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ASSESSING THE LOGISTICS EFFICIENCY OF EUROPEAN COUNTRIES BY USING THE DEA-PC METHODOLOGY

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Abstract. Data envelopment analysis is a non-parametric linear programming method widely used for the efficiency evaluation of decision making units active in the transport sector. However, it is seldom applied for the efficiency assessment of logistics efficiency at a macro level. The article presents such an example which is at the same time the very first application of a lately developed methodology where data envelopment analysis is combined with analytic hierarchy process to yield an appropriate tool for efficiency evaluation with full ranking. The logistics efficiency of 29 European countries is tested with the new DEA-PC (pairwise comparison) methodology while it is also compared with the results gained with the original DEA method. Furthermore, the outcomes are also evaluated in light of the 'Logistics quality and competence' index of the Logistics Performance Indicator (LPI), a major international survey into the logistics competence of countries. Thus, the results of traditional DEA and DEA-PC are both weighted against survey data which is also a novelty in the logistics sector.

Keywords: DEA; AHP; DEA-PC; logistics; efficiency; performance.

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Introduction

Performance, effectiveness and efficiency are interrelated but, nonetheless, different notions. Performance is present if 'the aim of the organisations is to serve the consumers more effectively and efficiently than its rivals do' (Neely *et al.* 2004), whereas Kaplan and Atkinson (2003) determine three dimensions of performance: service, quality and cost; and then create key performance indicators according to these dimensions. These can help verify whether the performance reaches the expected standards. Meanwhile effective 'is applied to that which produces a definite effect or result' (Goldman, Sparks 1996), thus effectiveness captures how the outputs, that is the results, match the predetermined objectives (Tibenszkyné Fórika 2008). Finally, efficiency can be regarded as 'the ability to produce a desired effect, product, etc. with a minimum of effort, expense or waste' (Goldman, Sparks 1996). As it can be seen when characterising organizations, or even regions and countries, these interconnected terms can and may all be used for analysis.

Performance of logistics can be assessed by different means: by surveys (Fawcett, Cooper 1998; Briggs *et al.* 2010; Lai *et al.* 2004), by performance measurement systems and frameworks (Schmitz, Platts 2004; Saiz *et al.* 2010) extending to key performance indicators (Cai *et al.* 2009) and by the balanced scorecard approach (Bhagwat, Sharma 2007). At the same time, efficiency can also be evaluated by different approaches: indexes (e.g. total factor productivity (Graham 2008)), parametric approaches (e.g. stochastic frontier analysis (Cullinane *et al.* 2006)) and non-parametric approaches.

One of these non-parametric methods is Data Envelopment Analysis (DEA). It is non-parametric because it does not require *a priori* knowledge about the production function of the given decision making units. It can be an adequate complementary tool for evaluating efficiency from different aspects.

However, there are no direct applications to be found in the literature, which deals specifically with the DEA evaluation of countries' logistics performance. Something close is achieved by Jiang (2010) who inves-

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tigates the efficiency of the logistics network of 25 cities (and with the help of these, regions) employing DEA. The inputs characterize the level of economic development, the accessibility of transport, while the output is freight transport performance measured in tonne-kilometre realized on the different elements of the transport network. Jiang and Fu (2009) carry out the assessment of 31 regions in a similar manner, using 6 inputs and 2 outputs. These studies intend to evaluate the efficiency of logistics network infrastructure. Furthermore, the work of Baležentis and Baležentis (2011) has to be mentioned, that has evaluated the Lithuanian transport sector on a year-by-year basis, including passenger and freight transport, with the help of DEA and MULTIMOORA (Multi-Objective Optimization plus the Full Multiplicative Form). Outputs and inputs are the transport performances and the energy consumed. Nevertheless, none of these studies aims to reach full ranking.

This article presents the lately developed DEA-PC methodology specifically aimed at full ranking and shows how it can be applied to rank European countries as based on their logistics efficiency. The novelty of the paper lies not only in this line of research, where DEA is used for the efficiency evaluation of logistics at a macro level but it is also the first article to apply the DEA-PC methodology (pairwise comparison) developed by Fülöp and Markovits-Somogyi (2012) in practice.

1. The DEA-PC method

1.1. Background

DEA assigns the efficiency value of 1 to the efficient units whereas the less than efficient units get a value between 0 and 1. The method is not capable of fully ranking the Decision Making Units (DMUs) because it often happens that more than one DMU proves to be efficient. Several researchers have tried to tackle this problem and so a multitude of techniques have been introduced to make full ranking possible. Examples include the super-efficiency DEA model (Andersen, Petersen 1993), the utilization of cross-efficiency (Sexton *et al.* 1986; Doyle, Green 1994), creating common weights (Wang *et al.* 2011), introducing multivariate statistical analyses (Adler *et al.* 2002), the slack-adjusted DEA model (Bardhan *et al.* 1996) or the application of fuzzy logic (Wen, Li 2009).

Furthermore, multi-criteria decision making methods (e.g. Kovács, Bóna 2009) can also be combined with DEA to provide full ranking. Sinuany-Stern *et al.* (2000) integrate analytic hierarchy process (AHP) with DEA: the pairwise comparison matrix of AHP is created through the objective evaluation of pairs of DMUs by DEA.

Fülöp and Markovits-Somogyi (Fülöp, Markovits-Somogyi 2012) have found this latter method particularly inspiring and by changing the DEA/AHP structure, they have further developed this technique thus making it more adept for ranking and enabling it to dispose of a better distinctive power than the original DEA/AHP methodology. With numerical examples coming from the literature, it has been shown (Fülöp, Markovits-Somogyi 2012) how the modified version can better distinguish between the DMUs.

1.2. Methodology

Traditional data envelopment analysis means solving the linear programming problem summarized by Eq. 1 (the multiplier model), where $X_{ij} \geq 0$, $Y_{rj} \geq 0$ are the observed input/output values of DMU_0 (DMU to be evaluated); the number of DMUs is $j = 1, 2, ..., n$; the number of inputs: $i = 1, 2, ..., m$; the number of outputs: $r = 1, 2, ..., s$, while u_r, v_i are the weights determined by linear programming and ε is a non-Archimedean element defined to be smaller than any positive real number:

$$\max z = \sum_{r=1}^{s} u_r Y_{r0} , \tag{1}$$

subject to:

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 ;$$

$$\sum_{i=1}^{m} v_i X_{i0} = 1 ;$$

$$u_r, v_i \geq \varepsilon > 0 .$$

The DEA/AHP as developed by Sinuany-Stern *et al.* (2000) uses the idea of traditional DEA for the pairwise evaluation of the DMUs A and B by Eq. 2. whereby it creates an index number, $E_{AA,}$ which characterizes the relationship between the two DMUs:

$$E_{AA} = \max \sum_{r=1}^{s} u_r Y_{rA} , \tag{2}$$

subject to:

$$\sum_{i=1}^{m} v_i X_{iA} = 1 ;$$

$$\sum_{r=1}^{s} u_r Y_{rA} \leq 1 ;$$

$$\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0 ;$$

$$u_r \geq \varepsilon,\ r = 1, ..., s,\ v_i \geq \varepsilon,\ i = 1, ..., m.$$

Then, the best cross evaluation of unit B is also created by Eq. 3:

$$E_{BA} = \max \sum_{r=1}^{s} u_r Y_{rB} , \tag{3}$$

subject to:

$$\sum_{i=1}^{m} v_i X_{iB} = 1 ;$$

$$\sum_{r=1}^{s} u_r Y_{rB} \leq 1 ;$$

$$\sum_{r=1}^{s} u_r Y_{rA} - E_{AA} \sum_{i=1}^{m} v_i X_{iA} = 0 ;$$

$$u_r \geq \varepsilon,\ r = 1, ..., s,\ v_i \geq \varepsilon,\ i = 1, ..., m.$$

The pairwise comparison is carried out for each pair of DMUs and the resulting index numbers (E_{AA} and E_{BA}) are then used to create a reciprocal pairwise comparison matrix as based on the ratio a_{AB}, in Eq. 4:

$$a_{AB} = \frac{E_{AA} + E_{AB}}{E_{BB} + E_{BA}}, \qquad (4)$$

where: $a_{jj} = 1$.

Subsequently this matrix is utilized as the reciprocal pairwise comparison matrix of AHP. The eigenvector method is used to elicit weights from the matrix which then provides the full ranking of the DMUs.

The new method called DEA-PC (DEA – pairwise comparison) and developed by Fülöp and Markovits-Somogyi (2012) relies on the DEA/AHP technique of Sinuany-Stern *et al.* (2000) but introduces the following improvements. The relationship between the pairs of DMUs is characterized by the index $\hat{E}_{AA}$ shown in Eq. 5:

$$\hat{E}_{AA} = \max \sum_{r=1}^{s} u_r Y_{rA}, \qquad (5)$$

subject to:

$$\sum_{i=1}^{m} v_i X_{iA} = 1;$$

$$\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} = 0;$$

$u_r \geq 0$, $r = 1, ..., s$, $v_i \geq 0$, $i = 1, ..., m$.

The main difference between the two models (Eq. 2 and 5) is that the maximizing constraint regarding the sum of the product of weights and outputs is omitted. The reason behind this is the basic idea of the new model: the aim with the exclusion is to provide an opportunity for a full comparison between the two decision making units, without limiting the evolving score. If that constraint is left untouched, the resulting efficiency value will very frequently be the unity and thus real distinction is not achieved between the two DMUs.

A further minor remark concerns the inequality in the third constraint of Eq. 2, which changes to equality in Eq. 5. This can be explained by the following: should we leave the inequality in Eq. 5, we could always choose an $u_r' = \alpha u_r$ (α being a scalar) in the objective function which modifies the constraint in question to equality. As the latter is mathematically much easier to handle, we can continue to use the resulting equality without any problem.

Carried out for all pairs of DMUs, the efficiency evaluation with Eq. 5 is sufficient to characterize all pairwise relationships between the DMUs, since it is a $n \times n$ non-reciprocal matrix that can be built with the help of $\hat{E}_{AA}$. Thus, there is no need for cross-evaluation but the model included in Eq. 5 alone is capable of providing us with an index number characterizing all the relationships. Hence, $\hat{E}_{AA}$ calculated for all pairs of DMUs will deliver the pairwise comparison matrix from which the weights can be elicited in an AHP like manner to provide full ranking. Moreover, the resulting matrix will dispose of a much higher distinction rate than that created by the original DEA/AHP method. For further reference regarding the proof the reader is referred to (Fülöp, Markovits-Somogyi 2012).

Regarding eliciting weights from the pairwise comparison matrix it has to be emphasized that there are several methods that can be used for that. Examples include the eigenvector method, the logarithmic least square method and the weighted least square method. Inevitably, one cannot give a definite answer to the question of which of the techniques is the best. This question is argued but is undecided in the more general multiattribute decision making, too. However, tests on numerical examples carried out with the new method, DEA-PC show that the correlations between the resulting rankings are satisfyingly high. The application of the DEA-PC method presented below will rely, just as AHP (Duleba 2009), on the eigenvector method.

It also has to be noted that unlike in standard AHP, the resulting pairwise comparison matrix is not reciprocal. However, this does not construe a mathematical problem as most of the methods for eliciting ranking weights can be extended to the nonreciprocal case as well (Fülöp, Markovits-Somogyi 2012).

2. Ranking Logistics Efficiency of European Countries

The aim of the present subsection is to apply the new method for the logistics efficiency analysis of European Countries. It has to be noted, however, that the presented method is only one in the possible range of methods capable of providing efficiency assessment in this context. The article provides a preliminary analysis, in which just a limited number of inputs and outputs are presented. Data envelopment analysis is constrained by the fact that the sample size needs to be three times as big as the number of the sum of the inputs and outputs. Thus, with a given sample of approx. 30 countries, only a maximum of 9 to 10 inputs and outputs can be integrated in the assessment. Even though the authors would have liked to extend the analysis to include water transport or warehouse capacities, this was infeasible with the present sample size. Nevertheless, the above factors can provide very good options for the future extension of the investigations.

It was also the aim of the research to find a parallel evaluation with which the results of DEA- and DEA-PC analysis can be compared. Reviewing the available published surveys and methods, the Logistics Performance Index (LPI) and, within that, one of its components, 'Logistics quality and competence' was found as the indicator most adequate for carrying out such a comparison. LPI and this component of it does not analyse input-output ratios, but it ranks according to absolute indicators. Even though it is not focusing strictly on efficiency, it can be viewed as one of the components of performance.

2.1. Ranking Using the Traditional DEA Method

In order to be able to compare the results of the full ranking, a preliminary research was carried out with the same data using the original DEA CCR method – named after Charnes, Cooper and Rhodes (Charnes *et al.* 1978; Markovits-Somogyi 2011a). In order to circumvent the problem of lack of information on country level regarding the investment in the logistic field, three different input-output structures have been created (see Table 1). The source of data concerning inputs 1 to 5, and outputs 1 and 2 is the database of EuroStat (2011), while outputs 3 and 4 originate from the 2010 LPI survey (Arvis *et al.* 2010), all data originate from the year 2009. The main difference between the cases is the following: in cases *A* the investment (or the 'cost') of the logistics sector was not taken into account by any means, while in case *B*1 it was estimated by using inputs 4 and 5. Cases *A*1 and *A*2 are different, because *A*2 does not take into consideration the GDP per capita ratio (Markovits-Somogyi 2011a).

The resulting efficiency values can be seen in Fig. 1 (and for clarity they have been included numerically in Section I of Table A in the Appendix). The data have been ordered according to case *A*1 which investigation has methodically the most defendable input-output structure. Here, it can be seen that 6 countries have been found to be efficient (Bulgaria, Germany, Latvia, Poland, Romania and Turkey have an efficiency value of 1).

It is interesting to see that Luxembourg has been ranked as the last DMU in this case, and also in case *B*1 it did not get a very high ranking. These phenomena can be explained with the GDP value being included in the investigation. Countries with proportionally very high GDP are often ranked very low, and *vice versa*, countries with very low GDP values are ranked high, because with their high GDP it would be expectable that they perform that much better. This is exactly the virtue of DEA that it can reveal the pure efficiency where such differences are also considered. This is to be discussed further later on.

Then, case *A*2 has been presented to show the differences in ranking when the GDP value is excluded from the investigation. Finally, *B*1 shows the effect of the inclusion of further two input values: Wages and salaries in the transport and storage sector and Gross investment in tangible goods. It has to be mentioned that in the case of this investigation only the data of 25 DMUs were available, and so, this test only satisfies the more lax condition to be found in the literature regarding the number of required DMUs by a given number of inputs and outputs. Thus, its results are only included here as a curiosity. It can be seen that in *B*1 13 out of 25 DMUs are classified as efficient – this can also be attributed to the comparatively large number of inputs and outputs as related to the number of DMUs.

Table 1. Description of inputs and outputs in the different cases (Markovits-Somogyi 2011a)

Cases: *Inputs/Outputs*	*A*1	*A*2	*B*1
Inputs			
1. Length of motorways/1000 inhabitants	×	×	×
2. Length of railway network/1000 inhabitants	×	×	×
3. GDP per capita in Purchasing Power Standards	×		×
4. Wages and salaries in the transport and storage sector			×
5. Gross investment in tangible goods			×
Outputs			
1. Road transport performance (million tonne-kilometres)	×	×	×
2. Rail transport performance (million tonne-kilometres)	×	×	×
3. Quality	×	×	×
4. Timeliness	×	×	×

2.2. Ranking with the DEA-PC Methodology

The same input-output structures have been tested with the DEA-PC methodology as described in the previous section. The first numerical results (attached as Section II in Table A in the Appendix) drew the attention to a very interesting phenomenon: it has become obvious that Latvia is an outlier in the sample, as its efficiency value was exceedingly higher than that of the rest. Looking closer at the input-output data has soon revealed the reason for that: Latvia's highway network is exceedingly

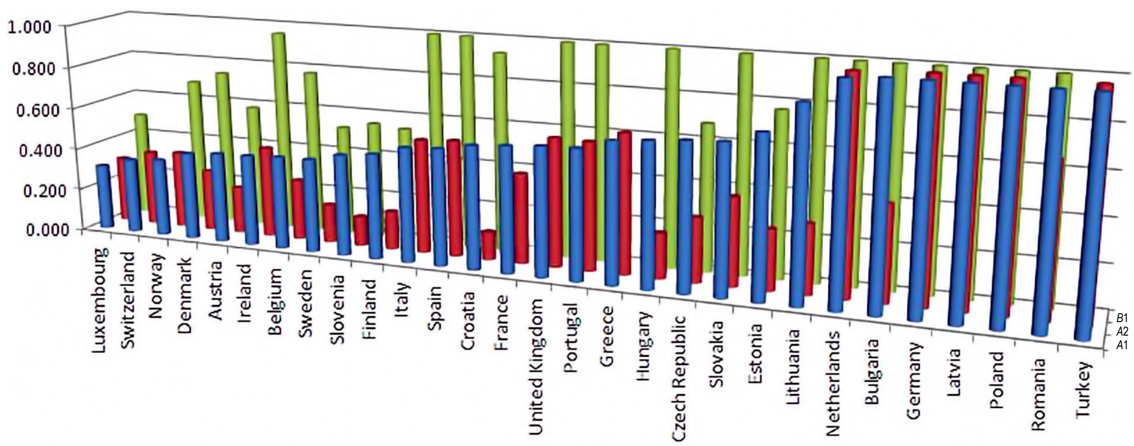

Fig. 1. Ranking with the original DEA method (Markovits-Somogyi 2011a)

short and this has led to its efficiency value being so large. It is the merit of the DEA-PC methodology that it has been able to point to this fact.

Subsequently new DEA runs have been carried out without the data of Latvia. Although the weights were dissimilar (see Fig. 2 here and Section III in Table A in the Appendix), the evolving rankings were not significantly different from the rankings gained in the DEA-PC including Latvia. The ranks showed a Spearman correlation of 0.973, 0.804 and 0.870 in cases *A*1, *A*2 and *B*1 respectively, all of which can be considered significant as based on (Zwillinger 2011).

It has to be emphasized that DEA-PC is not expected to yield the value of 1 for the most efficient unit. This is a full ranking procedure thus the results show weights which can discern all the units and create full ranking. Hence, the unit with the highest weight is automatically considered as the most efficient DMU.

Fig. 2 also shows the final full ranking: the data have been ordered according to the values of *A*1 which can be considered as the most viable test setup. Here again it can be seen that some countries with low GDP get high ranks. Also it is observable that all the countries have different ranking weights, thus DEA-PC can create full ranking. It is important to note that this order cannot directly be compared with the ranking created by DEA CCR in the first stage because there the outliers were not omitted. For this reason a further DEA CCR test has been carried out without the data of Latvia. Since *A1* was methodically the most viable case, only the results thereof are considered.

Fig. 3 presents the rankings with the DEA-PC and traditional DEA CCR method. The data have been ordered by the DEA-PC ranking. It should be noted that the diagram incorporates the absolute rankings and not the ranking weights, thus the smaller the number, the higher the ranking. The rankings correlate significantly, the Spearman correlation between them is 0.659 which is higher than the critical value of 0.484 required at a significance level of ρ = 0.01. Thus it can be stated that the full rank is satisfyingly reflecting the original order but it also has the advantage of being able to rank all the decision making units.

2.3. Conditions and Constraints of Application

There are certain conditions and constrains which have to be kept in mind when applying data envelopment analysis: outliers may influence the results and efficiency scores are relative to the study sample; thus, enlarging the sample might alter efficiency scores. These problems

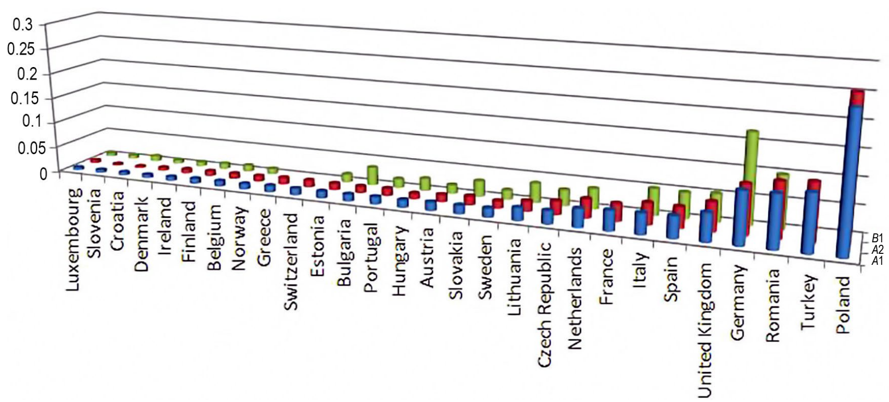

Fig. 2. Ranking weights in the DEA-PC method without the outlier Latvia (*source*: own research)

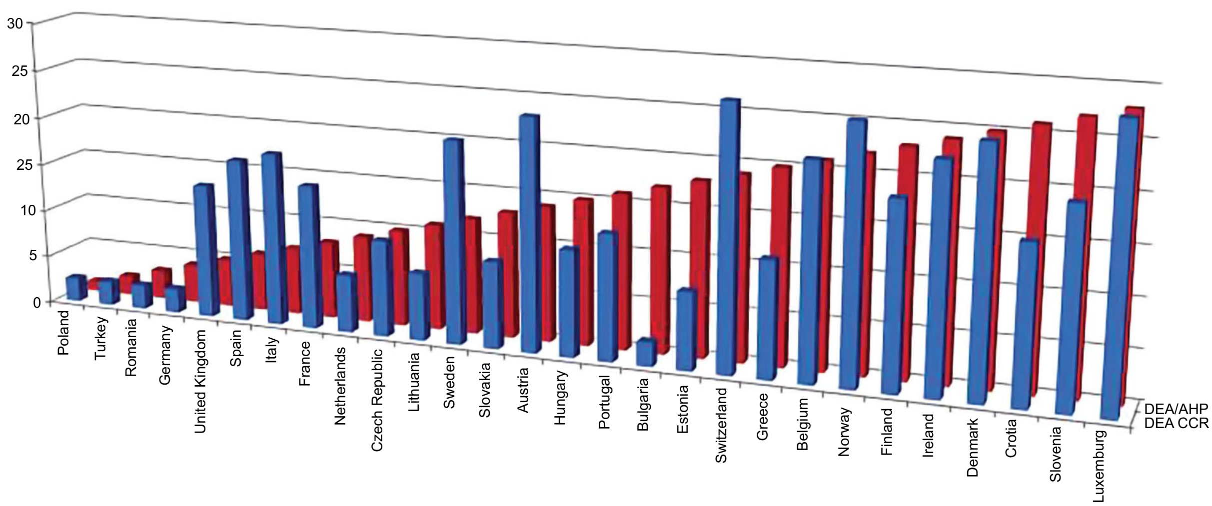

Fig. 3. Ranking orders with DEA-PC and DEA CCR method without the outlier (*source*: own research)

can be overcome by excluding the outliers by preliminary investigation, and second, by conducting sensitivity analyses. A further problem of the method is its sensibility to measurement errors and noise in data, if data are not of an objectively obtained nature; however, this can also be surmounted by joining statistical regression and DEA in a two-stage process (Markovits-Somogyi 2011b).

Concerning logistics efficiency specifically, the same limitations and constraints apply here as well. Thus, the resulting efficiency ranking can also be considered as a relative ranking only, evaluating solely the decision making units in the sample. Also, the conditions of application regarding the number of inputs and outputs are to be adhered to. This means that with a given sample size only a certain number of inputs and outputs may be analyzed by traditional DEA.

2.4. Comparison with an International Survey

The LPI is a set of indicators that measures, in the form of an international survey of the World Bank, the performance of the trade logistics environment of countries (Ojala 2011). It uses more than 5000 individual country assessments made by nearly 1000 international freight forwarders to compare the trade logistics profiles of 155 countries (Arvis *et al.* 2010). Thus it can be viewed as an objective indicator of the different countries' logistics performance. The country assessments are based on six pillars which measure how 'easy' or 'difficult' a country's trade logistics is seen from the outside. These six independently assesed indicators are the following:

- customs and other border procedures;
- transport and IT infrastructure and services;
- availability of affordable shipments;
- logistics competence and quality;
- tracking and tracing of shipments;
- timeliness of shipments.

Apart from the LPI, which is the international part of the survey, it also comprises a domestic one which evaluates the performance of the respondents' countries.

The significance of the LPI survey from the point of view of the present DEA and DEA-PC research is twofold.

First, with its indicators it provides important data regarding the quality of logistics performance: it enables the incorporation of quality aspects into data envelopment analysis. This is what has already happened in both the DEA and the DEA-PC investigation where 'Timeliness of shipments' from the international survey and 'Quality' from the domestic part have been used as output in the DEA and DEA-PC tests.

Second, it provides an even bigger opportunity by offering evaulative data in form of the fourth indicator called 'Logistics competence and quality'. It has to be noted that this indicator is independently assessed and neither of the input indicators metioned above have been utilized for the development of this measurement. Hence, it can be freely used as a benchmark against which the results of DEA and DEA-PC can be compared.

In its content 'Logistics quality and competence' is exactly what efficiency in logistics is about: it reflects the logistics performance of the different countries. Thus, the authors of the present paper find that it is viable to compare this ranking with the DEA and DEA-PC results (the scores themselves are presented in Table 2).

Therefore, in the following the ranking derived from the 'Logistics quality and competence' score of the LPI survey and the results of the traditional DEA and the DEA-PC in case *A*1 are compared with each other.

Table 3 shows the Spearman correlations of the different rankings for the preliminary investigations on 29 European countries, while Table 4 presents the correlations using the second DEA and DEA-PC run where the sample was considered without the outlier, Latvia, and the number of elements was $n = 28$.

To enable back checking, the critical values of complete independence in Spearman correlation are presented in Table 5.

First, it can be seen, as mentioned earlier, that with values 0.5324 and 0.6592, traditional DEA and DEA-PC correlate well in both cases which means that the two rankings are satisfyingly similar, as expected.

Table 2. Logistics quality and competence ranking scores of the selected countries in the international LPI survey (1 – lowest score, 5 – maximum score) (Arvis *et al.* 2010)

Countries	Logistics quality and competence
Belgium	4.13
Bulgaria	2.85
Czech Republic	3.27
Denmark	3.83
Germany	4.14
Estonia	3.17
Ireland	3.82
Greece	2.69
Spain	3.62
France	3.87
Italy	3.21
Latvia	2.96
Lithuania	2.85
Luxembourg	3.67
Hungary	2.87
Netherlands	4.15
Austria	3.7
Poland	3.26
Portugal	3.02
Romania	2.68
Slovenia	2.84
Slovakia	3.15
Finland	3.92
Sweden	4.22
United Kingdom	3.92
Norway	3.85
Switzerland	4.32
Croatia	2.53
Turkey	3.23

Table 3. Correlation between the rankings in case $A1$, considering all the countries in the sample (*source*: own research)

For all DMUs	Correlations
DEA – DEA-PC	0.5324
Log. qua. – DEA	–0.4099
Log. qua. – DEA-PC	0.0916
	$n = 29$

Table 4. Correlation between the rankings in case $A1$, without the outlier (*source*: own research)

Without outliers	Correlations
DEA – DEA-PC	0.6592
Log. qua. – DEA	–0.4704
Log. qua. – DEA-PC	0.04105
	$n = 28$

Table 5. The critical values of complete independence in Spearman's correlation (Zwillinger 2011)

n	$p = 0.90$	$p = 0.95$	$p = 0.99$
25	0.2646	0.3362	0.4654
30	0.2400	0.3059	0.4251

Then, comparing the rankings from the 'Logistics quality and competence' indicator and the traditional DEA investigation, an interesting phenomenon can be discovered. The correlations are negative and at a significance level of 0.05 they are in both cases significant. The test without the outlier is even significant at a 0.01 significance level. This means that the two rankings show opposite results. What can be the reason behind this behaviour?

The answer lies in the characteristics of data envelopment analysis itself. If countries are to be ranked along absolute values then the 'Logistics quality and competence' rank will be the adequate one to be considered. Here, the absolute competence of the country is reported without taking into account other, external circumstances. This is analogue to asking which animal is the strongest. Undoubtedly, the absolute answer would be the elephant. At the same time, if all circumstances are considered, the right answer would be the ant. This is how data envelopment analysis also takes into consideration all external factors and abilities and provides a ranking order by ensuring a level playing field for all decision making units. Here, countries with smaller possibilities are expected to perform less than countries with large GDPs which are expected to perform proportionally better. The negative correlation can also be explained by the fact that the 'Logistics quality and competence' rank correlates significantly with GDP (Spearman correlation 0.7670), while GDP is considered as an input in data envelopment analysis.

Finally, looking at the correlations between the 'Logistics quality and competence' rank and the DEA-PC rank, it can be stated that no correlation exists. This is due to the fact that DEA-PC is halfway between traditional DEA and absolute scoring, like in LPI. It takes factors like GDP into account but their influence is not omnipotent.

Conclusions

There are several different methods available for the purpose of efficiency and performance assessment. The present article, in a preliminary examination has adapted the non-parametric method DEA and DEA-PC to the field of logistics from a macroeconomic viewpoint; where it is rarely utilized even though its characteristics make it adequate for becoming one of the methods for efficiency evaluation.

First, by creating DEA-PC, it has been demonstrated that the original DEA/AHP developed by Sinuany-Stern *et al.* (2000) can be enhanced to make the resulting ranking weights more distinctive.

Then, the input-output structures for traditional DEA and DEA-PC have been introduced and they have been applied for 29 European countries. As based on the DEA-PC tests, it can be stated that the method can, and could also in this case, pinpoint the outlier in the sample. With this information in hand, new DEA and DEA-PC examinations were carried out. The DEA-PC method provided the full ranking which was the goal of the research.

The results have also been compared with the ranking originating from a major international survey and it has been shown that DEA and DEA-PC is capable of assessing one dimension of performance, efficiency. Thus, it can be viewed as a possible complementary method to other performance and efficiency measurement techniques.

Nevertheless, it has to be kept in mind that outliers may influence the results and that efficiency scores are relative to the study sample; thus, enlarging the sample might alter efficiency scores. Also it is to be noted that method is sensible to measurement errors and noise in data, if the data are of such nature. These problems have to be overcome by research planning and initial statistical analysis.

As based on the experience gathered during this research work, it can be stated that traditional data envelopment analysis and DEA-PC are both capable of assessing the logistics efficiency of regions and countries from a given technical-economic viewpoint, and including the necessary input-output factors, they can be applied in this field as well.

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APPENDIX

Table A. Numerical results (*source*: own research)

Countries	I. DEA CCR			II. DEA-PC			III. DEA-PC without outliers		
	*A*1	*A*2	*B*1	*A*1	*A*2	*B*1	*A*1	*A*2	*B*1
Belgium	0.437	0.286	0.775	0.00286	0.00285	0.00329	0.01049	0.01021	0.01193
Bulgaria	1.000	0.440	1.000	0.00142	0.00139	0.00435	0.01319	0.01271	0.03497
Czech Republic	0.678	0.299	0.681	0.0021	0.00209	0.0032	0.02506	0.02607	0.03071
Denmark	0.413	0.288	0.741	0.0014	0.00139	0.00161	0.00639	0.00626	0.00674
Germany	1.000	1.000	1.000	0.01835	0.01814	0.3304	0.09746	0.09322	0.1701
Estonia	0.739	0.280	0.767	0.00071	0.00061	0.00091	0.01305	0.01279	0.0157
Ireland	0.430	0.430	0.956	0.00137	0.00137	0.00158	0.00766	0.00799	0.00823
Greece	0.649	0.649	n/a	0.0048	0.00481	n/a	0.01262	0.01291	n/a
Spain	0.546	0.546	1.000	0.02835	0.02841	0.03245	0.0405	0.04009	0.0496
France	0.587	0.421	n/a	0.01041	0.01026	n/a	0.03834	0.03345	n/a
Italy	0.537	0.537	1.000	0.01898	0.01904	0.02182	0.03977	0.04113	0.05088
Latvia	1.000	1.000	1.000	0.78157	0.78245	0.79838	–	–	–
Lithuania	0.877	0.321	1.000	0.00191	0.00176	0.00256	0.02427	0.02004	0.03763
Luxembourg	0.311	0.311	0.497	0.00088	0.00088	0.00102	0.00524	0.00546	0.00565
Hungary	0.664	0.211	1.000	0.00207	0.00195	0.00437	0.01429	0.01071	0.02396
Netherlands	0.988	0.988	1.000	0.01907	0.01913	0.02176	0.03492	0.03586	0.03894
Austria	0.426	0.220	0.581	0.00173	0.00165	0.00197	0.01631	0.01394	0.01697
Poland	1.000	1.000	1.000	0.01594	0.01598	0.02643	0.25045	0.26386	0.24157
Portugal	0.603	0.596	1.000	0.006	0.006	0.00692	0.01421	0.01434	0.01729
Romania	1.000	0.688	1.000	0.00493	0.00479	0.00874	0.09823	0.10357	0.09884
Slovenia	0.475	0.139	0.552	0.00075	0.00066	0.00089	0.0056	0.0033	0.00677
Slovakia	0.686	0.407	1.000	0.00228	0.00227	0.00331	0.01644	0.01704	0.03064
Finland	0.493	0.180	0.539	0.00103	0.00101	0.00161	0.00985	0.00967	0.0104
Sweden	0.440	0.181	0.521	0.00143	0.00132	0.00195	0.01713	0.01392	0.01829
United Kingdom	0.599	0.599	1.000	0.01328	0.01333	0.01498	0.05288	0.05521	0.05295
Norway	0.366	0.366	0.686	0.00121	0.00122	0.00137	0.01049	0.01099	0.01044
Switzerland	0.354	0.354	n/a	0.00154	0.00154	n/a	0.01285	0.01337	n/a
Croatia	0.575	0.132	0.932	0.00062	0.00052	0.0015	0.00633	0.0035	0.01079
Turkey	1.000	1.000	n/a	0.05302	0.05319	n/a	0.10598	0.10842	n/a