

Basic efficiency measurement of Hungarian logistics centres using data envelopment analysis

Rita Markovits-Somogyi / Gergely Gecse / Zoltán Bokor

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Abstract

Data envelopment analysis (DEA) is a non-parametric linear programming method capable of evaluating the efficiency of decision making units (DMUs) of various kinds. It is widely utilised for the ranking of companies operating in the transport sector. It is, however, not very often applied for the analysis of logistics centres, although its characteristics make it perfectly suitable for this purpose. The present article investigates how DEA can be used for the evaluation of Hungarian logistics centres. The statistic data of 26 DMUs have been collected and the sample has been corrected so as to include only the firms with sufficient data available for an extensive efficiency rating, leaving 12 logistics centres in the pool. Their efficiency was examined as based on the following inputs: surface size of offices, number of employees, surface of available storage space (excluding external storage facilities). The output considered was the volume of total sales revenue and in a second test, the tons of freight handled. Aggregate, pure technical and scale efficiencies have also been determined.

Keywords

logistic centres · data envelopment analysis · efficiency measurement

Rita Markovits-Somogyi

Department of Transport Economics, BME, H-1111 Budapest Bertalan L. u. 2., Hungary

e-mail: rsomogyi@kgazd.bme.hu

Gergely Gecse

Department of Logistics and Supply Chain, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary

e-mail: gergely.gecse@uni-corvinus.hu

Zoltán Bokor

Department of Transport Economics, BME, H-1111 Budapest Bertalan L. u. 2., Hungary

e-mail: zbokor@kgazd.bme.hu

1 Introduction

Data envelopment analysis (DEA), a non-parametric linear programming method, is extensively applied for the appraisal of the efficiency of decision making units (DMUs) active in the transport sector. Airports [2], railways [19], public transport companies [10, 15] and ports [17] are evaluated with this technique. Although its features make it appropriate for the efficiency assessment of logistics centres as well, it is seldom utilized for that. In the broader logistics field, there can be found some applications where the logistics potentials of different regions are examined [9, 12]; or where the sustainability of the logistics sector is analysed [11]. Only two cases have been found where DEA is applied directly to logistics companies. Liu and Wu [13] investigate 20 firms but they utilize only fiscal inputs and outputs thus losing that potential inherent in DEA which enables an efficiency analysis based on different non-monetary parameters. Shen and Chen [16] examine 17 Chinese logistics companies, and also utilises fiscal parameters only. Given the advantages of the method and the possible room for improvement, it is reasonable to employ the DEA technique and look into the efficiency of Hungarian logistics centres. Even more so since logistics performances and costs have already been evaluated for instance within manufacturing companies [4].

2 The mathematical background of data envelopment analysis

The basis of data envelopment analysis has been laid down by Farrell [8] who formulated the basic definition: a DMU is technically efficient when no waste could be eliminated without worsening any input and output. This model was further developed by Charnes, Cooper, Rhodes [5] to yield the CCR DEA model (named after the initials of the authors, also called CRS – constant returns to scale) from which each DEA study starts even today.

The CCR DEA model can be described as follows [7, 14]: let us assume that there are n DMUs to be evaluated. Each DMU consumes m different inputs, and produces s different outputs. Thus e.g. DMU _{j} consumes x_{ij} of input i , and produces y_{rj} of output r . We also assume that $x_{ij} \geq 0$, $y_{rj} \geq 0$, and for each

DMU there is at least one positive input and one positive output. From these the ratio of outputs to inputs is used to measure the relative efficiency: $DMU_j = DMU_0$, the DMU to be evaluated relative to the ratio of all the $j=1,2,\dots,n$ DMU_js. Thus the function to be maximised is:

$$\max h_0(u, v) = \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i=1}^m v_i x_{i0}} \quad (1)$$

where u_r, v_i are weights,

y_{r0}, x_{i0} are the observed input/output values of DMU₀ (where DMU₀ is the DMU to be evaluated). The following constraints are introduced to limit the values:

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 \quad \text{for } j = 1, 2, \dots, n, \quad (2)$$

and $u_r, v_i \geq 0$.

Applying the Charnes-Cooper transformation results in the following equivalent linear programming (LP) problem:

$$\max z = \sum_{r=1}^s \mu_r y_{r0} \quad (3)$$

subject to

$$\begin{aligned} \sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} &\leq 0 \\ \sum_{i=1}^m v_i x_{i0} &= 1 \\ \mu_r, v_i &\geq 0 \end{aligned}$$

where (u, v) are exchanged to (μ, v) as a consequence of the Charnes-Cooper transformation. The equivalent dual LP problem of (2) is:

$$\theta^* = \min \theta \quad (4)$$

subject to

$$\begin{aligned} \sum_{j=1}^n x_{i,j} \lambda_j &\leq \theta x_{i0} \quad i=1,2,\dots,m \\ \sum_{j=1}^n y_{r,j} \lambda_j &\geq y_{r0} \quad r=1,2,\dots,s \\ \lambda_j &\geq 0 \quad j=1,2,\dots,n \end{aligned}$$

This formula is also known as the ‘‘Farrel model’’ because it was created by Farrel. But he did not apply the dual theorem of linear programming (according to which $z^* = \theta$, and either problem can be solved) and thus was not able to connect the models introduced above. (3) is also called as the ‘‘strong disposal’’ or ‘‘weak efficiency’’ model, because here non-zero slacks are ignored. If they are also to be taken into account, the following modified model is to be used, which is also called the envelopment model:

$$\min \theta - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \quad (5)$$

subject to

$$\begin{aligned} \sum_{j=1}^n x_{ij} \lambda_j + s_i^- &= \theta x_{i0} \quad i=1,2,\dots,m \\ \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ &= y_{r0} \quad r=1,2,\dots,s \\ \lambda_j, s_i^-, s_r^+ &\geq 0 \quad \forall i, j, r \end{aligned}$$

where ε is a non-Archimedean element, by definition smaller than any positive real number. The dual linear program of this model, also called the multiplier model, is:

$$\max z = \sum_{r=1}^s \mu_r y_{r0} \quad (6)$$

subject to

$$\begin{aligned} \sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} &\leq 0 \\ \sum_{i=1}^m v_i x_{i0} &= 1 \\ \mu_r, v_i &\geq \varepsilon > 0 \end{aligned}$$

In the framework of these, a DMU₀ is efficient if and only if $\theta^* = 1$ and $s_i^- = s_r^+ = 0$ for all i, r , and it is weakly efficient, if $\theta^* = 1$, and $s_i^- \neq 0$ and/or $s_r^+ \neq 0$ for some i and r in some alternate optima [7, 14]. Formulas (5) and (4) represent the input-oriented DEA CCR models (envelopment and multiplier form). The output oriented model is also very similar with the difference in the values to be maximised/minimised. The DEA BCC (as Banker, Charnes and Cooper in [1], or also called VRS – variable return to scale) model incorporates an additional constraint:

$$\sum_{j=1}^n \lambda_j = 1 \quad (7)$$

which creates the possibility to take into account the non-constant returns to scale.

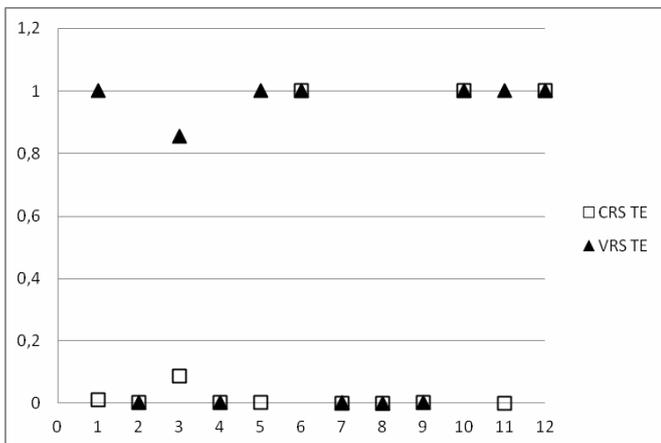
3 Methodology

The aim of the present investigation is to include as many inputs and outputs as possible, so as to get the most precise efficiency ranking. Statistic data of 26 Hungarian centres have been collected but the final sample includes only 12 companies, where data for all the inputs and outputs are available. Here the thumb rule specified in the literature has also to be used. According to this rule the number of observations should be three times greater than the number of the inputs plus outputs; and the number of DMUs should be equal or larger than the product of the number of inputs and outputs [3]. Consequently, only 3 inputs and 1 output are included in the investigation in the first tests. The inputs selected are the surface size of offices, number of employees and surface of available storage space (excluding external storage facilities). The output considered was the volume of total sales revenue, and in a second examination the tons of freight handled. The output oriented DEA model was used, as these firms are relatively free to alter the level of their inputs

and their aim is output maximization. The linear programming problems were solved by the DEAP software, version 2.1 [6].

4 Research results

As it can be seen from the mathematical background outlined above, in DEA a firm is efficient if its efficiency ranking is 1. These efficient companies lie on the frontier created by the model and the rest of the enterprises are compared to these firms. In the first step a basic efficiency analysis of the 12 companies was carried out, examining constant as well as variable return of scale (CRS and VRS) efficiency. The output selected here was the total sales revenue. The results are summarized in Fig. 1, where it can be seen that firms number 6, 10 and 12 are efficient both under constant and under variable return to scale (i.e. they are also scale efficient). Whereas firms number 1, 3, 5 and 11 could significantly improve their efficiency if they operated at scale efficient size. Although their VRS efficiency is high, their aggregate efficiency is low and this is due to the fact that they are scale inefficient. As it is known, CRS efficiency (or aggregate efficiency) can be decomposed into pure technical efficiency (VRS efficiency) and scale efficiency; CRS and VRS efficiency are not the same when there are scale inefficiencies in the case of some DMUs. This is due to the fact that DEA VRS draws a tighter frontier around the sample points and thus provides technical efficiency scores that are higher (or equal) to those of CRS [6].

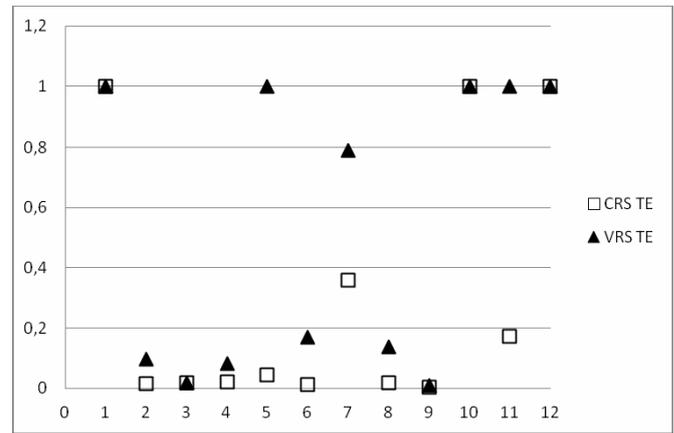


[source: own research]

Fig. 1. CRS and VRS efficiencies based on total sales revenue

Data envelopment analysis also reveals that they operate under *increasing* returns to scale, thus they could improve their efficiency if they increased their inputs.

In the next step the output of total sales revenue has been exchanged to the number of tons forwarded. The main question was how this change influences the efficiency ranking of the firms. From Fig. 2., containing the results, it is clearly visible that firms number 10 and 12 remain efficient, whereas number 6 loses its potentials, and number 1 joins the group of efficient firms. The gap between CRS and VRS efficiency opens up in case of firms 2, 4, 7 and 8.



[source: own research]

Fig. 2. CRS and VRS efficiencies based on tons forwarded

We could see that firms number 10 and 12 have remained efficient independently of the output chosen: this could be due to the fact that they do not only successfully utilize their inputs for maximizing the volume of freight forwarded, but their business policy is also adequate to translate this to maximum profits. Whereas firm number 1 is efficient in maximising the number of tons handled with the given levels of input but it does not seem efficient in converting that to total sales revenue as its efficiency ranking falls sharply once total sales revenue is regarded as output. The contrary can be observed in case of firm number 6, which is efficient in creating total sales revenue while it is not so efficient when regarding the amount of freight forwarded.

Tab. 1. Comparing efficiencies of scale

[source: own research]

	Total sales revenue	Tons handled
1	irs	–
2	–	drs
3	irs	–
4	–	drs
5	irs	irs
6	–	drs
7	–	drs
8	–	drs
9	–	drs
10	–	–
11	irs	irs
12	–	–

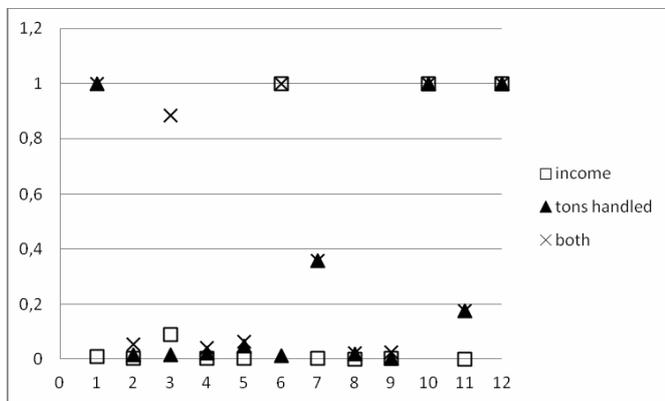
Apart from these absolute results it is worth looking at the change of scale efficiencies. It is interesting to note that the change in output factor, i.e. the change from total sales revenue to volume forwarded does not alter the direction of return to scale. This can be seen clearly from Table 1.

Firms number 5 and 11 remain clearly of increasing return to scale meaning that they should undoubtedly increase their scale efficiency via enlarging their inputs. The “irs” feature has vanished in case of firms 1 and 3 but it is evident that the direction

of scale has not changed: they represent constant returns to scale when investigating the tons handled. At the same time decreasing return to scale has emerged in case of all the other companies which are not efficient in the second examination. This indicates that there is scale inefficiency at this level due to too big input volume.

5 Inclusion of two outputs

As highlighted before, the setup of DEA in this investigation has been created in such a way that it enables the inclusion of the maximum number of inputs and outputs. According to the strictest thumb rules in literature this number could not be enlarged as there is a severe constraint on the size of our data set. There are some authors, however, who claim that these stringent requirements can be ignored and so a higher number of inputs and outputs can be included. Wu and Goh [18] for example argue that the number of DMUs should only be minimally two times as much as the sum of the number of inputs and outputs. Thus, keeping in mind the widely accepted way of carrying out data envelopment analysis, the authors decided to execute a further DEA in which the total number of inputs and outputs was 5 and the number of DMUs was 12. The aim with this further exercise was to see how the efficiency ranking would be influenced if both total sales revenue and tons handled were included in the examination. The outcome is summarized in Fig. 3, where the crosses indicate the results in question.



[source: own research]

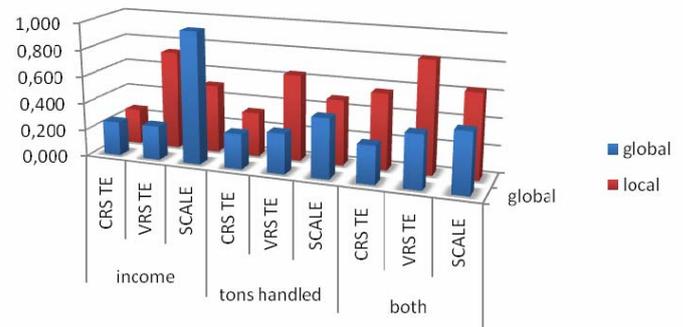
Fig. 3. Comparison of DEAs with 1 and 2 outputs

It is very interesting to note that in case of nearly all DMUs, the new efficiency ranking equals the highest efficiency ranking of the two previous tests. There is only one exception: DMU number 3, which performs equally low if the output considered is the total sales revenue or the tons handled, but if both of them are included in the investigation its efficiency rises above 0.8.

6 Comparison of local and global companies

The authors have also looked at the efficiency distribution from another point: the ownership of the companies. 8 out of the 12 companies investigated are locally owned firms whereas the rest are multinational enterprises present in the country. Fig. 4

shows the average CRS, VRS and scale efficiencies of the global and local companies, separately for the three test setups (1-2: where the only output is total sales revenue or tons handled respectively, and 3: where they are both included).



[source: own research]

Fig. 4. Efficiencies of globally and locally owned logistics centres

When the only output included is the total sales revenue, it is very interesting to see that the average CRS efficiency of the global and local firms do not differ significantly. When this is separated into VRS efficiency and scale efficiency, a very different picture emerges: global enterprises seem to be much more scale efficient (0.977) than their local counterparts (0.505) whose strength seems to lie in achieving pure technical efficiency (0.732). These dissimilarities are eliminated when the view is changed to the output of “tons handled”. When including both of the outputs into the examination, the results for the global firms show that relatively low VRS and scale efficiency values contribute to the low aggregate (CRS) efficiency. On the other hand, the CRS efficiency of the local companies is significantly higher than in the single output models (0.563 versus 0.263 and 0.328), and this is explained by the high VRS efficiency value (0.828). From these results it can be concluded that the efficiency of global firms present in the Hungarian market seems to originate from their scale efficiency, while pure technical efficiency is higher in case of their Hungarian counterparts.

7 Discussion

Before moving on to the conclusion there is one point which needs to be further discussed. When looking at the efficiency results in absolute values it is more than evident that there are some DMUs (2,4,8 and 9) whose efficiency is very low indeed and that does not change with the change in output. The reason behind this very weak performance is undoubtedly a point that needs to be further investigated in the further work of the authors. As for now, two facts could supposedly and partially explain these results. Without spelling out their names, it can be said of all the companies in question that they operate logistics centres with multiple base and are active not only in Hungary. Furthermore, it is also true that, as based on their subscribed capital, at least half of the firms concerned are partially owned by investors from abroad. These facts might explain why the

DEA setup with the structure outlined in the paper yielded those very low efficiency results. Nevertheless, this is surely a question which is to be further researched.

8 Conclusion

The authors have investigated the possibilities of applying data envelopment analysis for the efficiency appraisal of Hungarian logistics centres. Three DEA setups have been tested, all three utilized as input the surface size of offices, number of employees and surface of available storage space (excluding external storage facilities). The outputs have been changed during the course of the examination: in the first round it was the total sales revenue, in the second, the tons handled, and finally, in the third test, with methodological awareness, both of the outputs were included in the investigation. Results have shown which enterprises can be regarded efficient both from the financial and the technical perspective and which could improve their performances by a better translation of their operational achievements into financial results. The average efficiencies of globally and locally owned logistics centres were also examined. It has been found that although global companies show higher scale efficiencies, the VRS efficiency of local firms can be higher.

The efficiency investigation of Hungarian logistics centres could be continued by further research work by examining a larger sample with a smaller number of inputs and outputs and compare the outcomes with the present line of research. As this paper aimed to carry out a basic efficiency evaluation only, further work could also include the sensitivity analysis of the results with special attention to the inputs and outputs selected and omitted.

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