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Benchmarking Sustainable Development via Data envelopment Analysis:an Italian case study

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ABSTRACT: The need for monitoring the overall performance of countries in Sustainable Development (SD) is widely recognized, but scant attention has been devoted to methods for aggregating and analyzing vast amounts of empirical data. This paper describes the development and application of a Data Envelopment Analysis (DEA) methodology for addressing the challenges of benchmarking sustainable development. The methodology involves linear optimization techniques, and it is based on the identification of a number of attributes that provide proxy sustainable development indicators. Using these techniques, a SD index is derived, which might combine existing aggregate SD indices (developed by well-established organizations and/ or expert teams) into a single synthesizing overall SD index. We propose the use of four different modeling techniques to address these concerns and report the results of an Italian case study. From the results obtained, it is possible to note that the inefficient regions are, overall, southern regions and some central regions. In particular, their inefficiency comes from high poverty rate and CO2 emissions. Nevertheless, regional economic disparities are evident and with root in government's preferential policies towards on foreign investment for the northern regions, greater access to markets and better infrastructure. The political implication of these findings is that these regions have to concentrate to keep low the rate of CO2 emissions and to favor a good sustainable development from a social point of view. Exceptions are Basilicata and Sardegna regions, which exhibit a low poverty rate and a medium GDP per capita. The most inefficient DMUs are Sicilia, Calabria, Puglia, Campania and Abruzzo. Piemonte is borderline, even though the region has a good geographical position for the industrial placement. We view this approach as a first step towards more systematic international comparisons, aimed at facilitating the diffusion of the best practices and policies from the benchmark countries to the less developed world regions.

Key words: Data envelopment analysis (DEA), Efficiency, Sustainable Development, Benchmarking

INTRODUCTION

Since the United Nations Conference on Environment and Development (UNCED) in 1992, SD has been recognized by many countries as a fundamental development strategy. Notwithstanding its importance, there is still an interesting debate on the real meaning and practical implications of SD and it is therefore unclear how to turn an unsustainable development into a sustainable one. The international community promoted the discussion of specific measures to ensure a sustainable economic development. In this connection, strategies for optimizing the use of resources or environment in a more efficient way play a particularly important role. In this respect, a vast amount of literature has been devoted to the concept of Eco-efficiency, establishing a link between the environmental impacts and performance of an organization and its economic activity. However, although increased eco-efficiency might provide a route towards SD, eco-efficiency analysis is only a part of sustainable development measurement and the improvement of eco-efficiency does not guarantee sustainability. A broadening of the scope of SD has been proposed in the late 1990s to include social, environmental and economic sustainability. Sustainable development is then described in terms of three dimensions: economic development combined with environmental and social responsibility – the so-called "triple bottom line". Social aspects are an essential part of SD and also clearly part of human needs. One of the major problems in evaluating sustainability is the selection of social output measures that should consider the regions' con-

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tribution towards improving the present and future quality of life. This includes contributions to improving the quality of life of local communities, as well as longer-term strategic initiatives. In addition to the problem of selecting and quantifying social measures, there is also the problem of how to incorporate them into a DEA model. We explore the question of how social well being measures can and should be treated in a DEA model. To do this, we performed a case study, applying different techniques suggested in the literature to a real performance data for a group of Italian regions.

Sustainability is one of the most discussed concept in the international political debate, due to the inherent complexity tied to the simultaneous presence of three different and equally important aspects: economic, social and environmental. This interest has recently stimulated many studies aimed at developing suitable quantitative tools for an economy on the road of sustainable society. Kuosmanen et al. (2004) examines the so-called 'benefit of doubt' weighting method as a tool for identifying SD benchmarks, which combines 14 existing aggregate SD indices into a single synthesizing overall SD index. Hoffrén et al. (2008) study implementation of eco-efficiency and sustainable development in Finnish environmental companies. Harou et al. (2007) deal about environmental sustainable development in relationship with projects which have an important environmental dimension. Gladwin et al. (2006), after reviewing a broad array of indicators and origins of social un-sustainability, propose a set of working principles of socially sustainable business. However, in none of these studies DEA techniques for benchmarking SD has been a focal point of interest.
Data Envelopment Analysis (DEA) is a well established methodology for the assessment of performance of homogeneous decision making units (DMUs), with multiple inputs and outputs by some specific mathematical programming model. DEA has been extensively used to estimate the technical efficiency of DMUs in a variety of application areas. In the context of sustainable development performance measurements, a major concern is how to treat social (which often are quality of life measures) and environmental indicators into DEA models. In this respect, very often the concept of eco-efficiency has been used as a proxy for a sustainable development efficiency index. However, eco-efficiency is necessary, but not sufficient for sustainable development since it tries o combine economic efficiency and ecological efficiency of production systems under a single heading, ignoring the social dimension. The research area of eco-efficiency and its practical measurements is very diversified by nature. Within the DEA methodological framework, Scheel (2002) introduces a new radial measure that decreases undesirable output and desirable output as well, without separating the two categories. Chung et al. (1997) introduce a directional distance function and use it as a component in a productivity index. Korhonen et al. (2004), by analyzing various ways to deduce the eco-efficiency index, develop different models in two approaches that optimize the ecological performance in assorted input/output orientations or mix orientations, on the basis of the CCR standard DEA model (Charnes et al. 1978). Färe et al. (2004) join environmental technology and gauge performance in terms of increased good output and decreased undesirable output under directional distance function in an alternative approach. Dyckoff et al. (2001), starting on a generalization of basic DEA models, derive a multi-dimensional value function incorporating specifications for ecological applications.

Zhou et al. (2006) develop a two slacks-based efficiency measures for modeling environmental performance on the basis of environmental DEA technology to estimate the impacts of environmental regulations and economic-environmental performance. Zhou et al. (2008), instead, present a discussion about environmental DEA technologies and propose pure and mixed measures under different situations, with an application on measuring the carbon emission performance of eight world regions. Zaim et al. (2004), recognizing that air pollution is mainly a by-product of manufacturing activity, propose a new definition of pollution intensity and a new technique to measure the aggregate pollution intensity. Bosetti et al. (2004) discuss a methodology to assess the performances of tourism management of local governments considering both economic and environmental aspects. Ramanathan (2001) compares different energy technologies, in particular renewable technologies, using DEA. Avalos-Gonzalez et al. (2006) benchmark electricity distribution zones within the Mexican electricity industry using DEA. The economical and technical efficiency measures obtained suggest that internal (non-regulated) Total Quality Management (TQM) programs might also have a positive impact over efficiency, as measured by DEA.

Techniques for benchmarking sustainable development within the DEA framework

DEA is a linear programming technique for measuring the efficiency of multiple Decision Making Units (DMUs) where the structure of multiple inputs and outputs makes comparisons difficult. DEA provides a means of calculating relative efficiency levels within a group of DMUs. The sustainability concept, following the "triple bottom line" definition, takes into account an economic index, an environmental index and a social index. In this paper we extend the Fare et al. (2004) approach to develop an index of SD performance, by decomposing overall sustainability into the three dimensions. With this aim, let us consider the general case of k homogeneous Decision Making Units (DMUs). For each DMU, let us define :

$I \in \Re^n$ input set with index i;

$O \in \Re^t$ economical output set with index j;

$E \in \Re^q$ environmental undesirable output set with index p;

$S \in \Re^m$ social undesirable output set with index q.

x_i^k the amount of input i;

y_j^k the amount of economic desirable output j;

b_p^k the amount of environmental undesirable output p;

a_q^k the amount of social undesirable output w.

Taking in account these sets, variables and data, different models for SD efficiency are presented.

Model A

In the first model, we incorporate into a standard efficiency DEA model, the social and environmental outputs in order to achieve an SD efficiency index (Sustainable Development efficiency index).

The first model is based on the idea of presenting social and environmental outputs as inputs and of optimizing SD efficiency through the maximization of the good outputs production and the minimization of both undesirable social and environmental outputs and the inputs used.

An input orientation has been chosen to highlight the minimization of the inputs used and the importance of the minimization of unwanted environmental and social aspects.

The decisional problem can be mathematically represented as follows:

$$\max E = \frac{\sum_{j\in O} t_j y_j^0}{\sum_{i\in I} w_i x_i^0 + \sum_{p\in E} \beta_p b_p^0 + \sum_{q\in S} \delta_q a_q^0}$$

s.t.

$$\frac{\sum_{j\in O} t_j y_j^0}{\sum_{i\in I} w_i x_i^0 + \sum_{p\in E} \beta_p b_p^0 + \sum_{q\in S} \delta_q a_q^0} \le 1, \ \forall k$$

$$t_j, \beta_{j,} \delta_j, \omega_i \ge \varepsilon \ \text{(where } \varepsilon \ge 0\text{)}$$

The real number $\varepsilon > 0$ is a so-called non-Archimedean element defined to be smaller than any positive real number. The problem considered is a fractional programming model, thus, it is necessary to fix either the input set or the output set. Using a standard technique to transform it into a linear mode, we obtain the following model (Model A) adapted from (Korhonen, 2004):

$$d^* = \min\left[\theta + \varepsilon\left(\sum_{i\in I} s_i + \sum_{j\in O} s_j + \sum_{p\in E} s_p + \sum_{q\in S} s_q\right)\right]$$

s.t.

$$\sum_{k=1}^{K} \lambda^k x_i^k + s_i = \theta x_i^0 \qquad \forall i \in I$$

$$\sum_{k=1}^{K} \lambda^k y_j^k - s_j = y_i^0 \qquad \forall j \in O$$

$$\sum_{k=1}^{K} \lambda^k b_p^k + s_p = \theta b_p^0 \qquad \forall p \in E$$

$$\sum_{k=1}^{K} \lambda^k a_q^k + s_q = \theta a_q^0 \qquad \forall q \in S$$

$$\lambda^k \ge 0 \qquad \forall k = 1,\dots,K$$

$$s_i, s_j, s_p, s_q \ge 0$$

θ is free in sign

This primal model is a mixed standard input-output oriented primal model. The objective is twofold: to decrease the input value and, at the same time, to reduce the bad output quantity, in order to increase the SD efficiency.

The point on the efficient frontier, used to evaluate the performance of the DMU[0], is:

$$\hat{x}_i^0 = \theta x_i^0 - s_i^* = \sum_{k\in E^0} \lambda^{k*} x_i^k \qquad \forall i \in I$$

$$\hat{b}_p^0 = \theta^* b_p^0 - s_p^* = \sum_{k\in E^0} \lambda^{k*} b_p^k \qquad \forall p \in E$$

$$\hat{y}_j^0 = y_j^0 + s_j^* = \sum_{k\in E^0} \lambda^{k*} y_j^k \qquad \forall j \in O$$

$$\hat{a}_q^0 = \theta^* a_q^0 - s_q^* = \sum_{k\in E^0} \lambda^{k*} a_q^k \qquad \forall q \in S$$

Where E^0 is the reference set defined by:

$$E^0 = \{j, p, q \mid \lambda^{k*} > 0\}$$

with

$$j \in O, p \in E, q \in S \; .$$

Each inefficient DMU is associated with its optimal reference point. The reference point may be an observed DMU or a convex combination of observed DMUs. Clearly, the improved DMU with $(\hat{x}_i^0, \hat{y}_j^0, \hat{b}_p^0, \hat{a}_q^0)$ values is efficient.

Model B

Another practical model for measuring efficiency and providing a standardized index is the output oriented model firstly proposed by Tyteca (1996). We propose an adaptation of the abovementioned model and we call this model Model B, reported in the sequel.

$$\theta^* = \min \theta$$

s.t.

$$\sum_{k=1}^{K} \lambda^k x_i^k \le x_i^0 \qquad \forall i \in I$$

$$\sum_{k=1}^{K} \lambda^k y_j^k \ge y_j^0 \qquad \forall j \in O$$

$$\sum_{k=1}^{K} \lambda^k b_p^k = \theta b_p^0 \qquad \forall p \in E$$

$$\sum_{k=1}^{K} \lambda^k a_q^k = \theta a_q^0 \qquad \forall q \in S$$

$$\lambda^k \ge 0 \qquad \forall k = 1,\dots,K$$

θ free in sign

This outputs oriented model is particularly attractive because it provides a pure SD performance measure for DMU0, because only the adjustment of social and environmental outputs is allowed. It provides an aggregated and standardized efficiency measure (greater than 0 but not more than 1) for measuring SD performance. Note that Models A and B as well as other existing DEA-based models for environmental performance measurement adopt a radial efficiency measure. A limitation of these models is that they have a weak discriminating power (they do not consider the slacks in inputs nor in outputs), so that many DMUs with an efficiency rate equal to 1 cannot be directly compared and ranked.In addition, these models adjust social and environmental outputs by the same proportion. However, the obtained efficient targets may not be preferred by decision makers for economical or political considerations. Therefore, it is meaningful and practical to extend a radial efficiency measure to a non-radial one in the context of SD performance measurement.

Model C

Following the concept of a slacks- based measure (SBM) of efficiency in traditional DEA framework (Cooper *et al.*, 2000; Tone, 2001) and in an environmental context (Zhou *et al.*, 2006), we present the following *slack- based measures* model (Model C):

$$\rho^* = \min \frac{1 - \frac{1}{n}\sum_{i=1}^{n} \frac{s_i}{x_i^0}}{1 + \frac{1}{t}\sum_{j=1}^{t} \frac{s_j}{y_j^0}}$$

s.t.

$$\sum_{k=1}^{K} \lambda^k x_i^k + s_i = x_i^0 \qquad \forall i \in I$$

$$\sum_{k=1}^{K} \lambda^k y_j^k - s_j = y_j^0 \qquad \forall j \in O$$

$$\sum_{k=1}^{K} \lambda^k b_p^k = \theta^* b_p^0 \qquad \forall p \in E$$

$$\sum_{k=1}^{K} \lambda^k a_q^k = \theta^* a_q^0 \qquad \forall q \in S$$

$$\lambda^k \ge 0 \qquad \forall k = 1,\dots,K$$

$$s_i, s_j, s_p, s_q \ge 0$$

Notice that Model (C) can be used to evaluate the economic inefficiency of DMU0 by a slacks-based efficiency measure after its undesirable social and environmental aspects are adjusted to their minimum levels. In fact, the model uses the optimal value θ^* of the Model B to evaluate the value of the slacks in input and in desirable outputs.

A larger ρ^* indicates that DMU0 performs better in the aspect of pure economic performance; instead a

larger θ^* indicates that DMU0 performs better in the aspect of pure SD efficiency.
The slack variables could be used to identify and estimate the causes of economic inefficiency. A DMU is efficient if: $\rho^* = 1$ and $s_i^* = s_j^* = s_p^* = s_q^* = 0$, for each input and good output.

A value of $\rho^* < 1$ means that all inputs and all good outputs can be simultaneously increased/reduced without altering the mix proportions in which they are produced.
The point on the efficient frontier used to evaluate the performance of the DMU0 is:

$$\hat{x}_i^0 = x_i^0 - s_i^* = \sum_{k \in E^0} \lambda^{k*} x_i^k \qquad \forall i \in I$$

$$\hat{b}_p^0 = \theta^* b_p^0 = \sum_{k \in E^0} \lambda^{k*} b_p^k \qquad \forall p \in E$$

$$\hat{y}_j^0 = y_j^0 + s_j^* = \sum_{k \in E^0} \lambda^{k*} y_j^k \qquad \forall j \in O$$

$$\hat{a}_q^0 = \theta^* a_q^0 = \sum_{k \in E^0} \lambda^{k*} a_q^k \qquad \forall q \in S$$

where E^0 is the reference set and each inefficient DMU is associated with its optimal target value.

Clearly, the improved DMU with $(\hat{x}_i^0, \hat{y}_j^0, \hat{b}_p^0, \hat{a}_q^0)$ values is SD-SBM efficient.
By integrating environmental- social inefficiency and economic inefficiency, the slacks- based SD efficiency measure (SBSD) is the following:

$$\text{SBSD} = \theta^* \times \rho^*$$

This composite index contains information about the whole inefficiencies that interest each decision making unit since it combines economic and sustainability performance. Readily, if SBSD=1, the DMU0 is fully efficient in both sense, otherwise it presents some inefficiencies in the economic efficiency and/or in SD efficiency.

Model D

Another possibility is to adapt and extend the additive model as introduced by Charnes et al. (1985), to sustainable efficiency evaluation. The standard additive model avoids the problem of choosing between input and output orientations, and aims at maximizing outputs and minimizing inputs simultaneously. The proposed additive model reflects all inefficiencies that it is possible to identify in every input, good output and bad output.
The information on the reductions/increase of the input/output are given by slacks values, treated, directly, in the objective function. The use of slacks in the objective function insures that the resulting objective will be dimensionless. The Model (D) takes the following form:

$$z^* = \max \sum_{t \in I \cup O \cup E \cup S} g_t s_t$$

s.t.

$$\begin{aligned}
&\sum_{k=1}^{K} \lambda^k x_i^k + s_i = x_i^0 && \forall i \in I \\
&\sum_{k=1}^{K} \lambda^k y_j^k - s_j = y_j^0 && \forall j \in O \\
&\sum_{k=1}^{K} \lambda^k b_p^k + s_p = b_p^0 && \forall p \in E \\
&\sum_{k=1}^{K} \lambda^k a_q^k + s_q = a_q^0 && \forall q \in S \\
&\lambda^k \geq 0 && \forall k = 1,\ldots,K \\
&s_i, s_j, s_p, s_q \geq 0
\end{aligned}$$

The introduction of user-specified weights g_t is due to a generalization to improve the classical additive model. For example, the "range adjusted measure" (RAM) implemented by Cooper et al. (1999) could be used.

A DMU is efficient if and only if: $z^* = 0$ and $s_i^* = s_j^* = s_p^* = s_q^* = 0$, for each input i and output j. Otherwise, a DMU is inefficient if at least one component s_k of the slack variables is not zero.
In technical terms, efficiency can be regarded as weighted distance from DMU to a reference point on the efficient frontier defined by the value of λ^k ($\lambda^k \geq 0$). The reference set E0 represents the SD benchmarks, targets for each input and output (good and bad output) that would improve the DMU efficiency in order to achieve the maximum value.
Thus, the point on the efficient frontier used to evaluate the performance of the DMU0 is:

$$\hat{x}_i^0 = x_i^0 - s_i^* = \sum_{k \in E^0} \lambda^{k*} x_i^k \qquad \forall i \in I$$

$$\hat{b}_p^0 = b_p^0 - s_p^* = \sum_{k \in E^0} \lambda^{k*} b_p^k \qquad \forall p \in E$$

$$\hat{y}_j^0 = y_j^0 + s_j^* = \sum_{k \in E^0} \lambda^{k*} y_j^k \qquad \forall j \in O$$

$$\hat{a}_q^0 = a_q^0 - s_q^* = \sum_{k \in E^0} \lambda^{k*} a_q^k \qquad \forall q \in S$$

Clearly, the improved DMU with $(\hat{x}_i^0, \hat{y}_j^0, \hat{b}_p^0, \hat{a}_q^0)$ values is efficient.

RESULTS & DISCUSSION

In order to validate the proposed models, the first step is to establish a list of possible inputs and outputs that represents the three dimensions of sustainability (social-political, economic, and environmental).

These data generally provide imperfect proxies for what we would really like to measure. Besides, the selection of inputs and outputs also depends on data availability and coverage.

From the Italian Statistical Yearbook, we establish a dataset for 20 Italian regions for the year 2007.

The data collection activity has been carried out analyzing how the SD is performed in Italy and which are the most representative data to use into the models.

We have considered an economic input, energy consumption, and an economic output, the Gross Domestic Product (GDP) for each region. In addition an environmental output (CO_2 emissions) and a social output (poverty rate) have been introduced for the environmental and social dimensions, respectively. Summary data of these inputs and outputs for all the Italian regions are shown in Table 1.

There are obvious economic and social disparities between the northern and the southern areas in view of the fact that the mean GDP of the northern areas is almost twice with respect to GDP of the southern areas. Consequently, the poverty rate is higher for southern Italy.

All the four DEA models (A,B,C,D) used in this study are run to obtain indicators for the SD performance of Italian regions. The results are given in Table 2. It is

Table 1. Data for Italian Regions

Area	Regions	Energy consumption (kWh per capita)	CO2 emissions from road transportation (ton per capita)	Poverty rate (%)	GDP (Mln €)
NORTH	Piemonte	12322,9	2,4	5,3	23284
	Valle d'Aosta	568,9	5,3	3	27560
	Lombardia	25397,8	1,7	4	27429
	Trentino Alto Adige	2514,9	2,7	5,8	21245
	Veneto	12197,7	2,5	2,9	26345
	Friuli-Venezia Giulia	3455,7	2	4,2	24994
	Liguria	3228,6	2,4	3,9	24040
	Emilia Romagna	14055,4	2,1	3,7	26344
CENTRAL	Toscana	8861	2	5,2	23307
	Umbria	2359,6	1,7	5,7	20224
	Marche	3198,4	2	5,3	21675
	Lazio	10558,9	1,8	7,9	25131
SOUTH	Abruzzo	2861,4	2,9	7,9	17616
	Molise	515,9	2,1	11,3	15942
	Campania	6422,4	1,7	15,6	13727
	Puglia	9175,7	1,7	15,5	13979
	Basilicata	1002,5	1,7	12,8	15247
	Calabria	2123,3	2,3	14,3	13797
	Sicilia	7568,4	2	17,2	14091
	Sardegna	3085,9	1,4	13,9	16488

possible to note that the SD efficiency score of DMUs under the models A, B and D are rather consistent. It is also clear from the results that Model C has a very low discriminating power. This result is somewhat expected since it takes as input the optimal value of Model B.

Fig. 1, 2, and 3 give an idea of the general correspondence between the results obtained from the Models A, B, and D. There is good agreement for all the DMUs with some discrepancies in the efficiency scores of inefficient units.

Table 2. Efficiency scores

		Model				
Region		A	B	C	D	SBSD
Piemonte	DMU 1	0.72	0.69	1.00	0.64	0.69
Valle d'Aosta/Vallée	DMU 2	1.00	1.00	1.00	0.00	1.00
Lombardia	DMU 3	1.00	1.00	1.00	0.00	1.00
Trentino-Alto Adige	DMU 4	0.85	0.74	1.00	0.26	0.74
Veneto	DMU 5	0.79	0.76	1.00	0.13	0.76
Friuli-Venezia Giulia	DMU 6	1.00	1.00	1.00	0.00	1.00
Liguria	DMU 7	0.89	0.81	1.00	0.20	0.81
Emilia-Romagna	DMU 8	1.00	1.00	1.00	0.00	1.00
Toscana	DMU 9	0.87	0.85	1.00	0.44	0.85
Umbria	DMU 10	1.00	1.00	1.00	0.00	1.00
Marche	DMU 11	0.88	0.87	1.00	0.27	0.87
Lazio	DMU 12	1.00	1.00	1.00	0.00	1.00
Abruzzo	DMU 13	0.60	0.49	1.00	0.89	0.49
Molise	DMU 14	1.00	1.00	1.00	0.00	1.00
Campania	DMU 15	0.61	0.74	0.83	1.27	0.61
Puglia	DMU 16	0.60	0.68	0.80	1.29	0.54
Basilicata	DMU 17	1.00	1.00	1.00	0.00	1.00
Calabria	DMU 18	0.59	0.55	1.00	1.45	0.55
Sicilia	DMU 19	0.53	1.00	0.60	1.92	0.60
Sardegna	DMU 20	0.93	1.00	0.90	0.00	0.90

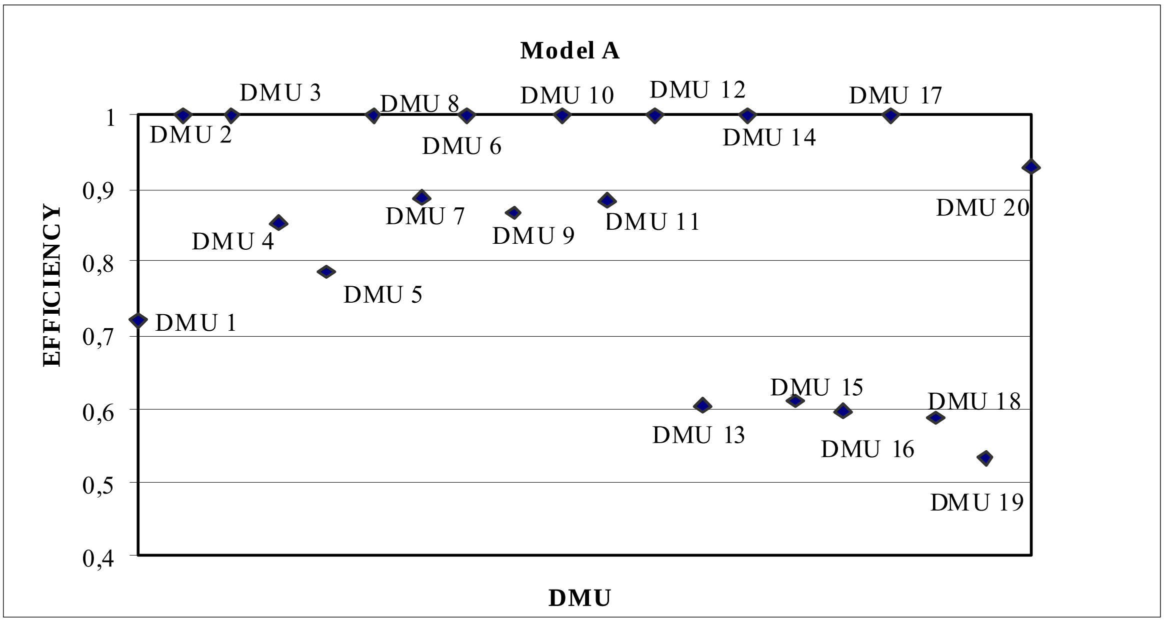

Fig. 1. Efficiency trend of Model A

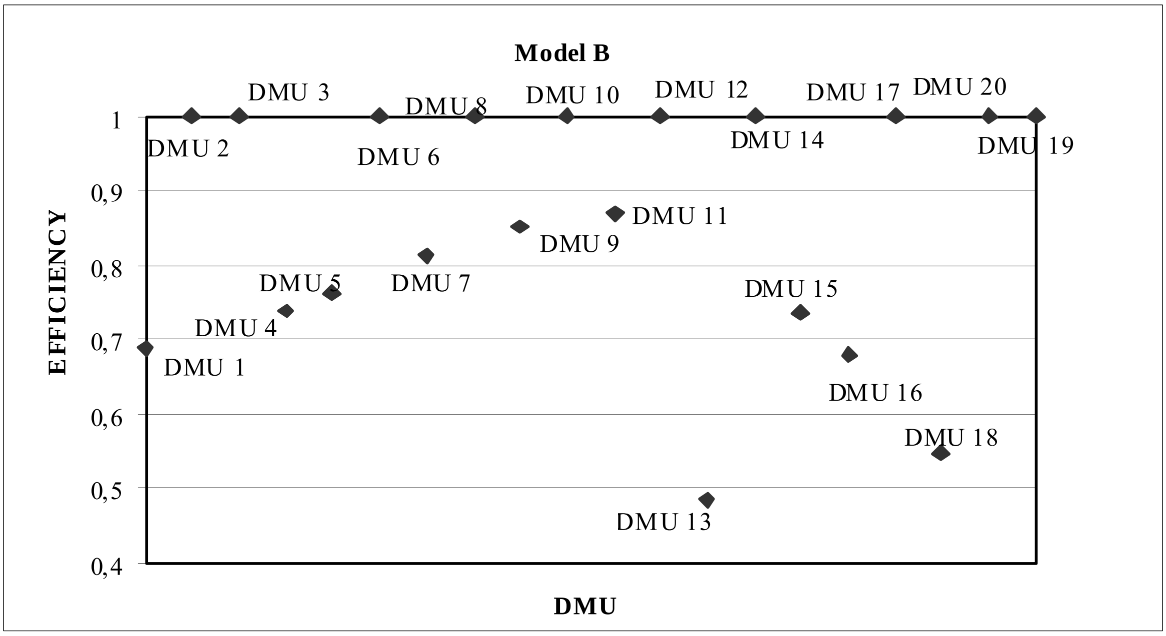

Fig. 2. Efficiency trend of Model B

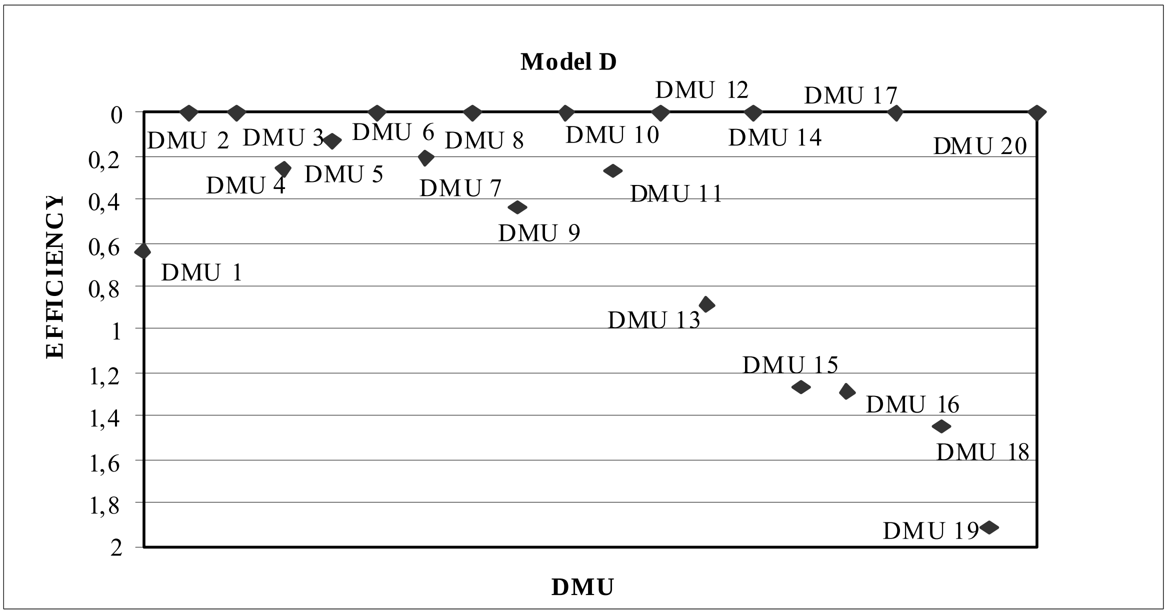

Fig. 3. Efficiency trend of Model D

It is important to highlight that the four models can only give results that are compatible with their definition, and that there are some differences in these latter: Models A and B are radial model, whilst models C and D are non-radial models. Furthermore, Model D identifies as efficient a DMU with optimal objective function equal to zero, instead of one (this is the reason of inverting the vertical axes in Fig. 3). Notwithstanding these differences, the results are quite homogeneous in identifying unison efficiency for all but two regions, namely Sicilia and Sardegna.

These two regions are deemed efficient by Model B, whereas behave as inefficient in Model A. In order to analyze this behaviour, it is beneficial to recall that Model A seeks a radial reduction in the input, the environmental and the social output, while Model B is only concerned with the reduction in the environmental and the social output. A lower efficiency score for Sicilia in

Model A is due to economic inefficiencies and a high poverty rate. This is further evident when we look at the efficiencies scores of the other three models (Models B, C and D). In particular, the score of Model B equal to one states that for the Sicilia region a reduction is not possible in poverty rate and CO2 emission, unless a reduction in GDP is tolerated. Sicilia's efficiency score of 0.6 for Model C supports this statement. In fact, this Model detects some infeasibility in the economic input and output, when the social and environmental unwanted aspects are set to their minimum.

From the results obtained, it is possible to note that the inefficient regions are, overall, southern regions and some central regions. In particular, their inefficiency comes from high poverty rate and CO2 emissions. The political implication of these findings is that these regions have to concentrate to keep low the rate of CO2 emissions and to favourite a good sustainable development from a social point of view. Exceptions are Basilicata and Sardegna regions, which exhibit a low poverty rate and a medium GDP per capita. The most inefficient DMUs are Sicilia, Calabria, Puglia, Campania and Abruzzo. Piemonte is borderline, even though has a good geographical position for the industrial placement.

The results of Model B show that, by joining the environmental and social aspects and fixing the good output and input, we can have a different vision of the Italian regions. In particular, Abruzzo presents the lowest efficiency rate. This can be explained from the high amount of CO2 emission evident in Table 1.

We recall in this respect, that this model does not consider the slacks in input and desirable outputs, but it integrates environmental and social inefficiencies. To obtain the SBSD, it is necessary to carry out the product between the two values of objective function coming from Models B and C, respectively. This composite index contains information about the whole inefficiencies that involve each DMU. Thus, it is possible to rank the inefficient DMUs and to detect the most inefficient DMU.

As far as Model D is concerned, we observe that the inefficient unit set is: DMU 1 (Piemonte), DMU 4 (Trentino Alto Adige); DMU 5 (Veneto); DMU 7 (Liguria); DMU 9 (Toscana); DMU 11 (Marche); DMU 13 (Abruzzo); DMU 15 (Campania); DMU 16 (Puglia); DMU 18 (Calabria); DMU 19 (Sicilia).

As noted from the efficiency score values reported in Table2 the DMU 1 (Piemonte) is the unit that needs adjustment in all the four variables. Particularly, the reduction of input used would be very large and, also, the bad environmental and qualitative output reduction would be important to achieve the efficiency. The other regions analyzed above, instead, Marche (DMU 11) and Calabria (DMU 18), require a reduction of social rate to increase, largely, the GDP (good output).

CONCLUSION

The environmental and social challenges we face today tend to have a greater widespread impact than in the past. It is becoming increasingly clear that what we do in one country affects people and ecosystems throughout the world. Environmental pollution has transcended national boundaries and is threatening the global ecosystem. The same considerations are in order for the social problem since the quality of daily life is compromised by different topics, for example the problem of multiethnic society, also consequence of globalization phenomena. In this respect it becomes of paramount importance to have a tool to compare different regions on the basis of their sustainability. The main focus of this study is methodological. We have demonstrated how a practical methodological tool can be used to assess the sustainability of developed countries through the case study of Italy. It is worth to stress at this point that this application highlights the potential practical usefulness of the approach, although the results might be debatable since the concept of sustainability in itself has stimulated harsh debates yet to be resolved. To keep our discussion focused, we have deliberately abstracted from such practical fine-tuning of our empirical analysis, but it should be clear that such extensions could be carried out by using the presented methodology. In this respect, the quality and coverage of data remains an ongoing concern. A further note concerns the exact interpretation of the reported values. We firmly stress that the proposed methodology is essentially comparative in its nature and can only assess overall SD in comparison to other countries. Hence, the comparative indices alone are clearly insufficient for thorough SD monitoring. Still, we strongly believe that they can be particularly useful for identifying and promoting sustainable policies and practices.

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