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ECO-EFFICIENCY AND HUMAN CAPITAL IN EUROPE: QUANTITATIVE ASSESSMENT

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Abstract:
Eco-efficiency of production has been an issue in decision making process on a firm level as well as macro-level of national economy. Quality of human capital can undoubtedly affect the efficiency of the process of transforming inputs into desirable outputs while keeping „bads“ as low as possible. In the paper, efficiency of European economies is assessed using non-parametric method of data envelopment analysis as an application of linear optimization. A specific slack-based measure is employed to capture sources of inefficiency in standard macroeconomic inputs – labour and capital stock. Human capital enters the model in the form of the labour-augmenting coefficient obtained from wage regressions and years of education. The results obtained by the proposed methodology can be informative as to determining sources of inefficiency in inputs as well as to giving the general picture of the human capital acting as input in the production process to provide a possible support for decision makers.

Keywords: eco-efficiency, human capital, data envelopment analysis, SBM model

1. INTRODUCTION

There is a massive body of research proving the role of variously defined human capital in creating the economic value. Microeconomic studies concentrate on.. On the macrolevel, the focus is directed to the quantification of the contribution of human capital (HK) to economic growth. Endogenous theory of growth considers HK being the main driver of economic development. Productivity studies have been incorporating HK into exogenously determined growth since Mankiw, Romer & Weil (1992). All these approaches are based on the parametric functional relationship between inputs and the output leaving no space to speak of efficiency as deviations from the maximal output prescribed by the production function are considered to be caused by other factors than included in the model. Taking alternative approach viewing input and output data as deterministic and barely a result of the production process, one can speak of efficiency of transformation of the inputs into the output or even multiple outputs. The core of non-parametric approach is thus to determine whether a unit under consideration transforms its inputs efficiently or not with respect to a given set of assessed subjects. The method of Data Envelopment Analysis (DEA) was pioneered by Charnes, Cooper & Rhodes (1978) giving rise to a number of modifications of the basic model. In non-parametric studies, Henderson & Russell (2005) decomposition method is noticeable determininig contribution of HK to productivity change.

There is an ongoing debate on *beyond GDP* assessment of economic development. One of the main dimensions considered to contribute to the welfare is the quality of the environment. This paper aims at incorporating ecological issues into non-parametric evaluation of technical efficiency with human capital involved, units under consideration being national economies in Europe. We proceed by introducing technical efficiency assessment via Slack-based (SBM) model in Section 1. Data and modelling strategy are described in Section 2 followed by results of computation in Section 3 presented in tables accompanied by comments. Section 4 concludes.

2. ASSESSMENT METHOD: DEA MODEL

2.1. Basic concepts and notation

In standard DEA subjects being evaluated are called Decision Making Units (DMUs). These are viewed as transforming *m* inputs into *s* outputs. Inputs and outputs are organized in matrices *X* and *Y*, element x_{ij} meaning amount of input *i* used by DMU *j*, the similar way for outputs in *Y*

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ . & . & \cdots & . \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \quad Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ . & . & \cdots & . \\ y_{s1} & y_{s2} & \cdots & y_{sn} \end{bmatrix}$$

in DEA, no specific form of production (transformation) function is assumed. Instead of that, the empirical production possibility set boundary is constructed as the set of linear combinations of the data of DMU under consideration. Thus, some unit can appear inefficient as one observes that actual activity of one DMU is outperformed by a composite unit formed as a linear combination of some other DMUs. Once DMU cannot increase one of the outputs without increasing at least one input or decreasing other output, it is efficient in Pareto-Koopmans interpretation.Given matrices *X* and *Y*, for every DMU_0 the following expressions hold:

$$\begin{aligned} \mathbf{x_0} &\geq X\boldsymbol{\lambda} \\ \mathbf{y_0} &\leq Y\boldsymbol{\lambda},\ \boldsymbol{\lambda} \geq 0 \end{aligned} \tag{1.1}$$

Thus production possibility set is described by inequations 1.1, its frontier being points are linear combination of the efficient DMUs “enveloping” the data. There is a variety of approaches as regards quantifying inefficiency with respect to the efficiency boundary, the problem amounts to measuring distance to the frontier.

2.2. SBM measure of efficiency

The most comprehensive measure of efficiency requires introducing input and output *slack* variables. In DEA, slacks act as exact measure of deviation from the frontier which stands to describe best practice available given the technology. The meaning of slacks in DEA differs from that in managerial science where it could be less exact and have more qualitative substance. Inequalities 1.1 can be then rewritten as

$$\begin{aligned}\mathbf{x_0} &= X\boldsymbol{\lambda} + \mathbf{s}^- \\ \mathbf{y_0} &= Y\boldsymbol{\lambda} - \mathbf{s}^+\end{aligned} \quad (1.2)$$

Output and input slack variables can be seen as a potential for underperforming units which can be reached by increasing output by $\mathbf{s}^+$ and/or reducing inputs by $\mathbf{s}^-$.

The slack-based model (SBM) introduced by Tone (2001) is one of the powerful developments to capture all sources of inefficiency. The objective function ρ which measures a "distance" of the DMU to the frontier has two important properties of unit invariance and monotonicity. Efficiency assessment is obtained by solving a fractional program

$$\min_{\boldsymbol{\lambda},\mathbf{s}^+,\mathbf{s}^-} \quad \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}} \quad (1.3)$$

$$\begin{aligned}\text{s.t.} \quad & \mathbf{x_0} = X\boldsymbol{\lambda} + \mathbf{s}^- \\ & \mathbf{y_0} = Y\boldsymbol{\lambda} - \mathbf{s}^+ \\ & \boldsymbol{\lambda} \geq 0,\ \mathbf{s}^- \geq 0,\ \mathbf{s}^+ \geq 0\end{aligned}$$

which can be linearized and solved for slacks and $\boldsymbol{\lambda}$. As described in the section 1.1, optimal non-zero solutions for λ define set of indexes of efficient DMUs with all slacks equal zero. Thus the measure of efficiency for efficient units is unit. Every inefficiency given by slacks is penalized so that $\rho < 1$.

To give the model input orientation in order to reflect preferences and feasibility of the policy, output slacks are omitted in the objective function of 1.3. Return to scale can be incorporated in the model the way proposed by Banker et al. (1984) which consists in the additional constraint $\mathbf{e}^{\mathbf{T}}\boldsymbol{\lambda} = 1$ (**e** denoting the unit vector) allowing for variable returns to scale (VRS). SBM input oriented model with VRS takes the form of

$$\min \quad \rho = 1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0} \quad (1.4)$$

$$\begin{aligned}\text{s.t.} \quad & \mathbf{x_0} = X\boldsymbol{\lambda} + \mathbf{s}^- \\ & \mathbf{y_0} = Y\boldsymbol{\lambda} - \mathbf{s}^+ \\ & \mathbf{e}^{\mathrm{T}}\boldsymbol{\lambda} = 1 \\ & \boldsymbol{\lambda} \geq 0,\ \mathbf{s}^- \geq 0,\ \mathbf{s}^+ \geq 0\end{aligned}$$

After determining relevant input and output variables, this measure can be used to assess efficiency of DMUs.

3. DATA AND MODELLING

In our modelling, we consider European countries as DMUs (n=28) transforming inputs (labour or human capital augmented labour and capital) into a single output – GDP. Thus efficiency scores for each individual country can be computed by solving linear optimization program.

3.1. Modelling human capital

Modelling human capital follows Hall & Jones (1999) as labour-augmenting coefficient H:

$$\hat{L}_{jt} = H_{jt} L_{jt} = h(\varepsilon_{jt}) L_{jt} = e^{\phi(\varepsilon_{jt})} L_{jt}$$

where function $\phi(\varepsilon)$ reflects the relative efficiency of a unit of labour with ε schooling years relative to one with no schooling. Thus if $\phi(0)=0$ then $h(0)=1$ and no augmentation of labour takes place.

The derivative $\frac{d \ln h(\varepsilon_{jt})}{d\varepsilon_{jt}} = \phi'(\varepsilon_{jt})$ is the return to schooling. The values are borrowed from estimations in Mincerian regressions (Psacharopoulos & Patrinos, 2004) where values of returns to educations for primary, secondary, and tertiary schooling are reported. ϕ is thus a piecewise linear function with segments corresponding to the three educational levels. To complete calculations of H for individual countries, Barro & Lee (2010) database values of average years of schooling was used. Difference made by taking HK into account in evaluating technical efficiency of the countries was showed in Nežinský and Fifeková (2014).

3.2. Eco-efficiency

To assess environmental and economic dimension at the same time, one needs to incorporate undesirable outputs into pure technical model. In this analysis, a proposed method of Korhonen & Luptáčik (2004) was adopted. Instead of dealing with “bads” as negative outputs, they can be considered additional input justified by additional costs associated with increased level of pollution. One can give eco-efficiency a Pareto-Koopmans interpretation as the state when DMU cannot increase its output without employing additional inputs, producing more undesirables. Korhonen & Luptáčik propose a number of radial models to assess eco-efficiency, all of them suffering from the possible slack variables which do not enter evaluation function and thus can cause a bias in assessment. SBM measure resolves that problem identifying and penalizing all sources of inefficiency.

3.3. Data sources and overview of the models employed

Modelling strategy consists of comparing two models – pure technical (*tech*) assessing output with respect to capital and human-capital-augmented labour. The second augmented model (*eco*) is supplemented by undesirable outputs – greenhouse gas emissions. An eco-efficient unit thus cannot produce more output without worsening at least one input, i.e. increasing technical input or pollute more. Data on GDP, labour, and greenhouse gas emissions come from Eurostat database. Average years of education are reported in Barro & Lee world database. The data have been used in the models listed in Table 1.

Table 1: Overview of the models employed

model	type	variables			
		inputs			output
tech	SBM-I-V	K	HL		Y
eco	SBM-I-V	K	HL	E	Y

Source: The author´s elaboration

Data on capital come from the database of the European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN) – AMECO. SBM input oriented models assume variable returns to scale incorporated to reflect variation in size of the European economies. Statistical properties of the data are given in the Table 2.

Table 2: Data properties

Statistics on Input/Output Data				
	K	HL	E	Y
Max	6735688,5	57564,9	936544,0	2294281,0
Min	13426,1	236,2	3035,0	8168,1
Average	1140743,5	10263,4	172033,8	430530,7
SD	1666930,2	13382,1	220836,6	588357,2
Correlation				
	K	HL	E	Y
K	1,000	0,968	0,963	0,995
HL	0,968	1,000	0,992	0,979
E	0,963	0,992	1,000	0,977
Y	0,995	0,979	0,977	1,000

Source: The author´s elaboration

4. RESULTS

Computation of SBM efficiency measures by a specific model involved computing 28 optimization programs formulated by 1.4 (one program for each DMU).

4.1. Technical efficiency

In Table 3, detailed results of the computations are presented. In the first column, DMUs (countries) are listed, the second column contains respective efficiency scores (ρ values)from model *tech*. The next three columns show deviations from the potential (slacks). Obviously, for input oriented model output (Y) slacks are zero. There are also zero slacks corresponding to efficient DMUs since there is no potential for further improvement. For inefficient ones, slacks reveal potential for input reduction. One can though not focus on absolute values of slack since the size of DMUs and their inputs is at big variance. There is more use having a look at relative size of respective slacks. Eight DMUs form efficiency frontier - Belgium, Germany, Lithuania, Austria, Poland, Slovakia, and United Kingdom.

Table 3: Model tech: slacks and inefficiencies

	score	excess		shortage	inefficiency		
		K	HL	Y	K	HL	Y
Belgium	1	0	0	0	0	0	0
Bulgaria	0,654	23804,1	2466,4	0	0,095	0,251	0
Czech Republic	0,783	65012,2	2410,8	0	0,063	0,154	0
Denmark	0,952	0	345,0	0	0	0,048	0
Germany	1	0	0	0	0	0	0
Estonia	0,628	17945,8	321,8	0	0,196	0,176	0
Ireland	0,964	29193,5	4,0	0	0,035	0,001	0
Greece	0,725	274119,6	1495,2	0	0,156	0,119	0
Spain	0,816	948302,5	2857,2	0	0,126	0,059	0
France	0,900	873854,1	1154,7	0	0,084	0,017	0
Italy	0,845	1525097,8	547,7	0	0,146	0,009	0
Cyprus	0,769	21541,1	4,9	0	0,227	0,004	0
Latvia	0,848	0	421,5	0	0	0,152	0
Lithuania	1	0	0	0	0	0	0
Hungary	0,841	34081,4	1078,1	0	0,069	0,090	0
Malta	1	0	0	0	0	0	0
Netherlands	0,974	0	603,3	0	0	0,026	0
Austria	1	0	0	0	0	0	0
Poland	1	0	0	0	0	0	0
Portugal	0,847	72554,4	918,0	0	0,062	0,092	0
Romania	1	0	0	0	0	0	0
Slovenia	0,731	49010,6	142,6	0	0,223	0,046	0
Slovakia	1	0	0	0	0	0	0
Finland	0,936	37114,6	117,6	0	0,045	0,019	0
Sweden	0,899	57188,3	831,9	0	0,037	0,064	0
United Kingdom	1	0	0	0	0	0	0
Norway	0,964	40300,7	0	0	0,036	0	0
Switzerland	0,888	147479,5	262,5	0	0,089	0,023	0

Source: Eurostat, AMECO, Barro & Lee, the author´s calculations

The rest of inefficient countries can be analysed so as to furnish potential improvement. Since the expression $\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}$ presents total penalty for slacks in the objective function in 1.4 individual summands s_i^- / x_{i0} can be interpreted as *i*-th input´s contribution to the total inefficiency. Thus relative size of the term gives picture of how the input is important in terms of efficiency. The lower the value of the less improvement is needed to achieve efficiency. Values of input inefficiency are exhibited in the rightmost four columns of Table 3. Again, output does not contribute to inefficiency due to input orientation of the model and there is no inefficiency detected for efficient DMUs. Countries are showing various patterns of inefficiencies being purely inefficient in HL (Netherlands, Latvia, Denmark) or in both inputs with a different proportion. Only Norway shows pure inefficiency in capital.

4.2. Eco-efficiency

As described in the sections 2.2, eco-efficiency scores reflect two-dimensional assessment of economic performance. Table 4 contains eco-efficiency scores obtained from Model *eco* as well as decomposition terms indicating inefficiencies in the same way as in Table 3 for Model *tech.*

Adding another variable cannot reduce the set of efficient DMUs though the *tech* score can be deteriorated (Denmark, Ireland, Netherlands, Finland, Norway). There are thus shifts in ranking. One can see changes in scores and inefficiencies resulting from augmenting the model. The set of efficient countries broadened by France, Hungary, Malta, Slovenia, Sweden, and Switzerland. It is interesting to see developed countries like Finland, Norway or Denmark performing relatively worse than new EU member states.

5. CONCLUSION

Having defined eco-efficiency and its measure, a comparison of the two models was made to identify possible ways for greening the production in Europe. Human capital was incorporated in labour input as augmenting coefficient which enables interpreting excess use as either excessive use of labour at the given level of education or overeducation of the labour force in use.

Some conclusions can be drawn from the number of countries an efficient DMU presents a benchmark for. There are two units – Malta and Switzerland being a peer for 7 and 8 countries respectively which allows for the interpretation that they can be viewed as masters in pursuit of improving eco-efficiency in related countries. On the other hand, Germany, Romania, Austria or Sweden have no other country to be benchmark for appearing lying aside of the main body of the data. It could be suggested that there would be no that easy way to approach them.

Non-parametrical approach proved helpful in multidimensional evaluation. The results can be helpful as a suggested tool to facilitate decision-making.

Table 4: Model *eco*: slacks and inefficiencies

		excess			shortage	inefficiency			
DMU	Score	K	HL	E	Y	K	HL	E	Y
Belgium	1	0	0	0	0	0	0	0	0
Bulgaria	0,860	0	0	25781,8	0	0	0	0,140	0
Czech Republic	0,957	0	0	17821,9	0	0	0	0,043	0
Denmark	0,861	0	230,0	21610,3	0	0	0,021	0,118	0
Germany	1	0	0	0	0	0	0	0	0
Estonia	0,797	0	0	12511,8	0	0	0	0,203	0
Ireland	0,806	25185,1	3,5	31945,5	0	0,020	0	0,174	0
Greece	0,800	5982,9	0,8	69950,3	0	0,003	0	0,197	0
Spain	0,997	0	0	3309,7	0	0	0	0,003	0
France	1	0	0	0	0	0	0	0	0
Italy	0,986	0	0	20917,8	0	0	0	0,014	0
Cyprus	0,894	0	0	3432,1	0	0	0	0,106	0
Latvia	0,969	0	0	1130,1	0	0	0	0,031	0
Lithuania	1	0	0	0	0	0	0	0	0
Hungary	1	0	0	0	0	0	0	0	0
Malta	1	0	0	0	0	0	0	0	0
Netherlands	0,920	0	384,2	43517,3	0	0	0,011	0,069	0
Austria	1	0	0	0	0	0	0	0	0
Poland	1	0	0	0	0	0	0	0	0
Portugal	0,855	12940,1	1,8	29134,9	0	0,008	0	0,138	0
Romania	1	0	0	0	0	0	0	0	0
Slovenia	1	0	0	0	0	0	0	0	0
Slovakia	1	0	0	0	0	0	0	0	0
Finland	0,778	5735,3	181,9	44120,4	0	0,005	0,020	0,197	0
Sweden	1	0	0	0	0	0	0	0	0
United Kingdom	1	0	0	0	0	0	0	0	0
Norway	0,910	5985,9	74,6	12949,3	0	0,004	0,006	0,080	0
Switzerland	1	0	0	0	0	0	0	0	0

Source: Eurostat, AMECO, Barro & Lee, the author´s calculations

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