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MEASURING ENVIRONMENTAL AND ECONOMIC EFFICIENCY IN ITALY: AN APPLICATION OF THE MALMQUIST-DEA AND GREY FORECASTING MODEL

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Title: MEASURING ENVIRONMENTAL AND ECONOMIC EFFICIENCY IN ITALY: AN APPLICATION OF THE MALMQUIST-DEA AND GREY FORECASTING MODEL

First Edition: January 2014

ISBN: 978 88 84 67 864 5

Via Is Mirrionis, 1
09123 Cagliari
Tel./Fax 070 291201
www.cuec.it

Measuring Environmental and Economic Efficiency in Italy: an Application of the Malmquist-DEA and Grey Forecasting Model

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Abstract

Economic and environmental efficiency has being receiving growing attention among researchers. In general terms, this concept is related to the capability of the economic systems to employ natural resources efficiently, so as to increase economic and human wealth. This clearly implies that both the economic and ecological aspects of decisions ought to be considered. Bearing this in mind, this paper considers economic and ecological performance together, by applying data envelopment analysis (DEA) and the Malmquist productivity index (MPI) to investigating the efficiency of the 20 Italian regions from 2004 to 2011. The results reveal that the northern regions have been more efficient than the southern ones, highlighting the strong geographical differences between the two. Furthemore this paper uses the Grey System Theory to forecast regional economic and environmental efficiency. The results of the forecasting analysis show that the North-south duality remains strong and will possibly increase since the regions in the south get worse in term of environmental and economic efficiency.

Keywords: Panel data; Data envelopment analysis (DEA); Malmquist productivity index (MPI); Grey system theory; Forecasting.
JEL Classification: C23, C14, C61, E17

1. Introduction

Measuring environmental performance has been of interest for researchers for some time. Over the last few years many empirical works have investigated the efficiency of economic systems or local municipalities in different countries from many different perspectives. Interest is particularly strong in certain European countries (such as Italy or Spain), where municipalities have faced tighter budget constraints since the approval of the law on budget stability, which established mechanisms for controlling public debt and public spending in an attempt to balance the budget (Balaguer-Coll, Prior and Tortosa-Ausina, 2013).

In recent years, several approaches have been developed for assessing efficiency. These have included those which use benchmarking techniques and activity analysis or Data Envelopment Analysis techniques (DEA). A large body of literature is now available on how the different environmental conditions facing DMUs (Decision Making Units) affect their efficiency in different contexts. Since the early contributions by Banker, Morey (1986), many scholars have investigated this issue. DEA-based models for assessing eco-efficiency consider the economic and ecological performance jointly, and this has led to a wide range of models being developed, depending on the weight given to economic production and environment factors. For instance Kuosmanen (2005) used the traditional Shephard distance functions to determine the eco-efficiency of road transportation in Finland. Kortelainen and Kuosmanen (2007) studied eco-efficiency in consumer durables. They used DEA techniques to measure efficiency in terms of absolute shadow prices

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and considered the financial losses due to inefficiencies. Zhang, Bi, Fan,Yuan and Ge (2008) considered undesirable outputs as inputs and used several linear programming transformations of conventional activity analysis models to evaluate the eco-efficiency of certain provincial industrial systems in China. Other papers that have assessed eco-efficiency from different perspectives are: Barba-Gutierrez, Adenso-Diaz & Lozano (1986); Lin, Li, Wuang, Cui and Wei (2010); Picazo-Tadeo, Reig-Martinez and Gomez-Limon (2011); Wursthorn, Poganietz and Schebek (2011).

The DEA procedure can be adapted to measure quality of life by including the indicators that use the drawbacks of living in specific areas as inputs (costly aspects that should be minimised) and the indicators that describe advantages as outputs (positive factors that should be maximized). It is a reasonable way of aggregating indicators, because it can easily handle multiple dimensions (inputs/outputs) without imposing tight structures on the relationships between the variables. Other methodologies, hedonic pricing for instance, require that the functional forms of the relationships between the indicators are specified. DEA generates a comparison frontier from the best units observed in the sample, based on a comparative assessment of the indicators. However, one must bear in mind that this procedure also has low discriminating power, especially when many dimensions are taken into account and the sample size is limited (Ali, 1994). The DEA setting also provides information of which regions act as frontier benchmarks for each low performing region in the sample.

For all these reasons, in this paper we rely on the DEA methodology to compute efficiency scores for the Italian regions. While the use of DEA to measure the quality of life is not common, there are several papers that use this methodology in different settings (Hashimoto and Ishikawa, 1993a; Despotis, 2005; Sommariba, 2009). These procedures allow one to derive a virtual input and output, computed within a multi-factor framework, and to make compare the regions. This paper employs this approach in order to develop environmental efficiency measurements of the Italian regions for the first time.

Following the above mentioned line of research, this paper considers economic and ecological performance jointly, by applying data envelopment analysis (DEA) and the Malmquist productivity index (MPI) to investigating the efficiency of the 20 Italian regions. Italy is characterised by strong, consistent and persistent differences between the North and South for almost all economic and social indicators. One objective of this work is to investigate whether such differences also exist in environmental performance paralleling the economic performance.

Using the DEA procedure, we begin the empirical analysis by identifying the changes in the best-practice (technical) frontier of the environmental index and the regional GDP, defined as the set of the most efficient production combinations in the area of outputs and inputs. A geometric mean of the two alternative Malmquist indices is then constructed, using the productivity change indices previously defined by the DEA, (Färe and Grosskopf, 1994).

The output variables under consideration are an environment index and the regional GDP per capita (outputs to be maximised). The input variables are: infrastructure; efficiency of the legal system; tourists; crime; high school qualifications and unauthorized buildings. Eight years of data are used (2004-2011 and there are a total of 1280 observations (DMUs) (8 variables for 20 regions over 8 years). Over-fit problems are avoided because the number of DMUs is more than twice the total number of inputs and outputs in the DEA (Min et al., 2008). The results reveal that the northern regions are more efficient than the southern ones, highlighting the great geographical differences.

This paper also uses a Grey Model GM(1,1) to forecast regional environmental and economic efficiency in Italy. The grey forecasting theory has become more popular in time-series forecasting because of its ability to characterize an unknown system with great precision only requiring limited amount of data to estimate the behaviour of unknown systems (Deng, 1989; Zhou, Ang and Poh, 2006; Tseng, Lin and Feng, 2003). In recent years, the grey system theory has been widely used for forecasting in various fields such as agriculture, industry and environmental systems studies, with satisfactory results (among many others Zhou, Ang and Poh, 2006; Lu , 2007; Tongyuan and Yue , 2007; Tsaur and Lia, 2007; Lin, Li, Wuang, Cui and Wei, 2010; Zhu , 2010; Kayacan, Ulutas and Kaynak, 2010; Zhan and Jin-Hua , 2011; Li, Chang, Chen and Chen, 2012; Xie, Liu, Yang and Yuan, 2013).

The results of the grey analysis show that in the forecasted three year period (2012-2013), the North-South differences remain strong and may increase, as the environmental and economic efficiency of the southern regions is worsening. The article is organized as follows. Section 2 describes the data set and the variables used. Section 3 describes the theory underlying the DEA and Malmquist models and the description of the grey theory. Section 4 supplies the results. Section 4 contains the results of the forecasting analysis. Section 6 concludes.

2. Data and variables employed

Measuring environmental performance, which is the main variable of interest in this study, has been an open challenge for researchers in recent years. One relevant issue is how to treat the pollutants in the production process, since there are both "bad" and "good" outputs. For instance Färe, Grosskopf, Lovell and Pasurka (1989b) distinguished between desirable and undesirable outputs, treating environmental effects as undesirable outputs in a hyperbolic measurement of efficiency. Tyceta (1996) made an extensive review of the literature on environmental performance indicators and emphasized that comparison indicators needed to be developed.

The characteristic of the undesirability of some variables has been used in Färe, Grosskopf and Pasurka (1996); Tyceta (1996); Chung, Färe and Grosskorpf (1997); Zofio (2001). However, although this approach is widely accepted among environmental economists, it has also criticised (Färe and Grosskopf, 2004, 2009; Kuosmanen and Podinovski, 2009). Several works using different data sets for the production process have used distance functions to construct desirable and undesirable outputs, and thus to measure the environmental performance of different units (Färe, Grosskopf, Lovell and Pasurka, 1989a,b; Chung, Färe and Grosskorpf, 1997; Zaim and Taskin, 2000; Zaim, 2004).

In our analysis we use data collected from different databases, these are: IlSole24ore (204-2011), National Institute of Statistics (2004-2001),Istituto Tagliacarne (2004-2011) and Legamabiente (2012). The ecological indicator used in this work (ECOL), was created by IlSole24ore (204-2011) which annually measures the quality of life in Italy, employing several socio-economic data sets. It is based on the Indice Legambiente Ecosistema Urbano (2012) which employs 25 thematic indexes based on more than 120 parameters. The bundle of indicators selected by Legambiente covers all the major urban environmental components, such as air, water, rubbish, transport and mobility, parks, energy and, environment policy. Such indicators allow both the weight and the quality of the environmental components to be evaluated, as well as the responses of the environmental management system. The indeces are normalised by employing utility functions whose construction is based on certain sustainability objectives. A score between 0 and 100 is then obtained for each 25 indices. The final score is obtained by defining a weight for each index ranging from 1.5 to 10 (for a total of 100). The weights given to the various indeces are distributed in the following way: transport and mobility 22%, air 19%, environment and rubbish 14%, water and energy 12% and environmental management 7% (TABLE 1).[1]

Together with the ecological indicator, the regional pro-capita GDP (GDP_Reg) is the output variable to be maximised by the linear programming (see section 3 below). The input variables are: an index of infrastructures (INFRA), an index of the efficiency of the legal system (JUSTICE) expressed as the number of concluded over pending trials, the number of tourists measured as tourist days over population (TOURISM), high school attainment over population (HI-SCHOOL) and an index of unauthorized buildings (UN-BUILDINGS) as an indicator of illegal use of land. The idea underlying the choice of the particular variables is that higher environmental performance depends a better social and institutional set up, which may create public awareness of and support for the quality of general environmental services (Dinda, Coondos and Pal, 2000).

Given the nature of the DEA specification, in order to make the process of maximization coherent, desirable inputs (infrastructures, justice system, tourism, school) are taken as their inverse value Schell (2001); Seiford and Zhu (2002); Färe and Grosskopf (2004); Hua and Bib (2007). Table 2 shows the mean values of all the variables for the period 2004-2011. It clearly emerges that all the indicators are consistently

[1] Weights have been slightly changed over the years according to the changes in the importance of the various indexes employed. Nevertheless comparison over time has not been compromised

worse in the southern part of the country. In particular, the unauthorized buildings indicator in the south appears to be five times larger than that in the north. The other indicators for the South compared as a percentage of those for the North are: the high school attainment indicator (85%), the ecological indicator (83%), the index of legal system efficiency (74%), the index of infrastructures (70%), regional pro-capita income (65%) and the tourism indicator (30%).

3. Metodology

3.1. Data Envelopment Analysis: general settings

DEA is a non-parametric frontier analysis method that has been extensively used to investigate the efficiency of production in firms and public organizations. Although DEA was initially developed for computing production efficiency, some applications of this procedure have been employed in empirical works, which used its properties as an aggregating tool. The aggregation is carried out by comparing the indicators of each unit with the best practices observed in the frontier of reference. The efficient production frontier allows one to calculate and compare a firm's efficiency with its own benchmark.

The efficiency of the DMUs is measured by using linear programming methods to envelop observed input-output vectors as tightly as possible. This may be an appropriate tool for quantifying the efficiency of a group of decision making units (DMUs) with respect to their performance over time, as well as the performance of the relatively most productive decision units within the sample set. Moreover, by employing a panel DEA an assessment can be made of how well units process their inputs, compared with their own past performances as well as their own benchmark. Furthermore one can also identify the source of inefficiency, thus providing useful information to economic agents who wish to improve their performance.

The variable employed in the DEA analysis are inputs (factors that ought to be minimised) and outputs (products that have a positive value and ought to be maximised). DEA consistently weighs inputs and outputs, in order to compute an index of productive efficiency. Two indicators, which are pure technical efficiency and scale efficiency scores, relate the performance of each DMU to the estimated production frontier. The frontier represents all those points at which a relatively optimal capacity to transform inputs into outputs is accomplished.

There are also other methods for estimating the efficiency frontier index numbers and the application of stochastic frontier production functions (Aigner,Lovell and Schmidt, 1977; Meeusen and van den Broek, 1977). Nevertheless, non-parametric techniques are the most widely used, because they do not require an a priori specification of the functional form of the production function for the units under investigation and also offer some other advantages, as was discussed above.

The DEA model can be divided into an input-oriented model, which minimizes inputs for a given level of output in order to achieve full technical efficiency, and an output-oriented model, which maximizes outputs without requiring any of the observed input values to be expanded. DEA analysis allows multiple inputs-outputs to be employed at the same time, without any assumptions being made on data distribution. Efficiency is quantified in terms of the proportional change in inputs or outputs. The variables of interest can also be employed jointly, regardless their scale of measurement Köksal and Aksu (2007). Within a given sample of productive units, a subgroup achieves a relative efficiency equal to 1 (or 100%) and the residual DMUs are considered as inefficient if it has reached a score of less than 1.

The output-oriented model can be employed for planning and strategic objectives (Culliname, Song, and Wang, 2004). For example, it is useful when decision units need to understand whether an expansion of their capacity is feasible, given the level of the inputs employed. Hence, an output-oriented approach is generally more appropriate for the estimation of capacity and capacity utilization.

DEA models can also be divided in term of returns to scale, by including weight constraints. Charnes, Cooper and Rodhes (1978) proposed the efficiency measurement of the DMUs for constant returns to scale (CRS) where all DMUs are operating at their optimal scale. Banker, Morey (1986) allowed for variable returns to scale (VRS) in production technology and the breakdown of efficiency into technical and scale efficiencies.

In this paper we use of the variable returns to scale frontier. This is based on the rationale that the regions used in our analysis are of different sizes, and thus it is very likely that not all regions are operating at an optimal level. The less restrictive VRS frontier allows the best practice level of outputs to inputs to vary across the units in the sample. Moreover the VRS model has been largely used and accepted in the last two decades.

Following Coelli (1996) let assume data on K inputs and M outputs on each of N DMUs. For the i^{th} DMU these are represented by the vectors x_i and y_i, respectively. The $K \times N$ represents the input matrix, X, the $M \times N$ represents the output matrix, and Y represents the data of all N DMUs. The objective of DEA is to obtain a non-parametric envelopment frontier such that all observed points lie on or below the production frontier. For the output-orientated VRS model, DEA can be expressed as follows:

$$max_{\phi,\lambda}\phi, \tag{1}$$
$$st \quad Y\lambda - \phi y_i \geq 0, \tag{2}$$
$$x_i - X\lambda \geq 0, \tag{3}$$
$$N1'\lambda = 1, \tag{4}$$
$$\lambda \geq 0, \tag{5}$$

where λ is an $N \times 1$ vector of constants and $N1$ is an N-order column vector of ones, $1 \leq \phi < \infty$, and $\phi - 1$ is the proportional increase in outputs that could be achieved by DMU_i while input quantities are hold constant. The term ($N1'\lambda = 1$) represents the convexity constraint. It ensures that an inefficient production unit is only compared with production units of a similar size (for the constant returns to scale case, this constraint is excluded). The λ weights sum up to a value different from one and the benchmarking may occur against production units that are substantially different from the production unit being analysed (Färe et al, 1989). It is worth underlining that $\frac{1}{\phi}$ defines the technical efficiency (TE) score which varies between zero and one. $TE = 1$ implies that the production of the i^{th} unit is (relatively) fully efficient and lies on the best-practice frontier [2].

3.2. The Malmquist Productivity Index

The Malmquist Productivity Index (MPI) was first proposed by Malmquist (1953) as a quantity for use in the analysis of consumption of inputs. Färe et al. (1994) developed a DEA-based Malmquist productivity index which measures productivity change over time. Basically MPI can be employed to estimate the performance change between two points in time by calculating the ratio of the distance of each point relative to a common technology. Its application to panel data allows one to evaluate the dynamic performance of the DMUs over time. This choice is based on the fact that regions may require more than one year to adjusting the output levels given the input factors. As for a moving average approach, regions in different years are treated as if they were different DMUs. This allows one to compare the efficiency of a DMU with its own efficiency in other years as well as with the other DMUs' efficiency (Bosetti, Adenso-Diaz & Lozano, 2003). Following Coelli, Rao, O'Donnel and Battese (2005), MPI between period, s, and the reference period, t, can be expressed as follows:

$$m_0^t(q_s, x_s, q_t, x_t) = \frac{d_0^t(q_t, x_t)}{d_0^t(q_s, x_s)} \tag{6}$$

This represents the productivity of the production point (q_t, x_t) relative to the production point (q_s, x_s). $m_0 > 1$ it indicates that there is a positive TFP growth from period, s to period, t. The contrary occurs for $m_0 < 1$. To avoid to either impose this restriction or to arbitrarily choose one of two performance changes between two periods, an output-based Malmquist productivity is conveniently defined as the geometric mean of these two output-based indices Färe and Grosskopf (1994). One index uses period s technology and the other period t technology:

$$m_1(q_s, x_s, q_t, x_t) = \sqrt{\frac{d_0^s(q_t, x_t)}{d_0^s(q_s, x_s)} \frac{d_0^t(q_t, x_t)}{d_0^t(q_s, x_s)}} \tag{7}$$

[2] It needs to be noted that the output- and input-orientated models will estimate exactly the same frontier and therefore, by definition, identify the same set of DMUs as being efficient. It is only the efficiency measures associated with the inefficient DMUs that may differ between the two methods (Coelli, 1996).

The distance function in this productivity index can be decomposed into two components, with one measuring the technical efficiency change index and the other measuring the index of technical change (Färe, Grosskopf and Pasurka, 1996):

$$m_0(q_s, x_s, q_t, x_t) = \frac{d_0^t(q_t, x_t)}{d_0^s(q_s, x_s)} \sqrt{\frac{d_0^s(q_t, x_t)}{d_0^s(q_s, x_s)} \frac{d_0^t(q_t, x_t)}{d_0^t(q_s, x_s)}} \tag{8}$$

The distance functions cannot be evaluated without knowing the frontier production set. Several methods have been employed to estimate this frontier (among others index numbers, stochastic frontier production functions and non-parametric techniques, such as data envelopment analysis). The DEA approach, which is used in this study and described above, is one of the possible methods available.

3.3. $GM(1,1)$

Grey system theory, was originally developed by Deng (1989). The main idea of this theory is to study uncertainty of system with amount of data and incomplete data. It avoids the inherent defects of conventional methods such as probability theory and mainly works on poor, incomplete or uncertain data, to estimate the behavior of uncertain system or a time series Li, Chang, Chen and Chen (2012). In system theory, a system is called a white system if its information is completely known and it is called black system if its information is completely unknown. The grey model contains both known and known information (Kayacan, Ulutas and Kaynak, 2010) and it has been successfully applied to system analysis, prediction, data processing, modeling, decision making and control. The Grey Model based on the grey system theory is a forecasting dynamic model and has been widley used in many applications (Huang and Jane, 2009; Hsu and Chen , 2003; Kayacan, Ulutas and Kaynak, 2010; Kung, 2005; Li and Wang , 2011). Grey prediction is able to consider as curve fitting approach that has extremely good performance for real world data. Among the family of grey prediction model, most of the previous researcher have focused on $GM(1,1)$ model in their predictions. $GM(1,1)$ model ensue a fine agree between simplicity and accuracy of the results.
Following Ashari and Askari (2011), a non-negative sequence of raw data as:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)) \tag{9}$$

where, n is the sample size of data.

Accumulating Generation Operator (AGO) is used to smooth the randomness of primitive sequence. The AGO converting the original sequence into a monotonically increasing sequence. A new sequence X^1 is generated by AGO as:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)) \tag{10}$$

where,

$$x^{(1)}(1) = x^{(0)}(1) \tag{11}$$

and

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(1)}(i), \quad k = 1, 2, 3, \cdots, n \tag{12}$$

The generated mean sequence of $x^{(1)}$ is defined as:

$$Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \cdots, z^{(1)}(n)) \tag{13}$$

where, $z^{(1)(k)}$ is the mean value of adjacent data, i.e.,

$$Z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), \quad k = 2, 3, \cdots, n \tag{14}$$

The $GM(1,1)$ model can be constructed by establishing a first order differential equation for $x^{(1)}(k)$ as:

$$\frac{dx^{(1)}(k)}{dk} + ax^{(1)}(k) = b \tag{15}$$

The solution, also known as time response function, of above equation is given by:

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{a}{b})e^{-ak} + \frac{b}{a} \tag{16}$$

where, $\hat{x}^{(1)}(k+1)$ denotes the prediction x at time point $k+1$ and the coefficients $[a,b]^T$ can be obtained by the Ordinary Least Squares (OLS) method:

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{17}$$

In that:

$$Y = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)]^T \tag{18}$$

$$B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix} \tag{19}$$

Inverse AGO ($IAGO$) is used to find predicted values of primitive sequence. By using the $IAGO$:

$$\hat{x}^{(0)}(k+1) = (x^{(1)}(1) - \frac{b}{a})e^{-ak}(1 - e^{a}) \tag{20}$$

Therefore, the fitted and predicted sequence $\hat{x}^{(0)}$ is given as:

$$\hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n), \cdots) \quad \text{and} \quad \hat{x}^{(0)}(1) = x^{(0)}(1) \tag{21}$$

where

$$\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \cdots, \tag{22}$$

are called the $GM(1,1)$ forecast values.

The residual sequence can be denoted as:

$$\epsilon^{(0)} = (\epsilon^{(0)}(2), \epsilon^{(0)}(3), \cdots, \epsilon^{(0)}(n)) \tag{23}$$

where,

$$\epsilon^{(k)} = x^{(0)}(k) - \hat{x}^{(0)}(k), \quad k = 2, 3, \cdots, n. \tag{24}$$

Prediction accurancy is a vital criterion for evaluating forecasting authority. In the present study the Absolute Mean Percentage Error (AMPE) criterion has been used to estimate model performances and reliability. AMPE is a general accepted percentage measure of prediction accurancy (Ismail, Jamaluddin and Jamaludin). This indicator is calculated as:

$$AMPE = \frac{1}{N} \sum_{k=1}^{N} \left| \frac{e(k)}{x^{(0)}(k)} \right| 100\% \tag{25}$$

where,

$$e(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \tag{26}$$

4. Estimation Results

4.1. Results of DEA and Malmquist models

The DEAP Version 2.1 software package was used to run the DEA panel analysis, (Coelli, 1996). The routine first calculates the distances (or technical efficiencies) necessary for the Malmquist calculations. Four distances are calculated for each firm in each year. These are relative to:

1. the previous periods CRS DEA frontier;
2. the current periods CRS DEA frontier;
3. the next periods CRS DEA frontier;
4. the current periods VRS frontier.

Firstly, the DEA model is used to obtain an initial best practice frontier. This is a necessary step in identifying the regions that are located on the frontier. The Malmquist indices are then calculated, based on the DEA results relative to the previous year (Coelli, 1996).

The DEA model is estimated as follows:

Outputs: *GDPReg*, *ECOL*

Inputs: *INFRA*, *JUSTICE*, *TOURISM*, *HI-SCHOOL*, *UN-BUILDINGS*

Table 3 summarizes the results of the output oriented DEA (VRS). Scores are computed on a three successive years base period moving progressively across the eight years considered. This allows for dynamic effects when measuring efficiency in cross sectional and time varying data (Charnes and Cooper, 1985). Considering the 8 years period under analysis, the results show marked inefficiencies in environmental and economic performance among the 20 regions examined [3].

Regions in the North of Italy have higher efficiency scores than those in the South. To be more precise, Liguria, Trentino, Veneto, Friuli and Emilia perform best, and they are all on the best practice frontier (TE=1). This can be interpreted as meaning that they could not make any (relative) improvements, given the data observed and the structure of the DEA program. From the same table it clearly emerges that Sicily, Calabria, and Sardinia consistently lag behind, followed by the other Southern regions. As it can be seen from the table, regions in the south consistently lag behind for the whole period under consideration. While average "waste" of efficiency is less than 3% in the north, it is 28% the south. These results confirm a marked and persistent geographical duality in Italy. This also suggests that there is room for output gains through improvements in the efficiency of the use of inputs.

One should also notice that regions on the DEA frontier when VRS is assumed are also efficient for CRS DEA. This suggests that these regions lie on the best-practice efficiency frontier and operate at an optimal level. For the remaining regions it emerges that they are neither in the optimal position nor at the optimal level. Finally, while in the northern regions scale efficiency is roughly equal to VRS technical efficiency, in the south of the country scale efficiency is about 12% higher than VRS technical efficiency. This suggests that such regions ought to concentrate on improving productivity.

Table 4 shows the results for the Malmquist DEA application for indices of changes in technical efficiency; technological change; and total factor productivity change over the period 2004-2011, using the same input and output measures as those described above. All indices are relative to the previous period. Five indices are presented for each region in each year (Coelli, 1996):

1. technical efficiency change (relative to CRS technology);

[3] In this analysis the North comprises 12 regions (Piedmont, Valle d'Aosta, Lombardy, Liguria, Trentino, Friuli, Veneto, Emilia, Tuscany, Umbria, Marche, Lazio) and the South comprises 8 regions (Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia).

2. technological change;
3. pure technical efficiency change (i.e., relative to VRS technology);
4. scale efficiency change;
5. total factor productivity (TFP) change.

The technical efficiency change index indicates the use of best available techniques such as the efficient use of inputs, while the technological change index indicates the benefits of technological improvement. Pure technical efficiency measures the transformation of inputs into outputs. The scale efficiency is equal to the ratio of the CRS TE to the VRS TE (Färe and Grosskopf, 1994). The Malmquist (total factor productivity) index is the Technical Efficiency Change index $*$ Technological Change index. The technical efficiency change index is the ratio of the output-oriented measurement of technical efficiency from period s to period t and the technological change index measures the geometric mean of the shift in the technology frontier from s to t. It is worth noting that both the VRS and the CRS assumptions are used for measuring the various distances used to generate the Malmquist indices.

The results show that there was a annual (though small) decrease in total factor productivity in both parts of the country. The change is -1.1% in the north and -2.3% in the south. The reduction in total factor productivity is mainly due to decreases in technical efficiency (about 0.8%) and technological change (0.3%) for regions in the north. For regions in the south the decline of TFP is due to a decrease in technical efficiency (some 4.5%) and an improvement in technological change (0.23%). At the regional level, only Veneto, Marche and Umbria show (weak) improvements in productivity (0.4%, 1.4% and 0.6% respectively). The technically inefficient regions have made the environment and the economy less effective in the eight year period under consideration.

To sum up, the analysis shows that, when environmental and economic measurements are considered jointly, Italy has not progressed, either in terms of efficiency or productivity. Nevertheless, since the average technological change is positive for all the regions in the south, it can be stated that there was an improvement in underlying technological progress in the environmental and economic area.

4.2. Results of the grey forecasting model $GM(1,1)$

In order to check the consistency of the Grey analysis, all the variables included in the model are predicted and reported in table 5. It emerges that the values obtained are reasonably close to the original data (average sample error is 0.67%) thus confirming the reliability of the procedure. With this information at hand, the grey model is then applied to forecast the values of the same variables for the three successive years (2012-2013). Once obtained the whole panel of the 11 year period (8 actual + 3 forecasted) the DEA is run to forecast the Economic and environmental efficiency in the successive triennium. Finally, in order the have a comparison and to check the solidity of the results, efficiency is also estimated trough the Grey procedure.

Table 6 summarises the results of the forecasting analysis. The two forecasting procedures confirm that the regional efficiency divide remains in the period considered. More in detail while in the northern part of Italy economic and environmental efficiency remains quite stable and close to the relative optimum, in the rest of the country efficiency gets possibly even worse, making the southern regions lag far behind with respect to the north. It is interesting to note that both the DEA and the Grey forecasting the regions which are in the frontier are practically the same of that in the analysis with the actual data (Trentino, Friuli, Emilia and Liguria).

5. Conclusions

This paper investigates the economic and environmental efficiency of Italy in the period 2004-2011. These concepts are related to the capability of the economic systems to employ natural resources efficiently, in order to increase economic wealth and human wellbeing. We use the DEA method to compute efficiency scores for the Italian regions, considering economic and ecological performance jointly. The DEA setting gives information of which regions act as frontier benchmarks for each low performing region in the sample. A geometric mean of two alternative Malmquist indices is then constructed, using the productivity change indices previously defined by the DEA. These procedures allow one to derive a virtual input and output, computed within a multi-factor framework, and to compare the regions.

DEA results reveal that the northern regions have been performing better in terms of environmental performance and economic performance than the southern ones, highlighting the strong geographical differences between North and South Italy for almost all economic and social indicators.

Successively, this paper uses a grey model GM(1,1) to forecast regional environmental and economic efficiency in Italy. The results of the grey analysis show that in the three year period forecasted (2012-2013), the North-south duality remains strong and may increase, because environmental and economic efficiency in the regions in the south is worsening.

Overall the analysis suggests that Italy has not progressed in terms of environmental and economic efficiency, while the regional divide has slightly increased. This is something that needs to be borne in mind when designing policies.

Table 1: Environmental indicator: weight distributions (2011)

INDICES	Air	Water	Mobility	Rubbish	Urban Environment	Energy	Management
Air quality: NO2	7						
Air quality: Pm10	9						
Air quality: O3	3						
Domenstic water consumption		3.5					
Water-network dispersion		2.5					
Depuration capacity		6					
Rubbish/waste				4			
Recycling				10			
Public transport: demand			8				
Public transport: supply			4				
Sustainable mobility			1.5				
Car index			2				
Motorcycle index			1				
Pedestrian areas					4.5		
Traffic limited areas					3		
Bicycle lanes			4				
Cyclability index			1.5				
Public parks					4.5		
Green areas					2		
Electric domestic consumption						3	
Renewable energy						6	
Environmental policy						3	
Env. Certification:ISO14001							2
Env. planning and participation							2.5
Ecological management							2.5
Total	19	12	22	14	14	12	7
Weight	19%	12%	22%	14%	14%	12%	7%

Source: Legambiente Ecosistema Urbano (2012)

Table 2: Descriptive Statistics: 2004-2011$^{(*)}$

REGION	GDPReg	ECOL	INFRA	JUSTICE	TOURISM	HI-SCHOOL	UN-BUILDINGS
NORTH							
PIDMONT	25138.37	50.10	99.37	51.61	1.79	53.91	4.46
	(729.18)	(0.79)	(5.80)	(2.84)	(0.06)	(1.10)	(0.25)
AOSTA	28983.85	55.71	61.75	52.54	25.03	49.00	4.46
	(1137.70)	(1.24)	(10.22)	(3.42)	(0.24)	(0.92)	(0.25)
LIGURIA	23922.50	52.07	132.28	47.08	11.42	59.50	12.80
	(637.35)	(1.64)	(4.46)	(2.70)	(0.08)	(1.94)	(0.80)
LOMBARDY	26046.47	55.63	112.00	50.33	4.18	56.27	3.73
	(982.01)	(0.96)	(4.14)	(3.00)	(0.09)	(1.06)	(0.24)
TRENTINO	29874.45	64.57	63.51	58.24	42.15	58.45	3.01
	(611.41)	(0.99)	(1.25)	(2.42)	(0.29)	(1.85)	(0.23)
VENETO	26422.92	52.54	104.40	44.86	12.99	54.00	4.56
	(896.30)	(1.00)	(1.28)	(2.74)	(0.13)	(1.39)	(0.31)
FRIULI	26554.89	55.14	139.95	53.49	7.10	56.46	3.01
	(523.81)	(0.70)	(6.62)	(2.62)	(0.05)	(0.93)	(0.23)
EMILIA	27118.27	56.48	109.82	47.25	11.41	57.73	3.51
	(943.64)	(1.09)	(0.49)	(2.81)	(0.10)	(1.17)	(0.24)
MARCHE	23473.10	52.79	92.38	46.19	7.52	55.63	5.36
	(613.11)	(0.86)	(1.68)	(2.28)	(0.42)	(0.74)	(0.46)
TUSCANY	24665.60	53.79	105.08	45.80	11.33	53.11	8.18
	(590.00)	(1.14)	(3.19)	(2.42)	(0.24)	(1.15)	(0.55)
UMBRIA	21879.84	57.39	101.17	43.10	5.56	61.62	10.76
	(481.70)	(1.26)	(10.14)	(2.08)	(0.11)	(1.08)	(0.85)
LAZIO	22459.09	42.79	110.16	37.89	3.51	61.67	9.01
	(820.73)	(1.18)	(4.56)	(2.95)	(0.06)	(2.00)	(0.52)
SOUTH							
ABRUZZO	19883.86	48.71	95.38	40.76	5.83	56.79	22.95
	(345.78)	(1.31)	(5.59)	(2.45)	(0.14)	(0.89)	(1.95)
MOLISE	18153.85	46.76	54.75	43.40	1.89	51.37	39.88
	(382.38)	(1.90)	(2.51)	(3.02)	(0.06)	(1.01)	(4.43)
CAMPANIA	15664.59	46.12	89.98	33.52	2.46	45.68	47.61
	(368.61)	(1.22)	(0.62)	(2.56)	(0.02)	(1.31)	(2.40)
APULIA	14866.53	45.98	86.17	31.11	3.35	43.86	23.08
	(515.05)	(0.69)	(1.35)	(2.69)	(0.12)	(1.05)	(1.14)
BASILICATA	16823.61	50.55	45.44	31.02	3.95	51.92	22.70
	(393.02)	(1.57)	(1.58)	(2.65)	(0.05)	(0.93)	(3.28)
CALABRIA	14765.27	39.35	78.94	32.88	4.98	49.07	38.25
	(336.45)	(2.03)	(3.48)	(2.79)	(0.10)	(0.68)	(4.54)
SICILY	15421.47	35.65	74.17	34.65	2.62	43.96	36.83
	(435.64)	(1.42()	(1.50)	(2.26)	(0.03)	(0.83)	(2.38)
SARDINIA	17734.53	44.92	48.61	36.22	4.38	43.79	16.16
	(462.77)	(2.02)	(1.35)	(1.57)	(0.18)	(1.02)	(1.19)
Total	21992.65	50.35	90.26	43.10	8.67	53.19	16.02
	(407.15)	(0.59)	(2.24)	(0.84)	(0.74)	(0.51)	(1.18)
North	25544.95	54.08	102.65	48.20	12.00	56.45	6.07
	(2919.29)	(5.27)	(8.89)	(6.53)	(2.07)	(4.95)	(0.72)
South	16664.21	44.76	71.68	35.44	3.68	48.30	30.93)
	(404.96)	(1.52)	(2.25)	(2.50)	(0.09)	(0.96)	(2.66)

* Standar error in parenthesis

Source: own calculations from ILSole24Ore, National Institute of Statistics (ISTAT), Istituto Tagliacarne and Legambiente

Table 3: Regional environmental and economic efficiency: Panel DEA results(*)

Region	2004	2005	2006	2007	2008	2009	2010	2011	VRS-TE 2004-2011	CRS-TE 2004-2011	Scale eff 2004-2011
NORTH											
PIDMONT	0.877	1	1	0.895	0.892	0.941	0.9	0.885	0.924	0.88	0.952
AOSTA	0.928	1	0.956	1	0.957	0.932	1	0.945	0.965	0.877	0.909
LIGURIA	1	1	1	1	1	1	1	1	1	1	1
LOMBARDY	1	1	1	0.988	0.985	0.942	0.962	0.991	0.984	0.966	0.982
TRENTINO	1	1	1	1	1	1	1	1	1	1	1
VENETO	1	1	0.997	1	1	1	1	1	1	0.985	0.985
FRIULI	1	1	1	1	1	1	1	1	1	1	1
EMILIA	1	1	1	1	1	1	1	1	1	1	1
MARCHE	0.903	0.86	0.879	0.902	0.905	0.874	0.839	0.906	0.884	0.859	0.972
TUSCANY	1	1	0.962	0.966	0.932	0.915	0.902	0.895	0.947	0.925	0.977
UMBRIA	1	1	1	1	0.954	0.99	1	0.945	0.986	0.974	0.988
LAZIO	1	1	0.888	1	1	1	1	0.801	0.961	0.859	0.894
SOUTH											
ABRUZZO	0.905	0.867	0.872	0.774	0.832	0.791	0.748	0.734	0.815	0.775	0.951
MOLISE	0.768	0.668	0.68	0.86	0.795	0.704	0.741	0.601	0.727	0.653	0.898
CAMPANIA	0.761	0.792	0.826	0.731	0.718	0.742	0.777	0.749	0.762	0.618	0.811
APULIA	0.819	0.743	0.744	0.779	0.751	0.748	0.758	0.708	0.756	0.592	0.783
BASILICATA	0.85	0.811	0.809	0.823	0.637	0.843	0.833	0.674	0.785	0.685	0.873
CALABRIA	0.664	0.675	0.723	0.684	0.688	0.597	0.576	0.511	0.64	0.533	0.833
SICILY	0.664	0.601	0.628	0.575	0.578	0.546	0.536	0.521	0.581	0.447	0.769
SARDINIA	0.632	0.593	0.676	0.642	0.757	0.753	0.73	0.77	0.694	0.525	0.756
Italy mean	0.889	0.881	0.882	0.881	0.869	0.866	0.865	0.832	0.871	0.808	0.928
North mean	0.976	0.988	0.974	0.979	0.969	0.966	0.967	0.947	0.971	0.944	0.972
South mean	0.758	0.719	0.745	0.734	0.72	0.716	0.712	0.659	0.72	0.603	0.838

* Output oriented DEA (VRS), scores are computed on a three successive years base period. TE scores relative to t-1 in year 2004 and t+1 in year 2011 are not defined

Table 4: Malmquist Index(*) summary of firm means (2004-2011)

Region	Eff. change	Technol. change	Pure eff. change	Scale eff. change	TFP change
NORTH					
PIDMONT	0.999	0.995	1.001	0.998	0.998
AOSTA	0.991	0.99	1.003	0.988	0.981
LIGURIA	1	0.996	1	1	0.996
LOMBARDY	0.99	0.996	0.999	0.991	0.986
TRENTINO	1	0.978	1	1	0.978
VENETO	1.005	0.999	1	1.005	1.004
FRIULI	1	0.955	1	1	0.955
EMILIA	1	0.995	1	1	0.995
MARCHE	0.992	1.021	1	0.992	1.014
TUSCANY	0.985	1.001	0.984	1	0.986
UMBRIA	0.988	1.018	0.992	0.996	1.006
LAZIO	0.948	1.025	0.969	0.979	0.972
SOUTH					
ABRUZZO	0.945	1.019	0.971	0.973	0.963
MOLISE	0.924	1.029	0.966	0.957	0.95
CAMPANIA	0.994	1.006	0.998	0.996	1
APULIA	0.979	1.004	0.979	0.999	0.982
BASILICATA	0.928	1.054	0.967	0.959	0.979
CALABRIA	0.914	1.015	0.963	0.949	0.928
SICILY	0.928	1.021	0.966	0.961	0.948
SARDINIA	1.025	1.037	1.029	0.996	1.063
Italy mean	0.976	1.007	0.989	0.987	0.984
North mean	0.992	0.997	0.996	0.996	0.989
South mean	0.955	1.023	0.98	0.974	0.977

* Malmquist index averages are geometric means

Table 5: environmental and economic efficiency (VRS-TE) Grey prediction results

Region	2004	2005	2006	2007	2008	2009	2010	2011	AMPE (*)
NORTH									
PIDMONT	0.877	0.985	0.966	0.948	0.93	0.912	0.894	0.877	2.446
AOSTA	0.928	0.986	0.98	0.975	0.97	0.965	0.96	0.954	2.047
LIGURIA	1	1	1	1	1	1	1	1	0
LOMBARDY	1	0.997	0.992	0.986	0.981	0.976	0.97	0.965	1.087
TRENTINO	1	1	1	1	1	1	1	1	0
VENETO	1	0.999	0.999	0.999	1	1	1	1	0.059
FRIULI	1	1	1	1	1	1	1	1	0
EMILIA	1	1	1	1	1	1	1	1	0
MARCHE	0.903	0.878	0.879	0.88	0.881	0.882	0.883	0.884	1.975
TUSCANY	1	0.992	0.974	0.956	0.938	0.921	0.904	0.887	0.683
UMBRIA	1	1.003	0.997	0.99	0.984	0.978	0.972	0.966	1.373
LAZIO	1	0.995	0.981	0.968	0.955	0.942	0.93	0.918	5.751
SOUTH									
ABRUZZO	0.905	0.871	0.847	0.824	0.801	0.779	0.758	0.737	2.081
MOLISE	0.768	0.745	0.737	0.729	0.721	0.713	0.706	0.698	8.332
CAMPANIA	0.761	0.786	0.778	0.77	0.762	0.754	0.746	0.739	3.122
APULIA	0.819	0.759	0.755	0.751	0.747	0.743	0.74	0.736	1.829
BASILICATA	0.85	0.813	0.8	0.788	0.775	0.763	0.751	0.74	7.042
CALABRIA	0.664	0.73	0.696	0.664	0.634	0.604	0.577	0.55	3.953
SICILY	0.664	0.619	0.601	0.585	0.568	0.553	0.537	0.522	1.516
SARDINIA	0.632	0.627	0.651	0.675	0.701	0.728	0.755	0.784	3.838
Italy mean	0.889	0.889	0.882	0.875	0.868	0.861	0.854	0.847	0.677
North mean	0.976	0.986	0.981	0.975	0.97	0.965	0.959	0.954	0.379
South mean	0.758	0.743	0.734	0.724	0.715	0.706	0.696	0.687	1.866

* Absolute Mean Percentage

Table 6: Regional environmental and economic efficiency forecasting results

Region	DEA forecasting(*)			Grey forecasting		
	2012	2013	2014	2012	2013	2014
NORTH						
PIDMONT	0.887	0.89	0.897	0.86	0.844	0.828
AOSTA	1	1	1	0.949	0.944	0.939
LIGURIA	1	1	1	1	1	1
LOMBARDY	0.969	0.976	0.986	0.96	0.955	0.949
TRENTINO	1	1	1	1	1	1
VENETO	0.969	0.966	0.968	1	1	1
FRIULI	1	1	1	1	1	1
EMILIA	1	1	1	1	1	1
MARCHE	0.873	0.864	0.852	0.885	0.886	0.887
TUSCANY	0.869	0.867	0.866	0.871	0.855	0.839
UMBRIA	0.976	0.946	0.922	0.959	0.953	0.947
LAZIO	1	1	1	0.905	0.893	0.881
SOUTH						
ABRUZZO	0.695	0.673	0.659	0.716	0.697	0.677
MOLISE	0.691	0.685	0.678	0.691	0.683	0.676
CAMPANIA	0.717	0.689	0.668	0.731	0.724	0.716
APULIA	0.722	0.698	0.68	0.732	0.729	0.725
BASILICATA	0.726	0.715	0.703	0.728	0.717	0.706
CALABRIA	0.5	0.501	0.502	0.525	0.501	0.478
SICILY	0.527	0.528	0.528	0.508	0.493	0.48
SARDINIA	0.812	0.842	0.873	0.814	0.845	0.877
Italy mean	0.847	0.842	0.839	0.841	0.834	0.827
North mean	0.962	0.959	0.958	0.949	0.944	0.938
South mean	0.674	0.666	0.661	0.679	0.67	0.661

* Output oriented DEA (VRS), scores are computed on a three successive years base period. The scores relative $t+1$ in year 2014 are not defined

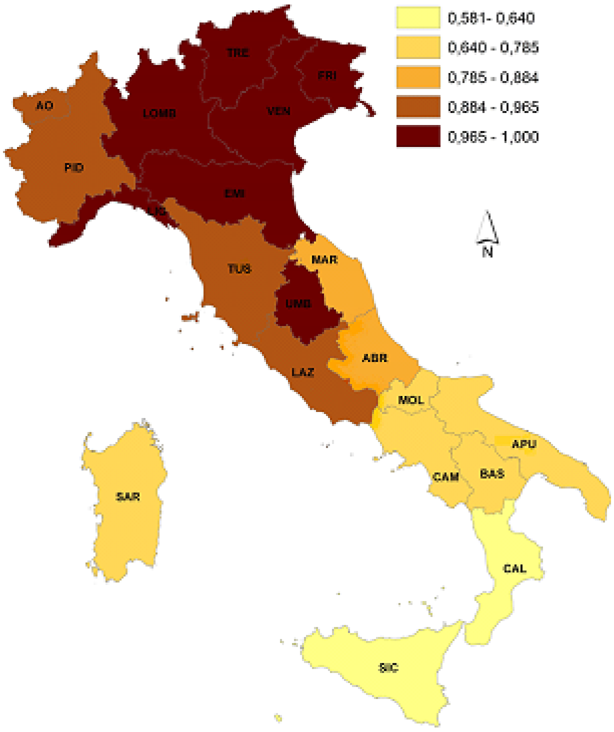

Figure 1: Italian Regional environmental and economic efficiency

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Finito di stampare nel mese di Giugno 2014
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ISBN 978-88-84-67-864-5

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