

# 1           **Non-metric Data - A Note on a Neglected Problem in DEA Studies**

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5           Data Envelopment Analysis (DEA) is widely used to compare the empirical performance of public  
6           institutions such as law enforcement agencies, judicial authorities or national health care systems.  
7           Many DEA analysts, however, ignore the fact that DEA efficiency values are non-metric. They  
8           consequently do not hesitate to compute (arithmetic) means. They do not hesitate either to treat  
9           DEA values as metric data in econometric analyses. Instead of providing useful insights into the  
10          performance of public bodies, the confusion of non-metric data with metric data constitutes a  
11          lack of internal validity that may cause serious fallacies. Against this background, we believe that a  
12          clear warning against an uncritical processing and interpretation of DEA values is pertinent and  
13          should be routinely considered by efficiency analysts as well as referees of efficiency papers.

14          *Not everything that can be counted [or computed] counts and not everything that counts can be*  
15          *counted (attributed to Albert Einstein).*

16          **Keywords** Data envelopment analysis; Scales of measurement; Non-metric character of technical  
17          efficiency values

18          **JEL Classification** C02, C61, H00, K00

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## 20          **Background of efficiency analysis**

21          A major goal of law and economics scholars is to improve the management and the perform-  
22          ance of public institutions such as law enforcement agencies, judicial authorities or national  
23          health care systems. This applies to input decisions and process management as well as to the  
24          adaptation of services towards outcomes that are socially desired. The attempt to contribute to  
25          an improved performance of public bodies has prompted researchers to search for “learning  
26          opportunities” by means of comparative analysis and benchmarking.

27          While private sector firms usually evaluate their performance on the basis of profitability in-  
28          dicators, economic criteria reach their limits when outputs and/or inputs cannot be mapped  
29          into monetary units. This is frequently the case in the public sector. Accounting for the mone-  
30          tization problem, technical efficiency analyses such as DEA have been widely used to extract  
31          information from data sets that provide quantitative but non-monetary information on the re-

32 sources that are used and the services that are provided by public bodies (cf., e.g., CHARNES et  
33 al. 1978; CHARNES et al. 1981; CHARNES et al. 1985; SCHNEIDER 2005; KOCHER et al. 2006;  
34 for an overview of DEA studies see Emrouznejad et al. 2008).

35 Besides its general meaning in economic theory, the term “efficiency analysis” has become  
36 known as a label attached to a specific class of mathematical procedures that are employed for  
37 the comparative analysis of the productivity of decision-making units in a sample. Efficiency  
38 analysis procedures identify benchmarks units which feature minimum input-output ratios that  
39 are understood as forming an empirical production function (frontier) relative to which the  
40 position of each decision-making unit is determined. Whilst the quality of the allocation deci-  
41 sion cannot be assessed as long as the values (“prices”) of outputs and inputs are not known, it  
42 is possible to identify – on this “lowest level of decision-making” (RAY 2004: 14) – at least  
43 those units that are inefficient in that they use too much input for a given output (avoidable  
44 input waste) or produce too little output for a given input (unrealized output potential).

45 In his textbook on DEA, RAY (2004: 5) issues the following warning: “At present, an over-  
46 whelming majority of practitioners remain content with merely feeding the data into the spe-  
47 cialized DEA packages without much thought about whether the LP model solved is really  
48 appropriate for the problem under investigation.” Ray’s warning refers to external validity. He  
49 emphasizes the need to check models regarding their capacity to answer the research question  
50 under consideration. An exemplary challenge would be the question whether using the num-  
51 ber of completed court cases as an output measure contributes to our understanding of the  
52 relative performance of courts in producing justice; it does so only if we can plausibly assume  
53 that there is little variability both in the complexity of cases and the quality of court decisions.

54 While representing a crucial issue, external validity is not our concern in this note. Instead, we  
55 look at a more fundamental problem which arises if the fact is ignored that efficiency values  
56 derived from DEA do *not* provide metric information with regard to “substantive” ineffi-  
57 ciency, i.e., the avoidable input waste or the unrealized output potential. Confusing non-  
58 metric data with metric data jeopardizes internal validity and may reduce the value of a study  
59 to less than nothing from the very start of the analysis. It is nonetheless a widespread flaw.  
60 We thence believe that an exposition of the level of measurement and a clear warning against  
61 an uncritical processing and interpretation of DEA efficiency values is pertinent. In the inter-

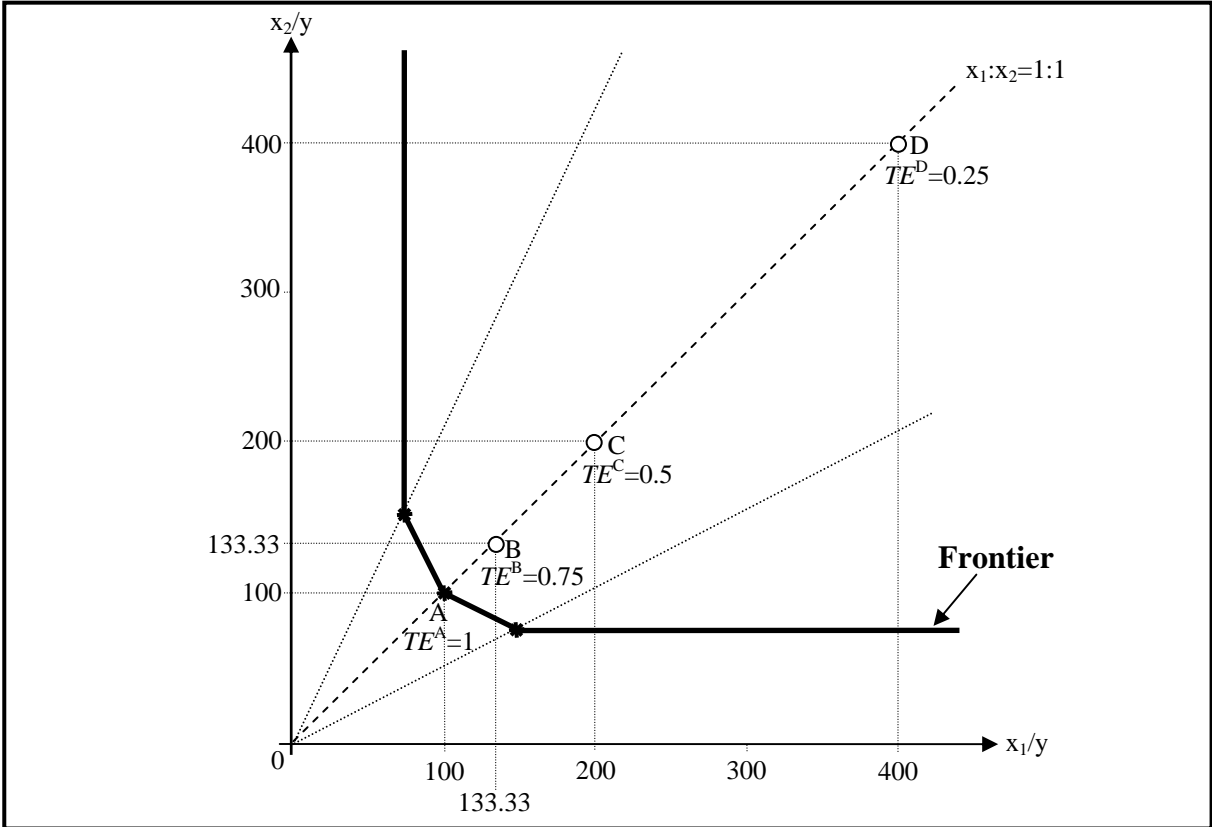
62 est of providing easy intuition how and why DEA values are non-metric, the exposition fo-  
 63 cuses on a stylized input-oriented DEA model. The non-metric measurement level of DEA  
 64 values, however, is a feature caused by its specific geometric design. It is thus shared by all its  
 65 variants including output-oriented DEA, overall (cost or revenue) efficiency, Malmquist in-  
 66 dex, super efficiency, and stochastic DEA estimators.

67 **DEA revisited**

68 DEA estimates a non-parametric frontier as an “envelope” of the input-output combinations that  
 69 are observed in the examined sample of decision-making units. At the same time, efficiency  
 70 measures are calculated based on the geometric distance between the input-output combination  
 71 of the respective unit and the frontier (cf. FARRELL 1957). DEA transforms partial productivities  
 72 into a *single* radial efficiency measure (ROSENBERG 1991). For this purpose, a linear program is  
 73 solved for each of the examined units (cf. COELLI et al. 1998: 133ff.; RAY 2004: 28ff.).

74 Figure 1 refers to an input-oriented DEA model for two inputs  $x_1$  and  $x_2$  and a single output  $y$ .  
 75 The frontier is formed by linear segments produced by piecewise linear combinations of the  
 76 empirically observed minimum input-output ratios (here: the three units represented by bold  
 77 points). Inefficient units above the frontier are represented by simple points.

78 **Figure 1: Technical efficiency values in the 2-input/single-output case**



79

80 Units on identical rays share an equi-proportionate mix of inputs. Figure 1 focuses on units B,  
 81 C, and D which all have a ratio of 1:1 between input  $x_1$  and  $x_2$ . Unit A, which has the same  
 82 input ratio, exhibits the minimum input-output ratio. It is thence the benchmark for the in-  
 83 creasingly less efficient units B, C, and D. Let us look at unit B to understand the DEA calcu-  
 84 lus. The so-called “technical efficiency” of B is a radial measure which corresponds graphi-  
 85 cally to the ratio of the distances  $\overline{0A}$  and  $\overline{0B}$  (cf. COELLI et al. 1998: 52). The technical effi-  
 86 ciency values of units A, C, and D are calculated correspondingly (cf. Table 1).

87 **Table 1: The non-metric character of “technical efficiency” values**

Unit	A	B	C	D
<i>TE</i>	$\overline{0A}/\overline{0A} = 1.00$	$\overline{0A}/\overline{0B} = 0.75$	$\overline{0A}/\overline{0C} = 0.50$	$\overline{0A}/\overline{0D} = 0.25$
Input 1	100	133.33	200	400
Waste 1	-	33.33	100	300
Input 2	100	133.33	200	400
Waste 2	-	33.33	100	300
Output	1	1	1	1

88

89 **What DEA users should consider**

90 Table 1 illustrates the efficiency assessment provided by DEA. To those interested in the  
 91 “true” efficiency of decision-making units within a sample, the question of interest is how  
 92 much avoidable input waste these units have. According to the DEA calculus, the decrease in  
 93 efficiency is a constant 0.25 from unit to unit. These equal differences, however, correspond  
 94 to input wastes that increase from 33.33 in the case of B, to 100 in the case of C, and to 300 in  
 95 the case of D. This is due to the fact that the DEA calculus changes its point of reference (de-  
 96 nominator) from unit to unit. Consequently, DEA values are non-metric data and differences  
 97 between them are not meaningful with regard to substantive efficiency. That is, an equal dis-  
 98 tance between DEA values must not be interpreted as an equal distance with regard to the in-  
 99 efficient resource use (i.e., the avoidable input waste).

100 There is an easy way out: using the reciprocals of the non-metric DEA values (e.g., 2 instead  
 101 of 0.5, and 4 instead of 0.25 etc.) provides a metric measurement in the form of an index that  
 102 reflects the inputs used by the unit under consideration compared with the inputs used by its

103 benchmark unit (base value). An index of 2 (4), for instance, informs us that the unit uses  
104 twice (four times) the amount of inputs compared to its benchmark. Deducting 1 from the in-  
105 dex, we could alternatively formulate that the unit is so inefficient as to have 100% (300%)  
106 input waste compared to the input use of its benchmark.

107 The input wastes of unit B ( $TE = 0.75$ ), unit C ( $TE = 0.5$ ), and unit D ( $TE = 0.25$ ) amount to  
108 33.33%, 100%, and 300%, respectively. The total input waste of these three inefficient units  
109 amounts to 433.33% of the inputs used by their benchmark A. Their average input waste is  
110 144.44% ( $= 433.33\% / 3$ ). While this average is meaningful, the 0.5 average of the three cor-  
111 responding DEA values (0.75, 0.5, 0.25) is not! A DEA value of 0.5 equals an input waste of  
112 100% and conveys the information “being half as efficient as the benchmark”. The three units  
113 B, C and D have neither an average input waste of 100% nor are they, on average, half as ef-  
114 ficient as their benchmark A. However, impairing internal validity, exactly that “information”  
115 is conveyed if one computes the arithmetic mean of DEA values.

116 In line with the “Theory of Scales of Measurement” (cf. STEVENS 1946), which is concerned  
117 with the question which mathematical operations are permissible for which measurement  
118 level, DEA users should consider the limited information content of DEA values:

- 119 • Arithmetic operations (addition/subtraction) and the calculation of arithmetic means re-  
120 quire variables to exhibit a metric scale level. These operations are meaningless for non-  
121 metric variables such as DEA values.
- 122 • Being non-metric implies that the formation of ratios in the sense of statements such as  
123 “business X is twice as efficient as business Y” is not permissible either for DEA values.
- 124 • While they could be transformed into their metric reciprocals, DEA values by themselves  
125 represent at best an ordinal-scaled variable for the units of a given sample. Hence, only the  
126 operations “more efficient” ( $>$ ), “less efficient” ( $<$ ) or “equally efficient” ( $=$ ) are permissi-  
127 ble within the respective sample.

128 Unfortunately, DEA values are not commonly transformed into their more easily manageable  
129 metric reciprocals even though this is the prerequisite for widespread operations, such as av-  
130 eraging and the treatment as metric data in econometric analyses.

131 Besides the level of measurement problem, attention should be paid to another critical issue:  
132 taking the very best units out of the sample will increase DEA values. In other words: DEA

133 values will be very high even if all units in the sample are substantially inefficient but homo-  
134 geneously so. It is thence impossible to compare DEA values between samples.

135 We will finally conclude by hinting at an imminent semantic problem. DEA is, first of all, a  
136 mathematical procedure which prescribes a certain way of how to process physical input and  
137 output data. Attaching the label “*efficiency*”, which is used in economic theory, to the values  
138 derived from this procedure entails the risk of misinterpretations. The results of a measure-  
139 ment procedure must never automatically be equated with the actual content of interest – even  
140 if identical terms are attached to both. While a critical appraisal in this regard is necessary for  
141 all measurements, it is especially relevant in the case of DEA because, due to its non-metric  
142 measurement level, the so-called “technical efficiency” conveys very little information re-  
143 garding the actual content of interest, i.e., the level of the inefficient resource use.

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