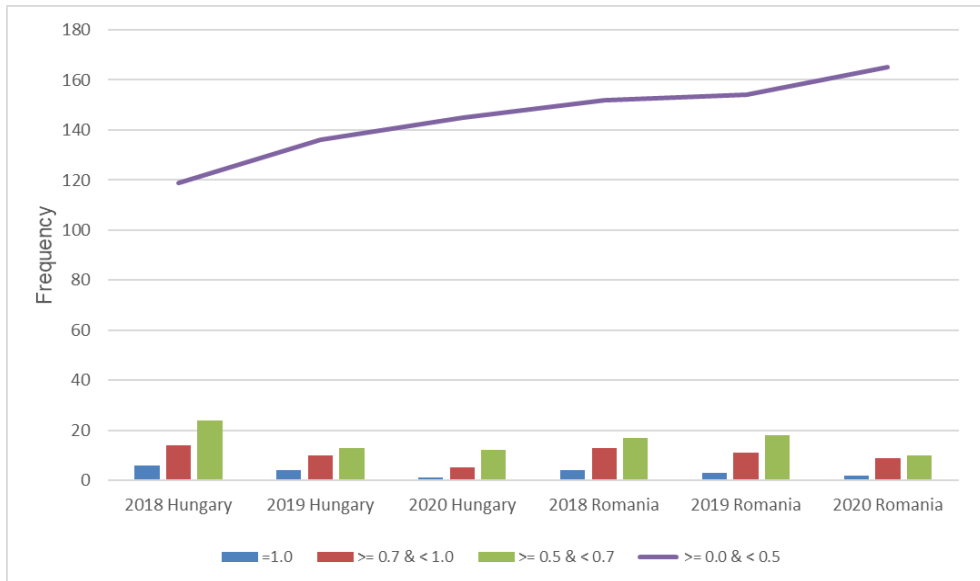


Figure 2: Distribution of efficiency scores in the case of the Poultry and Egg Production subsector

Source: created by authors

Conclusion

The analysis performed using Data Envelopment Analysis clearly showed that the efficiency of agricultural companies is very low in both Hungary and Romania. The analysis broken down by sub-sectors did not show a better result either, but it can be stated that there are significant differences in the case of some sub-sectors. As a continuation of the research, it would be useful to examine the dual solution of the DEA model to determine for which input variables the problems are present.

As there are many companies in the study database, it would be advisable to test the efficiency using stochastic frontier analysis (SFA). It would be useful to use a frontier analysis model that can also consider quality factors such as company size, county, etc. The groupings performed for the DEA group are the efficiency indicators calculated for the entire database, while the SFA can quantify these effects within a model.

The use of several methods will likely make it possible to identify more precisely the factors affecting the efficiency of agricultural companies and to determine the causes of inefficiency.

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