EFFICIENCY OF THE EUROPEAN STEEL SECTORS BASED ON DATA ENVELOPMENT ANALYSIS

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Abstract

The global issue in all sectors is to increase the efficiency. In heavy industry as in steel sector, there is also a question about the environment - the production of emissions. The European trading system with emissions of CO_2 had been established in order to increase the efficiency in production with respect to emissions production. The unfair allocation of emissions allowances or generally the impact of the system has been discussed in many studies. This paper evaluates the efficiency of national steel sectors in 22 European countries. The calculations and analysis are made at national level. The Data Envelopment Analysis method is used. To perform the analysis, the data on inputs (number of allowances allocated for free, energy consumption) and outputs (amount of production and CO_2 emissions) for year 2014 are used.

Keywords: Steel sector, Data Envelopment Analysis, efficiency

1. INTRODUCTION

The global climatic changes caused by people and human impact are seen all over the world. Nowadays, the attention to this topic is much bigger. In 2005, the EU ETS (Emissions Trading Scheme of the EU) has been established with the aim of the reduction CO_2 emissions in European countries. This system force industrial companies to cover their CO_2 emissions by emissions allowances. These allowances can increase costs of companies a lot. There have been many reasons for invention of the emissions trading system, the most important one was obviously to save the environment. It means to put the pressure on the companies and their environmental efficiency in production. As it is known, the environmental efficiency is related to amount of emissions released per each unit of production. This paper is devoted to measure the environmental efficiency of whole EU countries for iron and steel sectors. In particular, three Data Envelopment Analysis methods are used to evaluate the efficiency and the results are further compared.

The Data Envelopment Analysis (DEA) has been used in efficiency analysis of many applications - banking industry, insurance industry, health care and so on. The three most known and widely used DEA models are the CCR model by Charnes et al. [2], the BCC model by Banker et al. [1] and the Additive model by Charnes et al. [3]. These models were formulated for desirable inputs and outputs. However, in real applications, there are frequently needed undesirable inputs and/or outputs. This problem is also in the application of DEA for the iron and steel sector. More precisely, it is know that CO_2 emissions are undesirable outputs.

In the scientific literature, there are known some approaches and DEA models which deal with undesirable inputs and/or outputs. These models are usually a transformation of the basic DEA models. One of the most known and acceptable transformation is based on the ADD approach by Koopmans [4]. The transformation is given by the formula $f(Y) = -Y + \beta$. This type of the transformation has been used for example in work of Seiford and Zhu [8]. However, the weakness of this transformation is that the classification may depend on β as well as the final ranking can do so. Another transformation is given by the formula $f(Y) = 1/Y$ and this transformation is based on multiplicative inverse. This transformation was used in work by Lovell et al. [7]. There are also approaches that can avoid data transformation. The most known type of this type of approach suggests that undesirable inputs are regarded as desirable outputs and undesirable outputs are regarded as desirable inputs for an initial attempt to formulate the model. This was invented in work by Liu and Sharp [6], for example. The disadvantage of this method is that it is good just if the research is done for the operational efficiency. However, in this work all three above mentioned approaches are used and analyzed.

The paper is organized as follows. The analysis of the current state of Data Envelopment Analysis in the steel sector is provided in the Chapter 2. The Chapter 3 describes a structure of the problem and corresponding data sets. The results and the close analysis are in the Chapter 4. The final conclusion summarizes the main contributions of this paper and some proposals for a further research are provided in the last Chapter 5.

2. METHODOLOGY OF DATA ENVELOPMENT ANALYSIS

Data envelopment analysis (DEA) is non-parametric linear programming based technique for measuring the relative efficiency of a set of similar decision making units (DMUs). Since the work of Charnes et al. [3], DEA has demonstrated an effective technique for measuring the relative efficiency of a set homogenous DMUs. In application, DMUs may include banks, hospitals, schools, different types of industries and other. The basic idea of DEA is, each DMU allocates its resources into a number of inputs to produce various outputs. The relative technical efficiency of the DMU unit is define as the ratio of its total weighted output to its total weighted input or vice versa. DEA allows each production DMU unit to choose its own weights of inputs and outputs in order to maximize or minimize its efficiency score depending on the task. The technically efficient production DMU unit has such weights for its inputs and outputs that it lies on the production frontier. The production frontier represents the maximum amounts of output that can be produced by given amounts of input in the output maximization model or the minimum amounts of inputs required to produce the given amounts of output in the input minimization model. DEA calculates the efficiency score for each production unit and identifies peers for each production unit that is not technically efficient.

2.1. Classic DEA models

As it was mentioned above, the relative technical efficiency of the DMU unit is define as the ratio of its total weighted output to its total weighted input. Mathematically, it can be define as:

$$e_k = \frac{\sum_{j=1}^{S} v_j y_{jk}}{\sum_{i=1}^{R} u_i x_{ik}}, \text{ for } k = 1, ..., T. \tag{1}$$

where we suppose, a set of T DMUs (DMU$_k$ for $k = 1, \ldots, T$), let inputs and outputs data be $X = \{x_{ik}, i = 1, \ldots R; k = 1, \ldots, T\}$ and $Y = \{y_{jk}, j = 1, \ldots S; k = 1, \ldots, T\}$, respectively. Also, u_i for $i = 1, \ldots, R$ and v_j for $j = 1, \ldots, S$ be the weights of the i^{th} input and the j^{th} output, respectively.

Charnes et al. [2] have proposed the first CCR model to measure the efficiency score of the under evaluation unit, DMU$_Q$ where $Q \in \{1, \ldots, T\}$. The mathematical model is following:

$$\begin{aligned} &\max\ e_Q = \frac{\sum_{j=1}^{S} v_j y_{jQ}}{\sum_{i=1}^{R} u_i x_{iQ}}, && \\ \text{s.t.}\ &\sum_{j=1}^{S} v_j y_{jk} - \sum_{i=1}^{R} u_i x_{ik} \le 0, && k = 1, ..., T, \\ &u_i \ge 0, && i = 1, ..., R, \\ &v_j \ge 0, && j = 1, ..., S. \end{aligned} \tag{2}$$

However, it is non-linear model, more precisely it is the model of linear-fractional programming. ON the other hand, the model can be transferred by Charmes-Cooper transformation to the standard linear programming problem:

$$\begin{aligned}
&\max\ e_Q = \textstyle\sum_{j=1}^{S} v_j y_{jQ}, && \\
\text{s.t.}\quad &\textstyle\sum_{i=1}^{R} u_i x_{iQ} = 1, && \\
&\textstyle\sum_{j=1}^{S} v_j y_{jk} - \sum_{i=1}^{R} u_i x_{ik} \le 0, && k = 1,\dots,T, \\
&u_i \ge 0, && i = 1,\dots,R, \\
&v_j \ge 0, && j = 1,\dots,S,
\end{aligned} \tag{3}$$

Where $Q \in \{1, \dots, T\}$. DMU_Q is CCR-efficient if and only if e^* =1 and if there exists at least one optimal solution (u^*, v^*) with $u^* > 0$ and $v^* > 0$ for the set $Q \in \{1, \dots, T\}$. The inefficient units have a degree of relative efficiency that belongs to interval [0, 1). Note: The model must be solved for each DMU separately.

The model (2) is called a multiplier form of input-orient CCR model. However, for computing and data interpretation, it is preferable to work with model that is dual associated to model (2). The model is referred as envelopment form of input-oriented CCR model, see Charnes et al. [2]. There also exists the multiplier form of output-oriented CCR model. The output-oriented CCR model gives the same results as the input-oriented CCR model. It can also be seen in Charnes et al. [2].

Banker et al. in [1] extended the CCR model. The extended model is called the BCC model and considers variable returns to scale assumption. The model has convex envelope of data which leads to more efficient DMUs. The mathematical model of dual multiplier form of input-oriented BCC model is:

$$\begin{aligned}
&\max\ e_Q = \textstyle\sum_{j=1}^{S} v_j y_{jQ} - v_0, && \\
\text{s.t.}\quad &\textstyle\sum_{i=1}^{R} u_i x_{iQ} = 1, && \\
&\textstyle\sum_{j=1}^{S} v_j y_{jk} - \sum_{i=1}^{R} u_i x_{ik} - v_0 \le 0, && k = 1,\dots,T, \\
&u_i \ge 0, && i = 1,\dots,R, \\
&v_j \ge 0, && j = 1,\dots,S, \\
&v_0 \in (-\infty, \infty), &&
\end{aligned} \tag{4}$$

Where v_O is the dual variable assigned to the convexity condition $e^T \lambda = 1$ of envelopment form of input-oriented BCC model. The BCC model can also be rewritten into the envelopment form of changed into the output orientation.

2.2. Data Envelopment Analysis for Undesirable Outputs

The models in previous subsection are basic models where the inputs and outputs are desirable. However, in real applications, there are frequently needed undesirable inputs and / or outputs. In this paper we deal with one undesirable output. Also, according to the efficiency frontier of PROMETHEE method we use just BCC model so there results could be compared.

Suppose the DEA data domain Y contains desirable (good) and undesirable (bad) outputs, represented as Y^g and Y^b, respectively. Obviously, Y^g should increase and Y^b should decrease to improve the performance of DMU. However, in the standard BCC model (3), both Y^g and Y^b are supposed to increase to improve the performance as Y. In order to increase the desirable outputs and to decrease the undesirable outputs, there were found many approaches. In this paper, we use three of them - translation transformation based on work by Koopmans [4], transformation of multiplicative inverse used by Lovell et al. [7] and basic method - change the meaning of the variable used by Liu and Sharp [6].

Translation

Based upon work of Koopmans [4], the basic model (3) is used for the calculation if: the Y^b is multiplied by value (-1) and then the maximum value of max $|Y^b|$ is add to ($-Y^b$). Note: This model is known as Model A in this paper.

Inverse Multiplication

According to work of Lovell et al. [7], the basic model (3) is used for the calculation if the Y^b is changed as inverse value $1/Y^b$. Note: This model is known as Model B in this paper.

Change of Variables

Based upon the idea of work by Liu and Sharp [6], Y^b is changed into X and the basic model (3) is used. Note: This model is known as Model C in this paper.

3. VARIABLES

The variables which are involved in the analysis of this paper are result of the close analysis of previous research. There are not many studies about the iron and steel industry, but there are some studies about the heavy industry. These studies and analysis have been the inspiration for our paper. The classical production model for the heavy industry using DEA, such as the one in work of Kumar and Khanna [5], consider population and energy consumption as inputs. GDP and CO_2 emissions are considered as outputs (desirable and undesirable, respectively). As we are looking for the special part of the industry, we changed the input population and we have used the number of allowances allocated for free for this type if industry.

In **Table 1** there are closely described all inputs and outputs.

Table 1 Inputs and Outputs of the analysis

Inputs			
Name	**Units**	**Description**	**Origin**
Number of allowances allocated for free	pcs	Companies participating in the EU ETS system obtain certain amounts of allowances for free from the EU authorities. This factor influences costs on emissions trading as well as abatement costs.	Database: carbonmarketdata.com
Energy consumption	GW	The higher energy consumption by steel companies, the higher amount of emissions released and, also, the higher costs on emissions trading.	Database: Eurostat
Outputs			
Name	**Units**	**Description**	**Origin**
Number of CO2 emissions released	pcs	Emissions are considered as the undesirable output. The environmental efficiency weakens with increasing emissions.	Database: carbonmarketdata.com
Level of iron and steel production	tons	Total amount of iron and steel products manufactured in a country. Here, a slight simplifycation has been done because products are supposed to be homogenous (no differences in environmental burden of different iron and steel products are taken into account).	Database: Eurostat

All used data are of annual frequency and they are aggregated by all steel producing companies doing their business in a particular EU country.

4. THE RESULTS OF ANALYSES

All the DEA models have been performed using GAMS software. The results are shown in **Table 2**. It can be seen that generally all results are very similar. The biggest difference is between the Model A and the rest models. The difference is in the number of efficient countries. Seven countries are efficient - D, ESP, ITA, LAT, LUC, NED, POR if the calculation have been done for the Model B and the Model C. Ten countries are efficient for the Model A - same countries as before and three more - F, SLO, SWE.

Generally, the Model A gives same or highest efficient score then the rest models - for example: BEL has the efficient score for the Model A equal to 0.7681 and 0.6333 for the rest models. In case of GR, the efficiency score is different for all models - Model A (0.6419) > Model C (0.6185) > Model B (0.6006). Just for FIN and HU the highest efficiency score is in the Model C. If we have compared the Model B and Model C, we can see that the Model B gives the lowest efficient scores, for example in case of FIN the Model C gives the efficient score equal to 0.6182 and the Model B gives 0.5776. These differences are caused by different position of the undesirable output. We can see how each transformation influence the efficiency score.

Table 2 Results of DEA methods

DMU	Name of state	Model A	Model B	Model C
DMU01	Austria (AU)	0.9871	0.9871	0.9871
DMU02	Belgium (BEL)	0.7681	0.6333	0.6333
DMU03	Bulgaria (BLG)	0.8063	0.4364	0.4364
DMU04	Czech Republic (CZ)	0.4557	0.4557	0.4557
DMU05	Germany (D)	1.0000	1.0000	1.0000
DMU06	Span (ESP)	1.0000	1.0000	1.0000
DMU07	Denmark (DK)	0.6182	0.6182	0.6182
DMU08	France (F)	1.0000	0.5368	0.5368
DMU09	Finland (FIN)	0.5776	0.5776	0.6182
DMU10	Great Britain (GB)	0.9073	0.8189	0.8189
DMU11	Greece (GR)	0.6419	0.6006	0.6185
DMU12	Hungary (HU)	0.5052	0.5511	0.5052
DMU13	Italy (ITA)	1.0000	1.0000	1.0000
DMU14	Latvia (LAT)	1.0000	1.0000	1.0000
DMU15	Luxemburg (LUC)	1.0000	1.0000	1.0000
DMU16	Nederland (NED)	1.0000	1.0000	1.0000
DMU17	Poland (PL)	0.8341	0.6176	0.6176
DMU18	Portugal (POR)	1.0000	1.0000	1.0000
DMU19	Romania (RO)	0.3254	0.3254	0.3254
DMU02	Slovakia (SK)	0.7540	0.3492	0.3492
DMU21	Slovenia (SLO)	1.0000	0.1409	0.1409
DMU22	Sweden (SWE)	1.0000	0.4367	0.4367

It is really important to say, that DEA analysis is using generally for the calculation of technical efficiency and as it was said before, some transformation which have been done may cased some problems. For example, as little surprising may be seen, that the efficiency score for the Czech Republic is so low (0.4557). Also the problem of Slovenia is interesting (Model A = 1.0000 and Model B and C = 0.1409). According to this, we may say that Slovenia is the one country which is really influence by the dependency on the coefficient β and its relationship should be more closely analyzed. On the other hand, as it was mentioned, all results are really close, so we thing that these results may be used.

5. CONCLUSIONS

This paper deals with measuring the efficiency of national steel sectors in the EU. Three special types of Data Envelopment Analysis have been used - methods which have to be used for undesirable output variable. When comparing the results of all methods, significant differences have not been found. The number of efficient units are similar. On the other hand, there have been some a bit surprising results found - the Czech Republic has been one of the least efficient countries and big difference of classification was found for Slovenia. This may be causes by some the mentioned differences of the transformation and also by the fact that the standard DEA model is mainly used just for the technical efficiency.

For future work we would like to make closer analysis of inputs and outputs which may be used for this type of application. Also we would like to use the method of relocation of the allowances to see if there is better use of them. Another possibility for research is also to try different transformation models of DEA or try different method as PROMETHEE or so on.

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