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NON-CONTROLLABLE VARIABLE IN MACROECONOMIC EFFICIENCY ASSESSMENT

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Abstract: Up-to-date developments in the area of application of non-controllable variables in non-parametric efficiency evaluation either employ radial DEA models that suffer from the problem of weak efficiency neglecting non-zero slacks or give a general treatment with illustrative examples using unreal data. The aim of this study is to assess technical efficiency 25 European countries employing a simple slack-based DEA model with controlled variables supplemented by non-controllable variable of active population afterwards to demonstrate (i) the resulting difference in both scores and projected benchmarks from the two models and (ii) to justify proposed use of uncontrollable in such type of models. Results of the models involving capital, labour, GDP and population reveal relatively excessive use of capital in most European countries. Use of the uncontrollable was justified and made most difference in case of Bulgaria, Greece, and Netherlands. Ireland appears a technical benchmark economy for EU.

Keywords: data envelopment analysis, non-controllable variable, SBM model, technical efficiency

JEL classification: C61, E10

1 Introduction

Productivity studies present a massive bulk of supportive analytical work providing a basis for economic policy decision makers. The major interest consists of determining potential product, growth accounting and convergence issues which assumes a specific (e.g. Cobb-Douglas) type of production function. A different approach of DEA (data envelopment analysis) dating back to late 1970s lets the production function unspecified while the production possibility set (PPS) is formed by linear combinations of a number of observed activities named DMUs (decision making units characterized by their inputs and outputs). The boundary of production possibility set presents the maximum possible output which is achieved by at least one of the units under consideration. Thus no parameters are to be estimated, production function is approximated by a frontier of the constructed PPS. One can speak of efficiency or inefficiency in terms of the distance to the *best practice* level. For economic policy, this is specifically an opportunity to relatively compare use of inputs to multiple outputs which can be useful in terms of evaluating achieving multiple goals.

Non-parametric approach to efficiency measurement has become well-established tool in both microeconomic as well as macroeconomic productivity studies. It provides decision makers with an information on potential improvements in performance along with detailed detection of weaknesses. In setting up the model and further interpretation, it is important to consider feasibility of the proposed actions regarding input reduction or output expansion. An artificial DMU acting as benchmark is composed from observed units whose activities are assigned weights being optimal solutions resulting from optimization problem. This way of determining projections may be challenged if some other characteristics of DMUs are taken into account. Applying the usual benchmarking, projected value of non-controllable variable could become unachievable for DMU under consideration. In this case its inefficiency is overestimated and does not provide a proper information about the relative performance.

In DEA models, non-controllable variables are treated two ways. First strand, considering a variable as completely non-controllable, imposes constraints in the envelopment program

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warranting projection be equal the observed value. The other approach deals with non-discretionary variables allowing for a certain degree of control over the variable from a decision maker.

A macroeconomic application studies involving non-controllable variables represented by Kocher et al. (2006) consider economies as DMUs and aim to indicate sources of possible performance increase with respect to focus of research. In applied microeconomic works (Yang and Pollitt, 2009) incorporate a non-controllable into the radial measure of eco-efficiency evaluation that neglects slacks and cannot be reckoned as satisfactory measure of efficiency. A general theoretical treatment of non-controllables is given by Saen (2005) elaborating slack-based measure of efficiency with prescribed parameters assigned to individual inputs or outputs to determine the level of controllability from the DMU´s management. Later developments focus on introducing stochastics to efficiency evaluation combining stochastic frontier approach with deterministic DEA modelling in various multistage approaches (Azadi and Saen, 2012; Khodakarami et al., 2015). Multidimensional assessment of economic performance (Lábaj et al., 2014) which is of interest from the perspective of economic policy and its multiple goals can be made more precise by taking into account uncontrollable factors.

In our investigation, a slack-based efficiency measure (SBM) will be used on an aggregated level of national economies, the main interest being technical efficiency. We wish to demonstrate how efficiency score is affected by allowing for active population as a non-controllable variable augmenting the simple macroeconomic model relating capital stock and labour to output measured by GDP. We proceed as follows.

In Section 2, a standard tool in DEA analysis, and an SBM model is reviewed followed by modelling non-controllable inputs. Section 3 provides empirical analysis comprising data description, variables used and tables of results with some comments. Section 4 concludes.

2 DEA approach to productivity analysis

In this study, non-parametric approach is used to assess the level of labor utilization employing slack-based measure of efficiency. This goes around possible problems with *weak efficiency* which radial models may suffer from and captures all sources of inefficiency. A modification in constraints enables one to evaluate input utilization which may be sufficient for managerial purposes.

2.1 Data envelopment analysis

A considerable amount of input and output data requires arrangement Economic subjects under evaluation are called DMUs – Decision Making Units – to reflect their independent economic behavior. Let´s assume to have n DMUs transforming m inputs into s outputs. Data matrix $\mathbf{D}$ is partitioned into input and output component: $\mathbf{D}^{\mathrm{T}} = (\mathbf{X}^{\mathrm{T}} \,|\, \mathbf{Y}^{\mathrm{T}})$. Inputs are organized in the matrix $\mathbf{X}$, element x_{ij} meaning amount of input i used by DMU j, the similar way in the output matrix $\mathbf{Y}$.

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

Conceptual model of efficiency involves considering a general ratio

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$$efficiency = \frac{outputs}{inputs} \tag{1}$$

In classical DEA, every DMU aggregates its inputs and outputs by means of individually set weights so that the ratio (1) is maximized. In order to avoid unboundedness of maximization problem, the constraint is imposed so that normalized efficiency cannot exceed unit which also holds in case of using the weights of DMU under consideration (denoted DMU_0) for any other of *n–1* DMUs. Formally:

$$\max \quad h_0(\boldsymbol{\mu}, \mathbf{v}) = \frac{\sum_{r=1}^{s} y_{r0}\mu_r}{\sum_{i=1}^{m} x_{i0}v_i} \tag{2}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} y_{rj}\mu_r}{\sum_{i=1}^{m} x_{ij}v_i} \le 1 \qquad (j = 1, 2, ..., n) \tag{3}$$

$$u_r \ge 0 \qquad (r = 1, 2, ..., s)$$

$$v_i \ge 0 \qquad (i = 1, 2, ..., m)$$

The fractional program can be transformed into the linear one called CCR model as introduced by Charnes et al. (1978) which was first to evaluate performance in a non-parametric way. The model though suffered from the problem of weak efficiency enabling DMUs to assign zero weights to "unfavorable" inputs or outputs to maximize efficiency value.

2.2 Slack-based measure of efficiency (SBM)

The slack-based model (Tone, 2001) is a powerful development of DEA modeling capturing all sources of inefficiency going around the problem of weak efficiency. The objective function $\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}}$ is unit invariant and monotonous. It can be shown to be bound: $0 < \rho \le 1$ (Tone, 2001). Thus efficiency measure takes the form of a fractional program:

$$\min_{\boldsymbol{\lambda}, \mathbf{s}^+, \mathbf{s}^-} \quad \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}} \tag{4}$$

$$\text{s.t.} \quad \mathbf{x_0} = X\boldsymbol{\lambda} + \mathbf{s}^-$$

$$\mathbf{y_0} = Y\boldsymbol{\lambda} - \mathbf{s}^+$$

$$\boldsymbol{\lambda} \ge 0, \ \mathbf{s}^- \ge 0, \ \mathbf{s}^+ \ge 0.$$

Substitution $t = \frac{1}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}}$ yields a linear program:

$$(SBMt) \qquad \min_{t, \boldsymbol{\lambda}, \mathbf{s}^+, \mathbf{s}^-} \quad \tau = t - \frac{1}{m}\sum_{i=1}^{m} t s_i^- / x_{i0} \tag{5}$$

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$$\text{s.t.}\quad \mathbf{x_0} = X\boldsymbol{\lambda} + \mathbf{s}^-$$
$$\mathbf{y_0} = Y\boldsymbol{\lambda} - \mathbf{s}^+$$
$$\boldsymbol{\lambda} \ge 0, \qquad \mathbf{s}^- \ge 0, \quad \mathbf{s}^+ \ge 0,$$
$$t > 0.$$

Substituting $t\mathbf{s}^- = \mathbf{S}^-$, $t\mathbf{s}^+ = \mathbf{S}^+$ a $t\boldsymbol{\lambda} = \boldsymbol{\Lambda}$, *SBMt* could be converted into

$$(SBMt) \qquad \min \quad \tau = t - \frac{1}{m}\sum_{i=1}^{m} S_i^- / x_{i0} \tag{6}$$
$$\text{s.t.}\quad t\mathbf{x_0} = X\boldsymbol{\Lambda} + \mathbf{S}^-$$
$$t\mathbf{y_0} = Y\boldsymbol{\Lambda} - \mathbf{S}^+$$
$$\boldsymbol{\Lambda} \ge 0,\ \mathbf{S}^- \ge 0,\ \mathbf{S}^+ \ge 0,\ t > 0.$$

Linearization is important with respect to computational considerations as well as properties implied by duality of linear programs. After solving *SBMt* formulated by (5) or (6), one can go back to $\mathbf{s}^{0+}$, $\mathbf{s}^{0-}$, $\boldsymbol{\lambda}^0$ as optimal solutions of *SBM* and determine ρ^0 for DMU_0. Efficient DMUs will have values of ρ equal unit and zero slacks. Inefficient ones will have $\rho < 1$ due to positive slack variables $\mathbf{s}^{0+}$, $\mathbf{s}^{0-}$ which express deviation from the frontier or "potential". Projections to the frontier are thus given by

$$\begin{aligned} \hat{\mathbf{x}}_\mathbf{0} &\Leftarrow \mathbf{x_0} - \mathbf{s}^{-0} \\ \hat{\mathbf{y}}_\mathbf{0} &\Leftarrow \mathbf{y_0} + \mathbf{s}^{+0} \end{aligned} \tag{7}$$

Indexes of variables $\lambda_j > 0$ constitute the reference set R_0 (efficiency frontier), every frontier point $(\mathbf{x}_\mathbf{0}^*, \mathbf{y}_\mathbf{0}^*)$ being positive linear combination of the other elements of the reference set:

$$\hat{\mathbf{x}}_\mathbf{0} = \sum_{j \in R_0} \mathbf{x}_j \boldsymbol{\lambda}_j,\ \hat{\mathbf{y}}_\mathbf{0} = \sum_{j \in R_0} \mathbf{y}_j \boldsymbol{\lambda}_j \tag{8}$$

It obvious from the construction of ρ that it takes into account all the sources of inefficiency and therefore $\rho_{\mathrm{SBM}} \le h_{\mathrm{CCR}}$. *SBM* efficient DMUs are also CCR efficient but not the other way round. It is possible to give model input or output orientation in order to reflect preferences and feasibility of the policy. This measure of efficiency can be used for further analysis.

2.3 Non-controllable variables

In this section, only treatment of non-controllable (NCN) inputs is described. The general case including uncontrolled output is examined in Cooper et al. (2007), chapter 7.3. Data matrix **D** is now partitioned into output matrix **Y** as above and two input matrices indexed "*C*" and "*N*" indicating (non)controllability. Thus matrix $\mathbf{X}^C$ denotes controllable inputs (corresponding to matrix **X** in previous sections) and $\mathbf{X}^N$ standing for matrix of non-controllable inputs. In the similar manner we denote $\mathbf{x}_0^N$ vector of uncontrolled input of DMU_0 under evaluation. Non-controllables will not enter the objective function directly yet they affect the resulting optimization outcome by imposing additional envelope constraint affecting range of possible values of λ. The *SBM-NCN* optimization program reads as follows

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$$\text{(SBM-NCN)} \quad \min_{\boldsymbol{\lambda},\mathbf{s}^+,\mathbf{s}^-} \quad \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}} \tag{9}$$

$$\text{s.t.} \quad \mathbf{x}_0^C = X^C\boldsymbol{\lambda} + \mathbf{s}^- \tag{10}$$

$$\mathbf{x}_0^N = X^N\boldsymbol{\lambda}$$

$$\mathbf{y}_0^C = Y^C\boldsymbol{\lambda} - \mathbf{s}^+$$

$$\boldsymbol{\lambda} \geq 0, \quad \mathbf{s}^- \geq 0, \quad \mathbf{s}^+ \geq 0$$

In constraints (10), slack $\mathbf{s}^N$ which would describe deviation from the benchmark is set to zero to prevent infeasible way of proposed input adjustment.

3 Empirical example

Empirical investigation involves determining efficiency measures from technical model as well as its augmented version with NCN variable using aforementioned approach. The national economies are considered as DMUs transforming two production factors into GDP. Since the study is part of the broader research involving more variables in various periods of time, due to data availability 25 European countries in 2012 were analyzed.

3.1 Data and computation

To obtain a simple technical efficiency score, standard inputs capital and labor were used along with GDP as an output measure (model *tech*). GDP was measured in mil. PPS to account for price differences. The data on the net capital stock come from AMECO database, the rest – labour force in thousands as well as active population (15 - 64) used in model *tech-N* – is Eurostat data. Simplifying assumption of constant returns to scale is adopted since the aim of the exercise is to focus on the effects on optimal values of linear program resulting from including the NCN variable.

Table 1. Descriptive statistics and correlations

Statistics on Input/Output Data

	K	L	N	Y
Max	7791670,0	39126,5	52487,0	2661253,6
Min	23833,1	385,2	580,3	15844,4
Average	1531098,5	8280,7	12627,5	522862,1
SD	2143563,3	10323,9	15171,9	703464,5

Correlation

	K	L	N	Y
K	1	0,953	0,951	0,983
L	0,953	1	0,990	0,991
N	0,951	0,990	1	0,981
Y	0,983	0,991	0,981	1

Source: Eurostat, AMECO, the author´s computation.

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Table 1 exhibits basic data descriptive statistics along with correlations between the variables. To obtain desired measures of *tech* and *tech-N* efficiencies, programs (4) and (8) – (9) described in Sections 2.2 and 2.3. must be solved. Desired SBM measures were computed for both models, the outcome containes detailed results of optimization.

Table 2. Overview of models employed

model	type	variables			
		inputs			output
tech	SBM	K	L		Y
tech-N	SBM	K	L	N	Y

Source: author´s elaboration.

In Table 2, models and variables used are displayed. Slack based measures with constant returns to scale were used in computations. For each DMU_0 NCN vector $\mathbf{x}_0^N$ from (10) simplifies to scalar assuming value of N.

3.2 Results

Firstly the detailed results of computation SBM measures from model *tech* are reported in Table 3. The reported scores correspond to the value of objective function in (4). The set of efficient units consists of three DMUs – Ireland, Latvia, and Slovakia with the score equal one. In the columns jointly labeled "lambda" are optimal values of λ displayed. Indices of nonzero λ indicate efficient peer DMUs as described by (8). Obviously, only λ corresponding to the three efficient countries can assume nonzero values. Thus for example, for the Czech Republic peer DMUs are Ireland (λ_7 = 0,097) and Slovakia (λ_{22} = 2,023). Obviously, efficient units present peers for themselves, e.g. λ_{14} = 1 for Latvia. Slack variables are reported in three columns labeled "slack". As the model is non-oriented both input and output slacks can assume nonzero values indicating sources of inefficiency for decision maker.

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Table 3. *tech* model results

		lambda			slack		
DMU	score	7	14	22	s1-	s2-	s+
Belgium	0,941	2,228	0	0	21694,4	429,9	529,2
Bulgaria	0,721	0	2,679	0	33394,9	588,0	16,1
Czech Republic	0,809	0,097	0	2,023	181278,3	0	0
Denmark	0,841	1,227	0	0	50716,4	433,5	8015,8
Germany	0,887	16,895	0	0	151467,6	8076,4	683,8
Estonia	0,744	0	0,419	0,106	23736,3	0	0
Ireland	1	1	0	0	0	0	0
Greece	0,680	1,749	0	0	133356,1	481,5	58337,1
Spain	0,820	8,506	0	0	1026,3	2000,3	174418,5
France	0,851	13,586	0	0	91656,7	781,0	277345,2
Croatia	0,916	0,039	0	0,590	18190,7	0	0
Italy	0,862	11,463	0	0	718,5	1832,1	184982,5
Cyprus	0,898	053	0	0,124	9980,3	0	0
Latvia	1	0	1	0	0	0	0
Lithuania	0,263	0	0,744	0	40713,2	624,4	8327,4
Hungary	0,920	0	0,880	1,334	34998,8	0	0
Netherlands	0,876	3,957	0	0	2899,5	1152,5	36421,5
Austria	0,790	1,859	0	0	220683,9	766,5	5141,9
Poland	0,983	0	5,209	4,736	24187,1	0	0
Portugal	0,752	0,088	0	1,883	269224,5	0	0
Slovenia	0,886	0,035	0	0,369	18041,0	0	0
Slovakia	1	0	0	1	0	0	0
Finland	0,808	1,146	0	0	45193,3	377,6	15564,7
Sweden	0,715	2,232	0	0	426072,8	555,4	33996,3
United Kingdom	0,884	10,576	0	1,363	55,9	6815,6	0

Source: Eurostat, AMECO, the author´s computation.

Subsequently, the tech model was augmented by the non-controllable variable N (active population). Solving the program (9) - (10) yields the results displayed in Table 4. Apparently, the additional constraint had been active since the scores and optimal values of variables changed for some DMUs. The set of efficient countries broadened to include Bulgaria, Greece, Croatia, and Netherlands on top of the three from the *tech* model. Alongside, the range of nonzero lambdas corresponds to the new frontier of seven units. Notably, slacks corresponding to NCN variable are equal zero to meet the equality for x^N in (10). Making use of lambdas, it is possible to determine benchmarks (projections) for inefficient DMUs using (8) and reference set R_0 of the seven units. For selected countries, projections from both models *tech* and *tech-N* are reported in Table 5.

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Table 4. *tech-N* model results

		lambda							slack			
DMU	score	2	7	8	11	14	17	22	s1-	s2-	sN	s+
Belgium	0,944	0	2,169	0	0	0	0	0,101	0	145,1	0	14138,6
Bulgaria	1	1	0	0	0	0	0	0	0	0	0	0
Czech Republic	0,848	0	0,432	0	0	0	0	1,524	91575,4	546,5	0	0
Denmark	0,841	0	1,176	0	0	0	0	0	68206,4	502,5	0	1691,1
Germany	0,887	0	16,875	0	0	0	0	024	0	7267,3	0	53827,0
Estonia	0,778	0	012	0	0	0	0	0,217	14024,1	86,5	0	0
Ireland	1	0	1	0	0	0	0	0	0	0	0	0
Greece	1	0	0	1,321	0	0	0	0	0	0	0	0
Spain	0,861	0	5,324	0	6,530	0	0	0	1078618,5	0	0	15027,7
France	0,851	0	13,021	0	0	0	0	0	298158,2	1616,7	0	203007,1
Croatia	1	0	0	0	1	0	0	0	0	0	0	0
Italy	0,887	0	9,290	0	4,997	0	0	0	757498,5	0	0	85855,0
Cyprus	0,912	0	075	0	0	0	0	091	4064,1	36,0	0	0
Latvia	1	0	0	0	0	1	0	0	0	0	0	0
Lithuania	0,271	0	0	0	067	1,283	0	0	18804,0	0	0	31120
Hungary	0,976	0	0	0	0,924	0,666	0	0,801	0	0	0	4056,3
Netherlands	1	0	0	0	0	0	1	0	0	0	0	0
Austria	0,790	0	1,852	0	0	0	0	0	217918,9	756,1	0	5631,0
Poland	0,997	0	0	0	0,906	5,569	0	4,038	3842,4	0	0	0
Portugal	0,768	0	0,324	0	0	0	0	1,532	206148,9	384,3	0	0
Slovenia	0,923	0	080	0	0	0	0	0,302	5918,4	73,9	0	0
Slovakia	1	0	0	0	0	0	0	1	0	0	0	0
Finland	0,808	0	1,054	0	0	0	0	0	38699,1	334,7	0	15169,0
Sweden	0,727	0	1,810	0	0	0	0,055	0	517744,2	864,8	0	0
United Kingdom	0,885	0	9,935	0	0	0	0	2,319	0	4747,5	0	62829,7

Source: Eurostat, AMECO, author´s computation.

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In Table 5, projections from models *tech* and *tech-N* are to be seen. For inputs, benchmarks are lower in value than observed data displayed in the right end of the table. Benchmark outputs are the other way round higher than original data. For efficient DMUs, e.g. Slovakia, in both models *tech* and *tech-N,* projections and data are the same value.

Table 5. Projections and data

	tech			*tech-N*				data			
DMU	K	L	Y	K	L	N	Y	K	L	N	Y
Belgium	1007787	4094	350980	1029458	4373	7242	365087	1029494	4524	7242	350454
Bulgaria	63854	2346	87063	99100	2934	4924	87050	99100	2934	4924	87050
Czech Republic	294087	4890	229155	383762	4343	7229	229141	475375	4890	7229	229160
Germany	7643359	31050	2661936	7794812	31709	52487	2716185	7791670	39127	52487	2661254
Greece	791044	3214	275495	1016672	3695	7156	217160	1016672	3695	7156	217160
Latvia	23833	876	32496	23833	876	1352	32496	23833	876	1352	32496
Italy	5185771	21066	1806037	4472611	22899	39603	1701964	5186517	22899	39603	1621066
Lithuania	17725	651	24168	39539	1275	2006	48361	57461	1276	2007	15844
Netherlands	1789982	7272	623393	1792927	8424	10992	586988	1792927	8424	10992	586988
Austria	841158	3417	292948	842656	3423	5666	293470	1061862	4184	5666	287813
Slovakia	123625	2329	105707	123625	2329	3881	105707	123625	2329	3881	105707
United Kingdom	4953226	22612	1810464	4953266	24510	40632	1875546	4486713	29428	40632	1810481

Source: Eurostat, AMECO, author´s computation.

It is interesting to note the effect of NCN implementation. For Bulgaria, with the *tech* score of 0,721, it would be necessary to achieve levels of inputs given by $\lambda_{14} \times \mathbf{x}_{14}$ (inputs of its peer – Latvia), i.e. 2,679 × 23833 which is (due to rounding roughly) benchmark value of 63854 for capital and the same way for labour from model *tech*. If the NCN variable is treated similarly, Bulgaria should reduce N from the observed 4924 to 2,679 × 1352 = 3622. Since N cannot be controlled (at least in the short and medium run), model *tech-N* provides achievable way of input reduction which secures projection of NCN into just the observed value which can be viewed by comparing columns labeled "N" in *tech-N* and data sections of the table.

4 Conclusions

The results present a technical view on macroeconomic efficiency which cannot embrace all the goals of economic policy. The focus was placed on justifying the use of non-controllable variables in possibly more extensive analysis involving assessment of more than one dimensions of economic performance. In the context of Europe 2020 benchmarks, this may include environmental and social indicators. Including non-controllable variables can make recommendations and efforts based on the results more realistic.

A comparative analysis of efficiency measures employing presented models showed that non-controllable variable matters with respect to achieved score and projected benchmark values. This regards mainly Greece, Bulgaria and Netherlands whose scores changed dramatically (reaching unit) as opposed to developed Western economies of Denmark, Germany, Ireland, France, Austria, Finland, and United Kingdom with the score unchanged. For the most of the countries, Ireland appears to be a benchmark economy from the perspective of efficiently transforming capital and labour into GDP.

For individual countries, the detailed results can provide theoretical basis for decision making as to indicating slacks and possible ways to boost efficiency. Most identified slacks as potentials for

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improvement for inefficient countries (the two exception are Germany and Denmark) relate to capital indicating overcapitalization. Apparently, slack should be considered related to the level as the size of economies is at variance. Since in the short run the capital stock cannot be reduced and employing less labour would be in conflict with another goal of economic policy, boosting efficiency can only be achieved by expanding the output. Keeping in mind that GDP was measured In PPS, the recommendations for economic policy of facilitating labour productivity should be adjusted by possible change in relative price levels between countries as well. Economies with zero slack for labour, e.g. Estonia, Czech Republic, Portugal input may be considered operating at the optimal level of employment with respect to benchmark though which does not represent the socially optimal level.

For more precise results imposing variable returns to scale assumption would be required since it were small or medium-size economies that appear efficient which could indicate decreasing returns to scale type of technology in Europe.

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