



MEASURING EFFICIENCY IN TRANSPORT: THE STATE OF THE ART OF APPLYING DATA ENVELOPMENT ANALYSIS

Rita Markovits-Somogyi

*Dept of Transport Economics, Budapest University of Technology and Economics,
Bertalan L. u. 2., H-1111 Budapest, Hungary
E-mail: rsomogyi@kgazd.bme.hu*

Received 1 March 2010; accepted 10 January 2011

Abstract. Data Envelopment Analysis (DEA) is a non-parametric linear programming method used for determining the efficiency of a set of companies as compared to the best practice frontier. It can be employed to analyze private, public or non-profit organizations. The application of the method in the transport sector is wide-spread, especially in the evaluation of airports, ports, railways and urban transport companies. The present paper is aimed at giving a review of how DEA is applied in the transport sector with a special emphasis on the inputs and outputs selected in the DEA models employed in different fields. For this reason, the author has compiled data from 69 DEA applications found or reported in literature, investigated their characteristics and the field of applying them along with the inputs and outputs used.

Keywords: data envelopment analysis, transport, inputs, outputs, airports, ports, railways, public transport.

1. Introduction

Determining the efficiency of transport structures or companies has always been a challenging task due to the multitude of features that characterize these systems. Several approaches can be found in literature aspiring to solve this problem. Total Factor Productivity (TFP) (Oum, Yu 1995), the endogenous weight TFP method (Yoshida, Fujimoto 2004), the Malmquist Productivity Index (Odeck 2008), stochastic frontier analysis (Good *et al.* 1993) or even multiple linear regression (Pina, Torres 2001) are all good examples. The theoretical models and initial applications of transport efficiency analyses are available in the fields of cost, performance management (Bokor 2009), environmental pollution and energy consumption (Tánczos, Török 2007). This paper, however, deals with the application of Data Envelopment Analysis (DEA), a linear programming method of long standing which has been widely applied parallel to and also separately from these methods for the efficiency evaluation of companies involved in the transport sector.

The reason behind the choice is the strong theoretical background of the method that has proved its merits over the decades since it was introduced by (Farrel 1957) and (Charnes *et al.* 1978). This is also a method that has been used for the evaluation of several transport modes and thus makes a comparison between them feasible. The review of literature reveals that a comparison

of DEA application in different transport modes has not been carried out yet although the use of a broader perspective could contribute to raising the quality of individual studies.

The rest of the paper is structured as follows: Chapter 2 follows the introductory section and gives a brief overview of the DEA method highlighting its strengths and weaknesses and the main features of application; Chapter 3 contains the comparisons of 69 transport related DEA studies found in literature; Chapter 4 discusses the choice of inputs and outputs for different transport modes; Chapter 5 makes conclusions.

2. The DEA Approach

Data envelopment analysis (DEA) is a tool for evaluating the performance of different companies, organizations or even persons, i. e. decision making units (DMUs) that convert multiple inputs into multiple outputs. It is a method with a background in operational research supported by IT solutions (Tibenszkyne 2007) the strength of which, as compared to linear regression, lies in the fact that it does not relate the efficiency of these units to the average but to the best practice frontier created from the performance of the most efficient units. A further advantage is that it allows using multiple inputs and outputs and does not even require the conversion of these to the same dimension. Nor does it necessitate a priori

knowledge of a production function or information on prices, although a priori knowledge – if present – can be incorporated in the model.

However, the drawbacks of this method should not be forgotten either: it is true that outliers may influence the results and that efficiency scores are relative to the study sample; thus, enlarging the sample might alter efficiency scores. Both of these problems can be overcome: first, by excluding the outliers by preliminary investigation, and second, by conducting sensitivity analysis. The third problem of the method is its sensitivity to measurement errors and noise in data; however, this can also be easily surmounted by joining statistical regression and DEA in a two-stage process (Odeck 2008).

The basis of data envelopment analysis has been laid down by (Farrel 1957) who claimed a DMU technically efficient when no waste could be eliminated without worsening any input and output. It was his model that was further developed by (Charnes *et al.* 1978) to yield the CCR DEA model (named after the initials of the authors) which has been the starting point of each DEA study until the present day.

The CCR DEA model can be described as follows (Cooper *et al.* 2004): 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 relative efficiency DMU _{j} = DMU₀, DMU to be evaluated relative to the ratio of all $j = 1, 2, \dots, n$ DMU _{j} s.

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 (DMU to be evaluated).

We introduce the following constraints so as to give a limit to the values:

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

and $u_r, v_i \geq 0$.

Using the Charnes–Cooper transformation, this leads us to the following equivalent linear programming problem:

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

subject to

$$\sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0;$$

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

$$\mu_r, v_i \geq 0,$$

where: (u, v) change to (μ, v) as a result of the Charnes–Cooper transformation. The equivalent dual LP problem of (3) is:

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

subject to

$$\sum_{j=1}^n x_{i,j} \lambda_j \leq \theta x_{i0} \quad i=1, 2, \dots, m;$$

$$\sum_{j=1}^n y_{r,j} \lambda_j \geq y_{r0} \quad r=1, 2, \dots, s;$$

$$\lambda_j \geq 0 \quad j=1, 2, \dots, n.$$

This formula is also called the ‘Farrel model’ as it was created by Farrel. However, he did not apply the dual theorem of linear programming (by virtue of which $z^* = \theta^*$, and either problem can be solved) and hence was not able to make the connection between the models introduced above.

Formulae (4) is also called the ‘strong disposal’ or ‘weak efficiency’ model as it ignores non-zero slacks. Should we want to take them also into account, we have to use the following modified model that 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

$$\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = \theta x_{i0}, \quad i=1, 2, \dots, m;$$

$$\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{r0} \quad r=1, 2, \dots, s;$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \quad \forall i, j, r,$$

where: ε is a non-Archimedean element defined to be smaller than any positive real number. The dual linear program of this model, also known as the multiplier model, is:

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

subject to

$$\sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0;$$

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

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

Using these formulae, a DMU_0 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 (Cooper *et al.* 2004.). Formulae (5) and (6) represent the input-oriented DEA CCR models (envelopment and multiplier form). The output oriented model is also very similar and makes difference in the values to be maximized/minimized.

The DEA BCC (Banker *et al.* 1984) model incorporates an additional constraint:

$$\sum_{j=1}^n \lambda_j = 1, \tag{7}$$

which enables to take into account non-constant returns to scale. Certainly, the years since the introduction of DEA CCR have seen the advent of a wide variety in auxiliary methods and modifications to the original model, all altering the method from a different aspect so as to bring about further improvement. As these are not the main topic of this paper and there are space constraints, these cannot be discussed in our case, nevertheless, a short description of those especially present in the studies relating to transport can be found at the end of the next chapter.

3. Comparison of the DEA Studies Related to Transport

When reviewing found literature on the application of DEA, a very broad and colourful picture emerges. In this appraisal, 69 studies on the method have been gathered in order to enable the examination of data, supporting methods as well as the chosen inputs and outputs. These studies were elaborated either directly in the papers listed in the references, or were reported in the same articles (Azadeh *et al.* 2008; Barros 2008; Barros, Peypoch 2009; Bazargan, Vasigh 2003; Cullinane, Wang 2005; Hamdan, Rogers 2008; Jitsuzumi, Nakamura 2010; Karlaftis 2004; Martin, Román 2001; Odeck 2006; Pacheco, Fernandes 2003; Sampaio *et al.* 2008; Tongzon 2001; Wu, Goh 2010, etc.). We have to be aware that not always were all the data available to work with: sometimes the chosen inputs or outputs were not mentioned, or the reference to the place of application was missing. Nevertheless, for most of the studies the data needed were accessible, and surely, only the available information is included in this paper for further investigation.

Fig. 1 shows the distribution of the studies among different transport modes and clearly indicates that the majority of the studies deal with airports and ports; these two represent more than 50% of the studies. Public transport and railway companies also have a significant share while airlines are only mentioned in 4 studies.

When talking of public transport companies, we have to be aware that this is not a homogenous group. Urban just as well as rural companies, or the blend of the two have been investigated applying DEA; in some cases, these were companies operating buses only, whereas in other cases, there was a mix of fleet (bus, underground) present. However, this is not a factor which prevents us

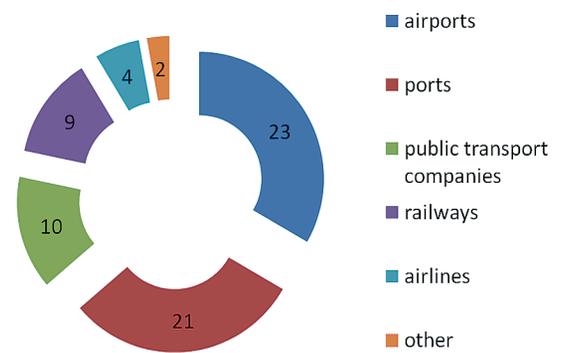


Fig. 1. The distribution of the studies found in literature (the number of studies) (source: own research)

from comparing these studies as the methodology and their chosen inputs/outputs were remarkably similar. Even the mixed fleet did not pose a problem for the application of DEA, since the ‘number of equivalent vehicles’ could homogenize the fleet from the point of view of the selected input.

Fig. 2 shows the distribution of DEA studies among different continents showing the share of different transport modes. It is evident that the most DEA applications can be found in Europe, Asia (the Near East and Japan having an important role) and North-America. Although it is not indicated in the figure, 11 out of 12 studies coming from North-America originate from the United States of America.

Looking at the share of different transport modes, we find that the majority of the studies in Europe deal with airports and public transport while in Asia port efficiency is investigated the most extensively. Although curiosity about railway efficiency is nearly evenly distributed between these two continents, it has a smaller share.

Fig. 3 presents the frequency of the number of DMUs in the samples of the investigated DEAs. Three outliers in the range above 70 have been excluded from the data so as to make graphical representation simpler. Nonetheless, these outliers also reveal an interesting phenomenon to be observed in choosing the number of DMUs. All three outliers (each with DMU number above 150) belong to the studies in the public transport area.

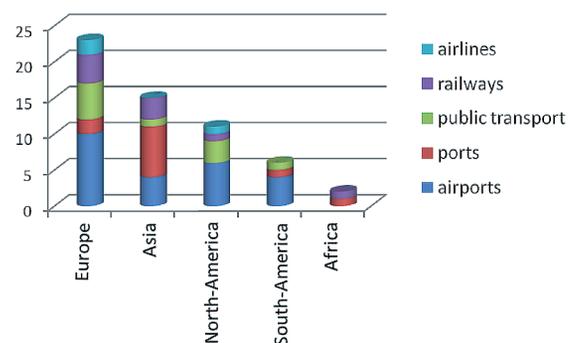


Fig. 2. The distribution of DEA applications among the continents according to the modes of transport (source: own research)

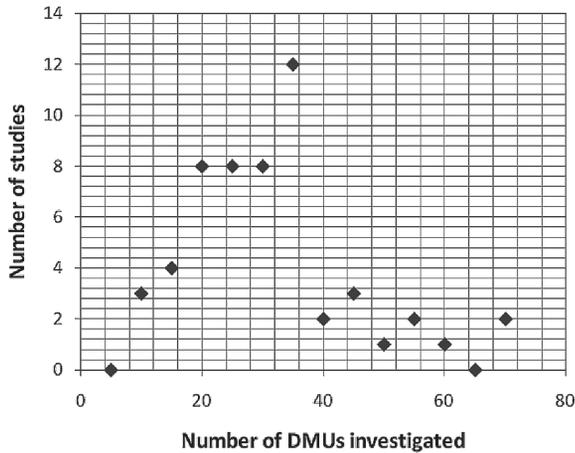


Fig. 3. The frequency of the number of investigated DMUs (source: own research)

This shows that the researchers of this mode of transport have a much larger provisional data set to choose from and are less limited by a lack of data.

Fig. 3 also indicates that the number of DMUs in DEA applications cluster around thirty (the average is 29.22), and the huge majority is between 15 and 40 (see descriptive statistics in Table). On the one hand, this can be explained by the data available (we shall remember that DMUs in the transport sector would for instance be airports, ports or railway companies) and on the other hand by the fact that there is a desired correlation between the number of inputs/outputs and the number of DMUs. As a thumb rule, the number of observations should be three times greater than the number of inputs plus outputs; and the number of DMUs should be equal or larger than the product of the number of inputs and outputs.

Table. Descriptive statistics of the number of DMUs

Average	29.22
Modus	19
Median	28
Deviation	13.79

Before proceeding to the analysis of the inputs and outputs used in the studies, we provide a short description of the modifications and supplementing methods of DEA that seem to be the most significant at present. The methods applied in DEA studies for investigation are first of all the input or output oriented DEA CCR and BCC methods, enabling the examination of technical efficiency and applying BCC, the variable returns to scale. From the review of the studies it seems that it is mainly output orientation that is preferred for the evaluation of airports and ports. This is rather reasonable as these dispose of facilities (e.g. runways, terminal buildings, terminal area of ports) which are difficult and/or very expensive to extend, and as such, most of the inputs chosen

for DEA would be hard to alter. For the evaluation of public transport organizations and railway companies, input orientation can also be a viable choice (and indeed it is observed among DEA studies) as they dispose of more inputs (e.g. the number of vehicles) that can be flexibly changed.

The calculation of allocative or overall efficiency next to technical efficiency can be observed in several DEA studies independently of transport mode.

The very important development of recent years is the Simar–Wilson method applied in more and more studies to bootstrap DEA scores with truncated regression and found to be more adequate in describing efficiency scores rather than Tobit or alternative bootstrap procedures (Barros, Dieke 2008). Barros and Dieke (2008), Von Hirschhausen and Cullmann (2010), Hung *et al.* (2010) clearly present the applied method.

The use of the super-efficient DEA model (also known as the A&P DEA model, named after the authors – Andersen, Petersen (1993)) is also gaining place as it enables to define a rank of all DMUs (we have to bear in mind that traditional DEA selects the most efficient units by allocating the efficiency score of 1 to all of them and does not fully rank them). For application, see for example (Adler, Berechman 2001).

Although not very widespread but very promising, the multi-activity network DEA (MNDEA) model is also worth to be mentioned, as a methodology that seems to be tailor-made for the evaluation of transport systems and makes it possible to separate transport efficiency from transport effectiveness. The former means the creation of transport opportunities (e.g. expressed by the number of seats available at a given flight) while the latter takes into account load factor (e.g. the number of seats sold). MNDEA enables us to investigate deeper connections between different parts of transport service. Yu and Lin (2008), and Yu (2008) apply MNDEA to the railway sector while Yu (2010) shows an example of applying it to the airports.

4. Comparison of the Inputs and Outputs Used

As already mentioned, the number of inputs and outputs chosen for DEA are quite restricted.

First, one has to adhere to the thumb rule which demands that the number of observations be three times the number of inputs plus outputs, and the number of DMUs be equal or larger than the product of the number of inputs and outputs. Given a dataset, sometimes the authors are forced to choose less inputs and/or outputs than desired. Then, there is also the tendency that the more inputs/outputs are included, the more DMUs prove to be efficient (Bunkoczi, Pitlik 2009).

Fig. 4 shows the frequency of the number of the studies opting for a given number of inputs, while Fig. 5 presents the same for outputs. It is clear that the number of inputs cluster around 3 and 4, whereas the number of outputs tends to be 1 or 2. This means that in most cases, 3 or 4 inputs are used (theoretically covering traditional labour, capital and energy inputs as highlighted in (Sharma, Yu 2010)) to produce 1 or 2 outputs. This coverage is

only theoretical as seen in the detailed analysis of inputs and outputs.

The same tendency is more or less valid when looking at the number of outputs distributed among transport modes (Fig. 6), although ‘airports’ show more even distribution. Regarding the number of inputs, both ‘airports’ and ‘ports’ show more even distribution (Fig. 7).

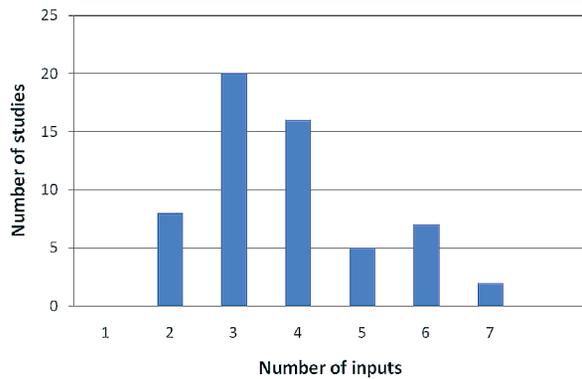


Fig. 4. The frequency of the number of the studies opting for a given number of inputs (source: own research)

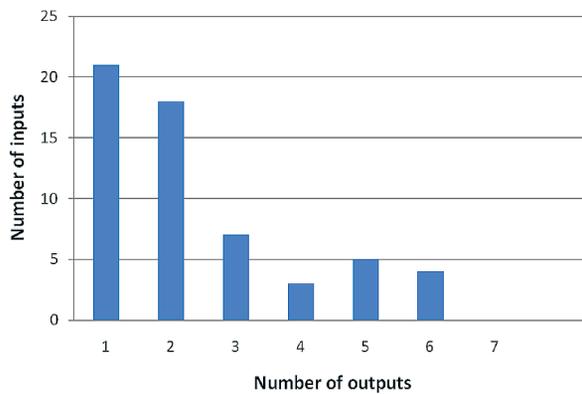


Fig. 5. The frequency of the number of the studies opting for a given number of outputs (source: own research)

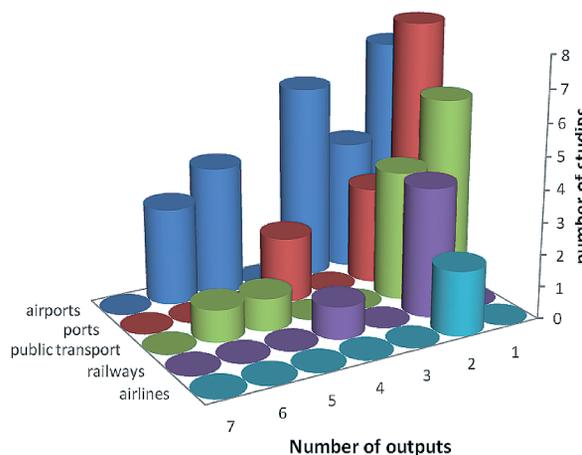


Fig. 6. The frequency of the number of the studies choosing a given number of outputs: distribution among different transport modes (source: own research)

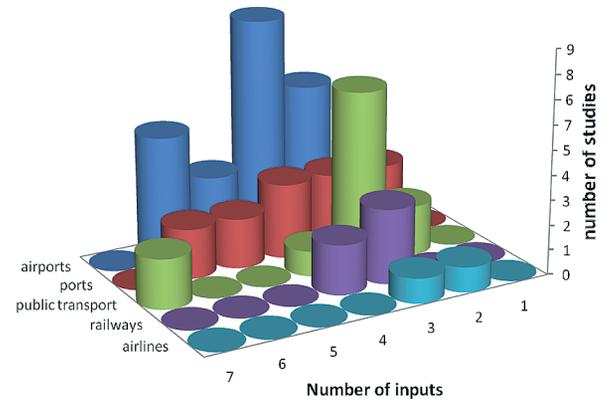


Fig. 7. The frequency of the number of the studies choosing a given number of inputs: distribution among different transport modes (source: own research)

Finally, let us examine inputs and outputs themselves. The appendix contains all the inputs and outputs gathered from the studies where they were selected for the evaluation of airports, ports, public transport companies, railways and airlines. It is not unexpected that the more studies are available for a given transport mode, the wider is the variety of the chosen inputs and outputs.

Labour (as the number of employees or the cost of labour) is input omnipresent in the studies and some sort of measurement unit is also nearly always vindicated for capital. However, energy consumption as input is only applied in the evaluation of public transport companies, although it could also be employed in the DEAs of airlines and railways.

A new category, ‘facilities’, has been introduced in the classification of inputs (even though it can be regarded as a part of ‘capital’ inputs) because the factors listed here seem to constitute a vital and integral part of inputs, especially for airports and ports. However, it is mildly surprising that there was only one study that employed more technical inputs like a ‘dummy z variable for slot coordinated airports’ and a ‘dummy z variable for time restrictions’ (Pels *et al.* 2003), although technical facilities at an airport (e.g. availability of ILS) or the level of air traffic control can significantly contribute to the results of an airport.

Regarding outputs, they could be ordered into two main categories: operational and fiscal outputs. Operational outputs are the measurement units created from the physical movement of vehicles or passengers and cargo while fiscal outputs are the ones that can be expressed in some monetary unit. The listings in the appendix also indicate that generally the number of inputs is higher and maximum one or two outputs are chosen for DEA study.

5. Conclusions

The examination of the studies dealing with DEA has revealed that data envelopment analysis is widely applied for the evaluation of companies in the transport sector. The biggest majority of DEA studies cover air-

ports, ports, public transport companies and railways, using principally the DEA BCC and/or CCR method. The number of DMUs investigated in the studies cluster around 29 with a deviation of nearly 14. The applied inputs are predominantly chosen from the areas of labour and capital (including 'facilities') and there are 3 or 4 of them. The number of outputs is mostly 1 or 2 and the outputs usually describe operational and/or fiscal characteristics. An extensive number of studies and a huge variety in the nuances of application show that DEA can be successfully employed for the assessment of decision making units in the transport sector.

Acknowledgement

This work is connected to the scientific program of 'The Development of Quality-Oriented and Harmonized R+D+I Strategy and Functional Model at BME' and the project 'Modelling and Multi-Objective Optimization Based Control of Road Traffic Flow Considering Social and Economical Aspects'. These projects are supported by the New Hungary Development Plan (Project ID: TÁMOP-4.2.1/B-09/1/KMR-2010-0002) and by the program CNK 78168 of OTKA.

References

- Adler, N.; Berechman, J. 2001. Measuring airport quality from the airlines' viewpoint: an application of data envelopment analysis, *Transport Policy* 8(3): 171–181. doi:10.1016/S0967-070X(01)00011-7
- Andersen, P.; Petersen, N. C. 1993. A procedure for ranking efficient units in data envelopment analysis, *Management Science* 39(10): 1261–1264. doi:10.1287/mnsc.39.10.1261
- Azadeh, A.; Ghaderi, S. F.; Izadbakhsh, H. 2008. Integration of DEA and AHP with computer simulation for railways system improvement and optimization, *Applied Mathematics and Computation* 195(2): 775–785. doi:10.1016/j.amc.2007.05.023
- Banker, R. D.; Charnes, A.; Cooper, W. W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science* 30(9): 1078–1092. doi:10.1287/mnsc.30.9.1078
- Barros, C. P. 2008. Airports in Argentina: Technical efficiency in the context of an economic crisis, *Journal of Air Transport Management* 14(6): 315–319. doi:10.1016/j.jairtraman.2008.08.005
- Barros, C. P.; Dieke, P. U. C. 2008. Measuring the economic efficiency of airports: a Simar–Wilson methodology analysis, *Transportation Research Part E: Logistics and Transportation Review* 44(6): 1039–1051. doi:10.1016/j.tre.2008.01.001
- Barros, C. P.; Peypoch, N. 2009. An evaluation of European airlines' operational performance, *International Journal of Production Economics* 122(2): 525–533. doi:10.1016/j.ijpe.2009.04.016
- Bazargan, M.; Vasigh, B. 2003. Size versus efficiency: a case study of US commercial airports, *Journal of Air Transport Management* 9(3): 187–193. doi:10.1016/S0969-6997(02)00084-4
- Bokor, Z. 2009. Elaborating Cost and Performance Management Methods in Transport, *Promet – Traffic & Transportation* 21(3): 217–224.
- Bunkoczi, L.; Pitlik, L. 1999. A DEA módszer felhasználási lehetőségei üzemhatékonyság méréséhez [Possibilities of applying the DEA method for the measurement of factory efficiency], in *Proceedings of National Conference 'Agrárinformatika'* [Agriculture informatics], Debrecen, 313–328 (in Hungarian).
- Charnes, A.; Cooper, W. W.; Rhodes, E. 1978. Measuring the efficiency of decision making units, *European Journal of Operational Research* 2(6): 429–444. doi:10.1016/0377-2217(78)90138-8
- Cooper, W. W.; Seiford, L. M.; Zhu, J. 2004. *Handbook on Data Envelopment Analysis*. 1st edition. Springer. 608 p.
- Cullinane, K.; Ji, P.; Wang, T.-F. 2005. The relationship between privatization and DEA estimates of efficiency in the container port industry, *Journal of Economics and Business* 57(5): 433–462. doi:10.1016/j.jeconbus.2005.02.007
- Farrel, M. J. 1957. The measurement of productive efficiency, *Journal of Royal Statistical Society. Series A (General)* 120(3): 253–290. doi:10.2307/2343100
- Good, D. H.; Nadiri, M. I.; Röller, L.-H.; Sickles, R. C. 1993. Efficiency and productivity growth comparisons of European and U.S. air carriers: a first look at the data, *Journal of Productivity Analysis* 4(1–2): 115–125. doi:10.1007/BF01073469
- Hamdan, A.; Rogers, K. J. 2008. Evaluating the efficiency of 3PL logistics operations, *International Journal of Production Economics* 113(1): 235–244. doi:10.1016/j.ijpe.2007.05.019
- Hung, S.-W.; Lu, W.-M.; Wang, T.-P. 2010. Benchmarking the operating efficiency of Asia container ports, *European Journal of Operational Research* 203(3): 706–713. doi:10.1016/j.ejor.2009.09.005
- Jitsuzumi, T.; Nakamura, A. 2010. Causes of inefficiency in Japanese railways: application of DEA for managers and policymakers, *Socio-Economic Planning Sciences* 44(3): 161–173. doi:10.1016/j.seps.2009.12.002
- Karlaftis, M. G. 2004. A DEA approach for evaluating the efficiency and effectiveness of urban transit systems, *European Journal of Operational Research* 152(2): 354–364. doi:10.1016/S0377-2217(03)00029-8
- Martin, J. C.; Román, C. 2001. An application of DEA to measure the efficiency of Spanish airports prior to privatization, *Journal of Air Transport Management* 7(3): 149–157. doi:10.1016/S0969-6997(00)00044-2
- Odeck, J. 2006. Congestion, ownership, region of operation, and scale: their impact on bus operator performance in Norway, *Socio-Economic Planning Sciences* 40(1): 52–69. doi:10.1016/j.seps.2004.05.001
- Odeck, J. 2008. How efficient and productive are road toll companies? Evidence from Norway, *Transport Policy* 15(4): 232–241. doi:10.1016/j.tranpol.2008.05.002
- Oum, T. H.; Yu, C. 1995. A productivity comparison of the world's major airlines, *Journal of Air Transport Management* 2(3–4): 181–195. doi:10.1016/0969-6997(96)00007-5
- Pacheco, R. R.; Fernandes, E. 2003. Managerial efficiency of Brazilian airports, *Transportation Research Part A: Policy and Practice* 37(8): 667–680. doi:10.1016/S0965-8564(03)00013-2
- Pels, E.; Nijkamp, P.; Rietveld, P. 2003. Inefficiencies and scale economies of European airport operations, *Transportation Research Part E: Logistics and Transportation Review* 39(5): 341–361. doi:10.1016/S1366-5545(03)00016-4
- Pina, V.; Torres, L. 2001. Analysis of the efficiency of local government services delivery. An application to urban public

- transport, *Transportation Research Part A: Policy and Practice* 35(10): 929–944. doi:10.1016/S0965-8564(00)00033-1
- Sampaio, B. R.; Neto, O.L.; Sampaio, Y. 2008. Efficiency analysis of public transport systems: lessons for institutional planning, *Transportation Research Part A: Policy and Practice* 42(3): 445–454. doi:10.1016/j.tra.2008.01.006
- Sharma M. J.; Yu S. J. 2010. Benchmark optimization and attribute identification for improvement of container terminals, *European Journal of Operational Research* 201(2): 568–580. doi:10.1016/j.ejor.2009.03.021
- Tánczos, K.; Török, A. 2007. The linkage between climate change and energy consumption of Hungary in the road transportation sector, *Transport* 22(2): 134–138.
- Tibenszkyne, F. K. 2007. Az oktatás hatékonyságának mérése a ZMNE 2006-ban végzett hallgatóin a DEA módszer segítségével [Measuring the efficiency of education applying the DEA method to the data of students graduated at ZMNE in 2006], *Hadmérnök* [Military Engineering] 2: 149–165 (in Hungarian).
- Tongzon, J. 2001. Efficiency measurements of selected Australian and other international ports using data envelopment analysis, *Transportation Research Part A: Policy and Practice* 35(2): 107–122. doi:10.1016/S0965-8564(99)00049-X
- Von Hirschhausen, C.; Cullmann, A. 2010. A nonparametric efficiency analysis of German public transport companies, *Transportation Research Part E: Logistics and Transportation Review* 46(3): 436–445. doi:10.1016/j.tre.2009.11.005
- Yoshida, Y.; Fujimoto, H. 2004. Japanese-airport benchmarking with the DEA and endogenous-weight TFP methods: testing the criticism of overinvestment in Japanese regional airports, *Transportation Research Part E: Logistics and Transportation Review* 40(6): 533–546. doi:10.1016/j.tre.2004.08.003
- Yu, M.-M. 2008. Assessing the technical efficiency, service effectiveness, and technical effectiveness of the world's railways through NDEA analysis, *Transportation Research Part A: Policy and Practice* 42(10): 1283–1294. doi:10.1016/j.tra.2008.03.014
- Yu, M.-M. 2010. Assessment of airport performance using the SBM-NDEA model, *Omega* 38(6): 440–452. doi:10.1016/j.omega.2009.11.003
- Yu, M.-M.; Lin E.T.J. 2008. Efficiency and effectiveness in railway performance using a multi-activity network DEA model, *Omega* 36(6): 1005–1017. doi:10.1016/j.omega.2007.06.003
- Wu, Y.-C. J.; Goh, M. 2010. Container port efficiency in emerging and more advanced markets, *Transportation Research Part E: Logistics and Transportation Review* 46(6): 1030–1042. doi:10.1016/j.tre.2010.01.002

APPENDIX: THE SELECTED INPUTS AND OUTPUTS IN CASE OF DIFFERENT TRANSPORT MODES

Airports		Ports	
Inputs	Outputs	Inputs	Outputs
<p>Labour</p> <ul style="list-style-type: none"> - labour expenditures / price of labour / payroll - number of employees <p>Capital</p> <ul style="list-style-type: none"> - capital input / capital invested / accumulated capital stock / capital (proxied by the book value of physical assets) - price of capital - intermediate expenses - other input – the residual of total operating costs (excluding capital input) - operating expenses / operational costs - non-operating expenses - capital expenditures - materials expenditures - Facilities - number of runways - length of runway(s) - size of the runway area - number of passenger terminals - size of the airport ramp area - size of a passenger terminal area / size of the airport area / airport surface area - size of the apron area - number of check-in desks - size of departure lounge - number of gates - number of aircraft parking positions at the terminal - number of remote aircraft parking positions - number of baggage collection belts - number of baggage claim units - size of the baggage claim area - number of public parking spaces - curb frontage <p>Expenditures not to be paid by the airport</p> <ul style="list-style-type: none"> - airport charge - access cost <p>Operation</p> <ul style="list-style-type: none"> - dummy z variable for slot coordinated airports - dummy z variable for time restrictions <p>Other</p> <ul style="list-style-type: none"> - minimum connecting times - distance to the nearest city centre 	<p>Operational</p> <ul style="list-style-type: none"> - number of planes / aircraft movement - number of passengers / passenger loading / commuter movement - amount of cargo/ freight (pounds, tons) handled - amount of mail cargo handled - general aviation / number of other operations - percentage of on time operations <p>Fiscal</p> <ul style="list-style-type: none"> - turnover - operating revenues - aeronautical revenues / aeronautical sales - non-aeronautical revenues / commercial sales - other revenues - sales to planes - sales to passengers <p>Other</p> <ul style="list-style-type: none"> - handling receipts - summed variables (specific to the given methodology) 	<p>Labour</p> <ul style="list-style-type: none"> - number of port authority employees (proxied by the number of stevedoring labour) - number of container terminal workers - labour expenditure <p>Capital</p> <ul style="list-style-type: none"> - depreciation charges - other expenditures <p>Facilities</p> <ul style="list-style-type: none"> - number of berths - total length of the berth / container berth length - number of cranes - number of tugs - number of quayside gantries - number of quay cranes - number of transfer cranes - number of yard gantries - ship-shore container gantry cranes - number of reach stackers - number of straddle carriers - terminal area of ports - total length of the terminal - total quay length 	<p>Operational</p> <ul style="list-style-type: none"> - container throughput (number of containers handled) - total cargo handled (tons) - ship working rate - number of ships - ship calls <p>Fiscal</p> <ul style="list-style-type: none"> - revenue obtained from rental of port facilities <p>Other</p> <ul style="list-style-type: none"> - service level - user satisfaction
Public transport companies			
		Inputs	Outputs
		<p>Labour</p> <ul style="list-style-type: none"> - labour hours (transport, maintenance, administration) - total number of employees - total labour costs - Capital - cost/km - cost/traveller - subsidy/traveller - operational costs - services cost systems - utilities costs - insurance costs - personnel costs - fuel costs - other variable costs - number of buses / total number of vehicles operated / number of equivalent vehicles - number of buses operated (under 35 seats, above 35 seats) - total number of seats - equipment <p>Energy</p> <ul style="list-style-type: none"> - fuel/100 km - fleet gallons/fuel - amount of fuel consumed <p>Other</p> <ul style="list-style-type: none"> - km of route - directional miles - effective driving hours - average speed - average fleet age - population density - input density index 	<p>Operational</p> <ul style="list-style-type: none"> - passenger trips / number of passengers transported - passenger-km - seat km - bus km / vehicle-miles / km year/bus - total annual vehicle miles - total annual ridership - km/employee - km year/inhabitant - km of the route served by the company - average speed of the buses - load coefficient (passenger-km over number of places available-km and population density) - 1/accident rate - 1/accident frequency <p>Fiscal</p> <ul style="list-style-type: none"> - total service and companies gross revenue - operating revenue (as a proxy when passenger-km not available)

Railways	
Inputs	Outputs
Labour - number of employees Facilities - length of lines - number of passenger cars - number of freight cars - number of train cars and electric multiple units Capital - fix assets - operating expenditure	Operational - passenger-train-kms - freight-train-kms - passenger-kms - ton-kms - passenger trips - train-car-kms Fiscal - externality (relative annual growth rate per capita taxable income)
Airlines	
Inputs	Outputs
Labour - number of employees - flight operation staff Facilities - number of an aircraft Capital - operational costs - residual expenditure	Operational - passenger-ton-kms - freight-ton-kms Fiscal - operational revenue by passenger-km - earnings before interests and taxes