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October 2013

The Efficiency of Healthcare Systems in Europe: a Data Envelopment Analysis Approach

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Abstract This paper aims at evaluating the efficiency of public healthcare systems in Europe, by applying a nonparametric method such is Data Envelopment Analysis. For the analysis, statistical data for 30 European states for 2010 have been used. We have selected three output variables: life expectancy at birth, health adjusted life expectancy and infant mortality rate and three input variables: number of doctors, number of hospital beds and public health expenditures as percentage of GDP. Findings reveal that there are a number of both developed and developing countries on the efficiency frontier, while the great majority of the countries in the sample are inefficient.

Key words: healthcare system, efficiency, data envelopment analysis, Europe

1. Introduction

Assessing the efficiency of healthcare systems is a difficult process, which often encounters methodological problems. Starting with the health status of the citizens, which influences the productivity level, the welfare level or socio-economic stability, increasing the efficiency of healthcare services is a standing objective, which becomes highly important and necessary to those countries that have a low or medium human development index. On the other hand, the states with a high development index are obliged to assure a high level of efficiency and quality of their health services.

For the past years, society has made impressive progress in ensuring better health services, especially those services channelled towards improving maternal and infant health or towards increasing life expectancy. Nevertheless, an increase in the indicators at national levels did not result in the improvement of the indicators for the groups of citizens predisposed to certain maladies, while the progress in some cases stagnated and the overall results were not significant.

This paper aims at describing the efficiency of public healthcare systems in Europe, by applying a nonparametric method such is Data Envelopment Analysis. The paper presents the most relevant results

in the literature in section 2, followed by a brief description of the method. Section 4 describes the data used as input and output variables, while section 5 discussed the results. Last section concludes the paper.

2. Literature

Healthcare systems capable of ensuring equitable and efficient services are essentials for a general and continuous improvement of the population's health status. In time, the efficiency of the healthcare system has become synonymous with health expenditures. Furthermore, for both the economies with a high development index and the economies with a medium development index, the increase in the efficiency of the expenditures seems to be the only option that would allow public systems to overcome the pressure of the expenditures associated with age and tax increase (Heller et Hauner, 2006).

In his paper, "Public Spending on Health Care: How are Different Criteria Related?", Musgrave (1999) identifies at least nine relevant criteria which should be considered when adopting health expenditures decisions, including: the economic efficiency criterion (public goods, externalities, cost-efficiency), moral grounds (fighting poverty, vertical and horizontal equity), political considerations (special requests from the population).

In analyzing the efficiency of the healthcare systems from the public point of view of health expenditures, an important contribution was made by Rivera (2010), Ahs A. et al., (2005), Cicea et al., (2009), in papers focusing on the relation between public health expenditures and health status self-estimation. Thus, in his paper, Rivera starts from the hypothesis that an increase in public health expenditures would automatically lead to an improvement in the self-estimated health status and aims at identifying and quantifying the relations between the various levels of health and the resources in the domain by taking into account a group of biological and socio-economic factors that influence the individual's health. In building his model, Rivera (2010) takes into account the way health expenditures are built, and emphasizes that investing in preventive treatments can become a more important factor than the expenditures themselves, while Ahs emphasizes the permanent necessity to research the impact of unemployment rate changes on the population's health status. By applying a regression model on health data for people over 16 years old, the results proved that the probability to estimate a certain health status is significantly influenced by health expenditures; it is more probable that an individual will self-estimate a better health status as health expenditures increase.

Portafke (2010) demonstrates how for a 1% increase in the GDP per capita, health expenditures increase by 0.4%. Bredenkamp et al. (2010), Deaton A. (2006) and Economou, (2009) study the effect of health expenditures on personal income in the Balkan countries, where informal payments are mentioned.

Economou ends the article by leaving room for later discussions on how to decrease the pressure of health expenditures on those with below the average income. Furthermore, Schoenberg et al. (2007) and Thomson et al. (2009) demonstrate in their studies that for citizens over 60 years old the costs of maladies increase exponentially, especially since these individuals suffer an average of 2.2 chronic diseases per person. These studies demonstrate how health expenditures are influenced not by the age of the patients but by the patients' getting closer to their demise. Thus, it was shown that 5% of the patients of 65 years or more who were in the last year of their life in 2012 represented more than 50% of the hospital's expenditures.

Payne et al. (2007) emphasize the effect of increased life expectancy has on health expenditures. Thus, the article demonstrates that increased life expectancy can represent a pressure factor for health expenditures if morbidity is not decreased or kept constant. In other words, prolonging life by keeping the patients in the morbidity status leads to the increase in aggregated health expenditures because the morbidity period is more expensive than the health period (Atkinson et al., 2008), (Mathers et al., 2006).

Zhu (2002) provides a series of Data Envelopment Analysis (DEA) models for efficiency assessment and for decision making purposes. Rhodes and Southwick (1986) use DEA to analyze and compare private and public universities in the USA, Roman et. Suciu (2012) provide an efficiency analysis of research activities using input oriented DEA models and Nitoi (2008) assesses the efficiency of the Romanian banking system using an input oriented, variable return to scale, DEA model. DEA has also been used to assess different aspects of the medical field like hospital efficiency (Tambour et al., 1997; Zhu, 2003; Nedelea et al., 2010; Mecineanu et al., 2012), public policies efficiency (Coppola et al., 2003; Sherman, 1984; Rosko, 1984; Miller et al., 1996), heart surgery efficiency (Chilingerian, 1995) or health facilities efficiency (Clement et al., 2008; Hollingsworth, 2008; Ferrier et al., 2006; Ozcan, 2008).

3. Method

One of the most widely used methods in assessing the efficiency of a set of DMUs is Data Envelopment Analysis (DEA). DEA is a non-parametric method which identifies an efficiency frontier on which only the efficient Decision Making Units (DMUs) are placed, by using linear programming techniques.

First presented in 1978 and based on the paper of Farrell, the first DEA model is known in the literature as the CCR model, after its authors, Charnes, Cooper and Rhodes. Thus, by using linear programming and by applying nonparametric techniques of frontier estimation, the efficiency of a DMU can be measured by comparing it with an identified frontier of efficiency. The DEA model is input or output oriented. An output oriented DEA model is channelled towards maximizing the outputs obtained

by the DMUs while keeping the inputs constant, whilst the input oriented models focus on minimizing the inputs used for processing the given amount of outputs. In present paper, the method applied for assessing the efficiency of European healthcare systems is DEA for an input oriented specification. DMUs are European countries for which a number of inputs and outputs are selected.

In the particular case of our research, the linear programming problem to be solved, in the intput oriented and variable-returns to scale hypothesis, is presented below (Charnes, Cooper and Rhodes, 1978). There are k=2 inputs and m=3 outputs for n=30 DMUs. We can also define X as the (k×n) input matrix and Y as the (m×n) output matrix. The specifications of the mathematical programming problem, for a given i-th DMU are described below, and it has to be solved one problem for each DMU:

$$
\begin{cases}
\min_{\theta, \lambda} \theta \\
-y_i + Y\lambda \geq 0 \\
\theta x_i - X\lambda \geq 0 \\
N_1 \lambda \leq 1 \\
\lambda \geq 0
\end{cases}
$$

In problem above, θ is a scalar that ranges between 1 and ∞. The inverse of θ ranges between 0 and 1 and is the technical efficiency score. If it is equal to 1, it implies that the DMU is efficient, while if it is less than 1, the DMU is inefficient. Vector λ is a (n×1) vector of constants that measures the weights used to compute the location of an inefficient DMU if it were to become efficient.

The model specification under the hypothesis of variable return to scale implies the condition of convexity of the frontier. This presume that the restriction the restriction $N_1 \lambda <= 1$ is introduced in the model, N_1 being a n-dimensional vector of ones. The absence of this restriction would imply that returns to scale were constant.

We apply in this paper DEA model considering both the constant and variable return to scale and we also compute the scale efficiency for the DMUs in the sample. This is the ratio between the efficiency scores in CRS and VRS hypothesis and accounts for the increasing, decreasing or constant return to scale.

4. Data and variables

For the analysis, statistical data for 30 European states for 2010 have been used, extracted from the Eurostat online database. This ensures the accuracy and comparability of data, which are important features in DEA models. The selection of variables and their number is crucial in efficiency analysis. We selected three output variables: Life expectancy at birth, Health adjusted life expectancy and Infant

mortality rate and three input variables: number of doctors, number of beds and public health expenditure as percent of GDP.

According to Eurostat, *life expectancy at birth* represents the mean number of years a person will live, if subjected throughout his or her life to the current mortality conditions (age-specific probabilities of dying). Life expectancy at birth was chosen as output variable because it is considered to be one of the most direct indicators of the efficiency of the healthcare systems. Moreover, life expectancy is often used in international studies as an output variable, which confirms its capacity to assess the efficiency of the healthcare systems (Tudorel et al., 2009). Also, as the variable is the estimator of the citizens' living period, it is considered that it actually incorporates the influence of more variables. Jaba et al. (2011), demonstrate that in the EU for 2007, education, gender, health status, income and marital status influenced life expectancy and Jaba et al. (2012) analyze the determinants of life expectancy at regional level in Europe.

Health adjusted life expectancy (HALE) (also called disability-free life expectancy) measures the number of remaining years that a person of a certain age is supposed to live without disability. It is a solid indicator to monitor health as a productivity/economic factor. HALE introduces the concept of quality of life. It is used to distinguish between years of life free of any activity limitation and years experienced with at least one activity limitation. This variable is important for the current study as HALE is a measure of the economic and productive factor of the economies. Increasing the value of HALE is one of the constant objectives of the policies of the EU. Besides the social benefits, increasing the value of HALE would decrease the costs for the healthcare systems and would increase employee productivity.

As defined by Eurostat, *infant mortality rate* represents the ratio of the number of deaths of children under one year of age during the year to the number of live births in that same year. The value is expressed per 1000 live births.

Hospital Beds are included in the model as input variable.Total hospital beds are all hospital beds which are regularly maintained and staffed and immediately available for the care of admitted patients per 10.000 inhabitants. Total hospital beds are broken down as follows: curative care (acute care) beds; psychiatric care beds; long-term care beds (excluding psychiatric care beds); other hospital beds.

The second input variable describes the human resource most valuable in healthcare system: *the number of doctors*. The indictor includes: persons who have a degree in medicine at university level (proved by an adequate diploma) and who are licensed to practice; interns and resident physicians (with an adequate diploma and providing services under the supervision of other medical doctors during their postgraduate internship or residency in a health care facility); salaried and self-employed physicians delivering services irrespectively of the place of service provision; foreign physicians licensed to practice and actively practicing in the country.

In both cases, statistical data are calculated for 10.000 inhabitants.

The third input variable refers to *the percentage of GDP allotted to healthcare*. The percentage of the GDP allotted to health consists of recurrent and capital spending from government (central and local) budgets, external borrowings and grants (including donations from international agencies and nongovernmental organizations), and social (or compulsory) health insurance funds.

5. **Results and discussions**

Before discussing the results of DEA models, it would be useful to briefly describe the input and output variables, by the mean of descriptive statistics (see table 1). The number of hospital beds for 10,000 inhabitants ranges from 21 beds per 10,000 inhabitants in Sweden, to 82 beds per 10,000 inhabitants in Germany. On the average, the countries from the sample have 54.3 beds per 10,000 inhabitants. With a standard deviation of 15.7 beds per 10,000 inhabitants and a coefficient of variation of 29%, the sample is homogeneous.

The number of physicians ranges from 19.2 physicians per 10.000 inhabitants in Romania to 60.4 physicians per 10.000 inhabitants in Greece. The number of physicians has a standard deviation of 7.7 physicians per 10.000 inhabitants and a coefficient of variation of 22.72%, thus the sample for the variable is homogeneous.

The percentage of health expenditures has a minimum of 2.45% (Cyprus) and a maximum of 9% in (Denmark and France). The percentage of public health expenditures has a standard deviation of 1.65% and a coefficient of variation of 25.3%, which means that the sample of 30 states is homogeneous from this point of view.

Life expectancy has a minimum of 72.8 in Lithuania and a maximum of 81.6 in Italy. Life expectancy has a standard deviation of 2.8 years and a coefficient of variation of 3.63%, which means that the sample of 30 states is homogeneous from this point of view.

The infant mortality rate ranges from 2.2 deaths per 10,000 inhabitants in Iceland, to 9.8 deaths per 10,000 inhabitants in Romania. On the average, the countries from the sample have 4.1deaths per 10,000 inhabitants. With a standard deviation of 1.8 deaths per 10,000 inhabitants and a coefficient of variation of 43.11%, the sample is homogeneous.

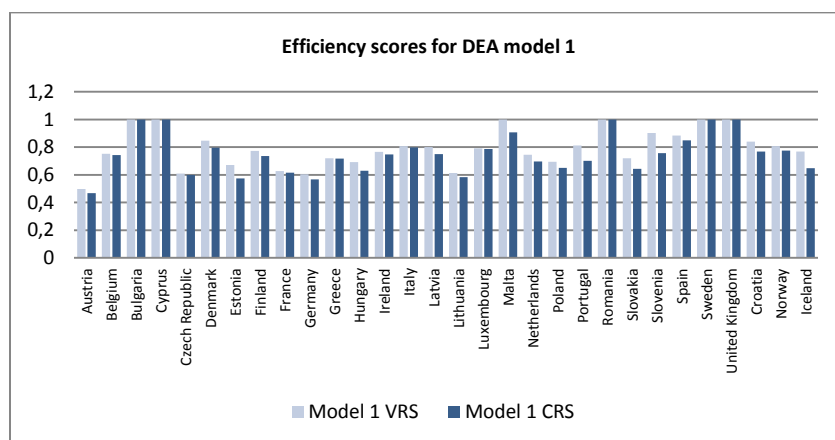Table 1. Descriptive statistics for input and output variables

	Number of beds	Physicians	Health Exp. as % of GDP	Life expectancy	Infant Mortality Rate
Max	82.0	60.4	9.0	81.6	9.8
Min	21.0	19.2	2.5	72.8	2.2
Average	54.3	34.0	6.5	78.4	4.1
SD	15.5	7.7	1.6	2.8	1.8
Coeff. of Variation	28.49%	22.72%	24.90%	3.63%	43.11%

Source: authors' computations based on Eurostat data (2010)

There is a strong and positive correlation between HALE and life expectancy (coefficient of correlation is 0.7) and therefore we employ these variables in two separate DEA models. In the first model the inputs are HALE and infant mortality rate, while in the second model the inputs are life expectancy and infant mortality rate. In both models we include the three mentioned output variables.

Model 1 has average efficiency scores of 0.74 for CRS and 0.75 for VRS, with a standard deviation of 0.13. Six countries out of 30 are efficient: Bulgaria Cyprus, Malta, Romania, UK, and Sweden. Interestingly, alongside with developed countries such are the former two, we find developing countries, with less financial resources. Other 7 countries have an efficiency score higher than 0.8, while most of the countries in the sample (16) have efficiency scores between 0.6 and 0.8. One country (Austria) has a technical efficiency lower than 0.5 (see figure 1). Among the countries that have efficiency scores less than average there are Germany and France, but also Lithuania, Czech Republic or Hungary (see figure 1).
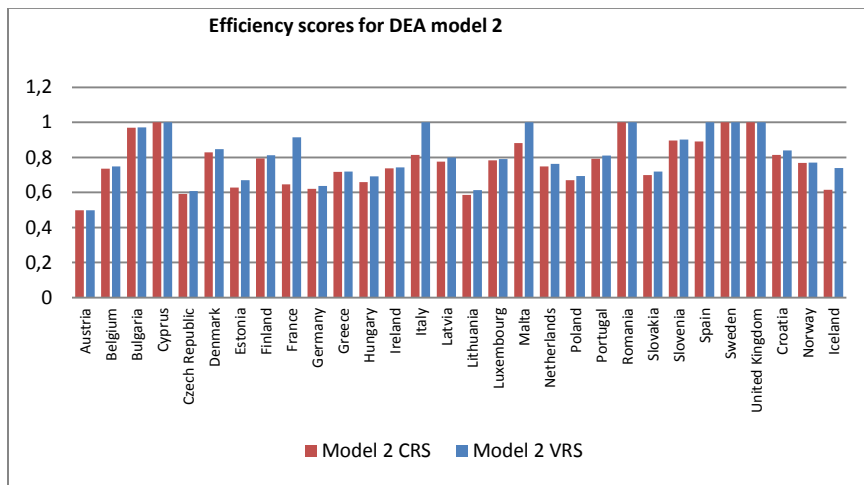
Figure 1.

The second model provides average efficiency scores slightly higher compared to previous one: 0.81 for CRS and 0.77 for VRS, with a standard deviation of 0.14. In the case of VRS model, 7 countries

out of 30 are efficient: Cyprus, Latvia, Malta, Romania, UK, Spain and Sweden. The group of efficient countries is almost unchanged in the two models. Again, 7 countries have efficiency scores higher than 0.8, while half of the countries in the sample (15 countries) have efficiency scores between 0.6 and 0.8. Austria is the least efficient country with a technical efficiency score of 0.49 (see figure 2). Among the countries that have efficiency scores less than average we find the same countries as in previous case (Germany, Lithuania, Czech Republic or Hungary); France has a better position compared to model 1 results (rank 9 in the VRS model) with an efficiency score of 0.91.

The scale efficiency was also considered in the analysis, and scale was computed as the ratio between efficiency scores in the CRS and VRS models. Not surprisingly, the findings from both models reflect decreasing return to scale for the great majority of the DMUs, with a coefficient of returns to scale lower than 1. This implies that an increase in inputs will generate a smaller increase in outputs. Four countries that were efficient in both models present a constant return to scale: Cyprus, Romania, Sweden and the UK.

Figure 2

6. Conclusions

The main findings of the paper reflect that some developed countries are efficient in using their inputs in healthcare system and there are several developing countries that also proved to be on the efficiency frontier. Among these, surprisingly there are Romania and Bulgaria. Romania has the highest infant mortality rate in Europe and one of the lowest numbers of doctors per 10.000 inhabitants. Although, the results of the model proof that the resources, even if they are limited, are efficiently used.

On the contrary, we also found developed countries that generate high GDP per capita and which are not technically efficient.

There are minor differences between the two models, in countries distribution according to the efficiency scores. Therefore, in both models most of the countries have a medium efficiency level, while Austria has the lowest value.

These conclusions raised the need of continuing the research by extending the list of input and output variables. Particularly, the research will be adjusted with a new set of output variables that takes into account the death rates on specific diseases, while input variables will be supplemented with the number of radiotherapy units. At the same time, a dynamic approach could be employed, by applying Malmquist Index.

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