PP - FAR, 15, 2023, No 1 10.31577/PPFAR.2023.15.002

FRONTIER APPROACH TO ENVIRONMENTAL EFFICIENCY: LEAST-DISTANCE BENCHMARKS FOR SLOVAKIA

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Abstract

Environmental efficiency of production and value-added creation has been a central concern of European environmental agenda for the last decades. In the paper, the frontier analysis is employed to illustrate the procedure how policy-related benchmarks could be determined. Underperforming entity is projected onto the production possibility set boundary that is constructed via deterministic data envelopment analysis method. Besides the conventional benefit-of-the-doubt aggregation weighting scheme, the procedure is guided by the least-distance criterion for projection location as well as the bounds imposed by the Climate Act commitments regarding emissions reduction. The differences between the conventional and the least-distance-adjusted-model results are demonstrated within the technology involving value-added as economic desirable outcome whereas emissions and particles acting as "bads". For Slovakia, the results identify Germany and Malta as best-performing peers suggesting alongside that a current level of GDP could be retained even after adopting the environmental constraints.

Keywords

Environmental Efficiency, Closest Distance, Production Frontier, Data Envelopment Analysis

I. Introduction

The EU's commitment to environmental protection and sustainability has evolved over time, reflecting changing priorities and global challenges. The history of environmental policy in the EU is marked by significant developments and milestones. The recognition of environmental protection as a key objective and the integration of environmental considerations into the development of the single market started as early as 1970s. The Treaty on European Union (Maastricht Treaty, 1992) established environmental protection as a shared competence between the EU and its member states. Amsterdam Treaty (1997) integrated sustainable development as a guiding principle and gave the EU a mandate to establish environmental policies and legislation. Integration of climate considerations into all relevant EU policies was ensured in the Lisbon Treaty (2009) while Europe 2020 Strategy (2010): introduced targets for smart, sustainable, and inclusive growth. Paris Agreement (2015) set out even more ambitious global climate targets, primarily aiming for a reduction of greenhouse gas emissions (GHG) by at least 40% by 2030. European Green Deal (2019) went further to commit to achieving

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climate neutrality by 2050. The transition should be accelerated by directing investments toward sustainable and resilient sectors according to COVID-19 Recovery and Resilience.

The environmental policy of the EU is articulated through the formulation and pursuit of specific targets. The latter serve as tangible expressions of the EU's commitment to addressing environmental issues and fostering sustainability. Through these targets, the EU outlines its ambitions in areas such as carbon emissions reduction, renewable energy adoption, waste management, biodiversity preservation, air and water quality improvement, and more. Among the various aspects of EU environmental policy, carbon emissions reduction and renewable energy adoption are often considered two of the most important focal points.

While the European Union sets overall **renewable energy** targets for the entire bloc, it also requires each member state to contribute to the collective goal by setting their own specific renewable energy targets. The EU's renewable energy targets are binding for each member state, and it's up to each country to develop and implement policies and measures to achieve their respective targets. The targets are typically set as a percentage of each country's gross final energy consumption (the total energy consumed for all end uses, such as heating, electricity, and transport) to be sourced from renewable energy. These national targets are designed to reflect the varying starting points and potential for renewable energy development in each EU country, taking into account factors like existing energy infrastructure, natural resources, and economic conditions. Member states with higher renewable energy potential may have more ambitious targets, while those with fewer available resources may have more modest goals.

Carbon dioxide (CO_2) emissions are a significant driver of climate change and are primarily generated from the burning of fossil fuels for energy production, industrial processes, transportation, and other human activities. Since the 1990s, Europe has been making efforts to reduce its carbon dioxide emissions to mitigate the impacts of climate change and fulfil international commitments like the Kyoto Protocol and the Paris Agreement. European countries have set various targets to reduce CO_2 emissions by specific percentages compared to the levels recorded in 1990. These targets are often set for certain years in the future, typically in five or ten-year increments.

In shaping effective environmental policies a whole variety of decision making tools is typically involved. The latter may comprise Cost-Benefit Analysis (CBA), Environmental Impact Assessment (EIA), Life Cycle Assessment (LCA), Multi-Criteria Decision Analysis (MCDA), Scenario Analysis, Risk Assessment, stakeholder engagement, adaptive management, Regulatory Impact Assessment (RIA), GIS and Remote Sensing, structural economic models or behavioural insights. Multicriteria methods are often employed in multidimensional quantitative assessment within the multiple subindicators environment. In the latter, data envelopment analysis (DEA) has proved to be a fruitful approach offering decision makers relative performance measures and benchmarks for effective goal-setting. While originally rooted in production theory, DEA has evolved to be capable of dealing with undesirable outcomes of economic activity, such as emissions, making it appropriate tool for assessing performance with discernible environmental impact.

II. Least-distance DEA computation

Conventional frontier analysis

A specific nonparametric frontier analysis method, data envelopment analysis (DEA), pioneered by Charnes et al. (1978), is a deterministic technique used to estimate the production or cost efficiency of individual entities within a given dataset. The approach is particularly useful when the underlying data distribution is unknown or difficult to model using traditional parametric methods when specific functional forms are assumed for the production or cost functions. The concept of a "frontier" refers to the hypothetical best-performance production possibility frontier (PPF) that can be achieved by the subjects (decision making units, DMUs) given their inputs. Within the DEA framework, the estimated frontier is constructed from multidimensional facets determined by datapoints of the best-performing DMUs that are assigned the efficiency score of 1 (100%), while relative underperformers obtain scores below 1. Figuratively, the PPF boundary rests upon the extreme datapoints and “envelops” the data, giving the name to the method. The efficiency score indirectly corresponds to the distance of inefficient entity from the boundary. Moreover, the inefficient DMU can be projected onto the frontier obtaining its benchmark for potential improvement. The linear programming nature of the score calculation allows for the dual approach. In the latter, the "benefit-of-the-doubt" weighting scheme is optimized by assessed units to maximize their virtual output-to-input ratio. (BoD, OECD, 2008, pp. 92-94). Here, DEA model again assigns efficiency scores between 0 and 1 to evaluated DMUs where 1 signifies best-performance (full efficiency). Since DEA does not model the process of transforming inputs into outputs, its use is confined to serving as a ranking and benchmarking procedure. In contrast, other decision-making tools, e.g the Balanced Scorecard, SWOT analysis, CBA, and Six Sigma, are geared specifically towards focusing on process optimization, quality improvement, feasibility analysis, or strategic planning.

In environmental studies, DEA is often used to accommodate ecological and economic environments within a common framework. In the latter, along with the desired economic outcomes, emissions present undesirable outputs (UO, “bads”). Aggregation with other desirable outputs could be computationally problematic due to the negative values of UO that would evaluate the contribution of the latter to total outcome. In Korhonen & Luptáčik (2004) approach, UO act as additional inputs in the DEA model. The procedure is justified by additional abatement cost or taxation. Thus, environmental efficiency could be conceptually expressed as the ratio of desirable economic outcome and UO, i.e. economic value per virtual unit of aggregated "bads", for instance emissions.

Closest-target projection

Along with the efficiency scores, DEA models are capable of generating benchmarks. These are typically more important for policy decisions than the relative ranking. As regards the targets for making improvements, it is by noticed Coelli (1998) that the target point identified by the conventional DEA radial model is the farthest point from the assessed DMU. He proposed a multi-stage method for solving a sequence of radial models to determine the closest efficient point (closest target) for the evaluated DMU to reach with the least adjustment effort. Other efforts as to identify the closest target comprise Gonzalez & Alvarez (2001), Cherchye & Van Puyenbroeck, (2001) or Portela et al. (2003). Aparicio (2007) proposed an approach that allows to avoid multi-stage procedures and offers a general approach for finding the closest targets for a given unit.

Considering *n* DMUs with *m* inputs organized in matrix **X** with elements x_{ij} and, in a similar way, *s* outputs organized in matrix **Y** with elements y_{rj}, the conventional DEA identifies best performing DMUs from the whole pool of the data. Indices *j* of frontier-located best-performers comprise now the set *E* of efficient units. For any DMU_0 characterized by the inputs-outputs mix $(x_{i0}\,, y_{r0})$ we formulate least-distance *mADD-I* input oriented assessment procedure as follows:

$$\min \quad \textstyle\sum_{i=1}^{m} s_{i0}^{-} \qquad (r = 1, 2, ..., s) \qquad (1)$$

$$\text{s.t.} \quad \textstyle\sum_{j\in E} \lambda_j x_{ij} = x_{i0} - s_{r0}^{-} \qquad (i = 1, 2, ..., m) \qquad (2)$$

$$\textstyle\sum_{j\in E} \lambda_j y_{rj} = y_{r0} + s_{r0}^{+} \qquad (r = 1, 2, ..., s) \qquad (3)$$

$$\textstyle\sum_{j\in E} \lambda_j x_{ij} \le U_i \qquad (4)$$

$$\textstyle\sum_{j\in E} \lambda_j x_{ij} = 1 \qquad (5)$$

$$\textstyle\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \qquad j \in \text{E} \qquad (6)$$

$$v_i \ge 1 \qquad (i = 1, 2, ..., m) \qquad (7)$$

$$\mu_r \ge 1 \qquad (r = 1, 2, ..., s) \qquad (8)$$

$$d_j \le \text{M}b_j \qquad j \in \text{E} \qquad (9)$$

$$\lambda_j \leq \mathrm{M}(1 - b_j) \qquad j \in \mathrm{E} \qquad (10)$$

$$b_j \in \{0,1\} \qquad j \in \mathrm{E} \qquad (11)$$

$$d_j \geq 0 \qquad j \in \mathrm{E} \qquad (12)$$

$$\lambda_j \geq 0 \qquad j \in \mathrm{E} \qquad (13)$$

$$s_{r0}^{-},\ s_{r0}^{+} \geq 0 \qquad (14)$$

In (1) – (14), Apparicio (2007) model is tailored to (i) assume input orientation (ii) assume variable returns to scale and (iii) impose upper bounds on benchmarks. The former is realized in the objective (1). As follows from (2), slacks s_{r0}^{-} represent deviations of individual inputs of the evaluated DMU_0 from the artificial DMU on the frontier which is generated as a combination of observed best-performers picked from the set *E*. In the similar way, output slacks s_{r0}^{+} are defined in (3). Distance is measured by means of the norm L1 which would be expressed by the sum of all the input and output slacks. However, to render the model input orientation, output slacks are discarded from the distance measure. Thus, least-distance (LD) objective is expressed by minimizing sum of input slacks only. Apparicio (2007) procedure combines variables from primal and dual formulations of the additive (*ADD*) DEA model from Ali & Seiford (1990). Dual variables from the latter compose the conditions (6) – (8). Additive model structure matches the L1-based distance measure. While in *ADD* the objective is to maximize total sum of slacks, i.e. find the largest distance, the proposed *mADD* seeks to find the least distance. The model can be additional features by imposing upper bounds Ui by (4) restricting the set of potential benchmarks for input improvement. Convexity condition (5) may render the model variable return to scale. Constraints (9) – (10) adopted from Apparicio (2007) link primal- and dual-based parts of the model while conditions (11) – (14) express nonnegativity of the variables. Notably, constraint (11) turns the mADD into a mixed linear programming optimization (MILP), in contrast to a regular LP of conventional DEA.

Data

For illustrational purposes, environmental efficiency of European countries is assessed by the proposed procedure. Economic outcome is represented by GDP (mil EUR) whereas two main environmental indicators – share of renewables (transformed by subtracting from the unit to the share of non-renewables and expressed in absolute values of mil. tonnes of oil equivalent) and aggregated emissions (tonnes of CO_2 equivalent) represent resources (cost of damages regarding the latter) used to achieve the output. Ceteris paribus, higher values of inputs thus represent less desirable use of resources while higher output is considered more favourable.

Data were collected from 2021. Luxembourg, Iceland and Norway were excluded due to unavailable and/or outlying data. The complete dataset of the raw data as well as computed values of above described variables EMIS and NON_RENEW are exhibited in Appendix Table A1.

III. Results

From variable selection it follows that in *mADD-I* model (1) – (14), $m = 2$ and $s = 1$. As a necessary step, the set E of best-performing countries should be determined. The estimated production possibility set, and consequently its boundary, does not vary across the conventional DEA models given the assumed returns to scale. We apply BCC-I (Banker et al., 1984) input oriented procedure with a less restrictive assumption of variable returns to scale. The latter yields the set E (reference set) constituted by Germany, France, Malta and Sweden. Thus, j runs from 1 to 4 throughout (1) – (14). Subsequently we run a set of variant DEA models to illustrate the merit of the least-distance procedure. Although the procedure is generally applicable to all countries, we focus on Slovakia as the only DMU to assess and determine projections for.

Table 1: Projections and peers from variant models (DMU 24, Slovakia)

Model	Variables			Reference set			
	GDP	NON_RENEW	EMIS	[6] Germany	[10] France	[17] Malta	[26] Sweden
BCC-I	100,3	2,37	3,19	0	0	0,838	0,162
ADD-I-C	100,3	2,20	1,36	0	0	0	0,186
ADD-I-V	100,3	2,37	3,19	0	0	0,838	0,162
mADD-I-C	100,3	4,72	21,79	0,028	0	0	0
mADD-I-V	100,3	4,55	20,95	0,024	0	0,976	0

Note: "-I": input orientation, "-C" and "-V": constant and variable returns to scale respectively
Source: Eurostat, author´s calculation

Slovakia´s environmental performance is characterized by the actual values of indicators EMIS = 33,7 and NON_RENEW = 9,42. Computed benchmarks should reflect the suggested reduction. Reduction in NON_RENEW is interpreted in a reverse manner as an increased use of renewables. For each variant, benchmark for i^{th} input is determined as a projection onto the frontier by means of the expression $\sum_j \lambda_j x_{ij}$, where λ_j represent intensity variables by whose nonzero values (solutions from the model) the data of top-performers are combined to generate the benchmark. Particular index j corresponds to a particular best-performing DMU that are identified by nonzero values in the "Reference set" section of the Table 1.

In Table 1, selected results from five models are exhibited. All models are input oriented therefore "-I" indication is omitted hereafter. Input orientation renders the output benchmark be fixed at the initial value (original data). The most important results to compare are from the conventional DEA model and its least-distance alternation, i.e. *ADD-V* and *mADD-V*. Complete results from MILP for the latter can be found in Appendix Table A2. If the model is geared to identify maximum total deficiency (the former) and the one minimizing adjustment effort (the latter) differ as to proposed peers – Malta and Sweden vs Malta and Germany. The two models project the evaluated DMU on different facets which makes it possible for the inputs projections to be individually less restrictive in the case of least-distance. On the same facet of PPF, the points are without additional criteria, i.e. costs, indistinguishable. The main difference is to be observed in suggested benchmarks where *mADD* is substantially more benevolent allowing both the higher level of NON_RENEW at 4,55 as opposed to 2,37 from *ADD-V* and 20,95 of EMIS vs 3,19 from *ADD-V*. One can as well observe that the dataset at hand, variable-returns non-LD models, i.e. BCC and *ADD-V* yield the same peers as well as projections.

For the sake of comparison, one may inspect how returns-to-scale assumption affects the results. Variable returns to scale assumption is imposed by adding convexity constraint (5) restricting the space for optimization. Thus *ADD-C*, involving sum of slacks maximization, yields larger slacks than *ADD-V* along with more stringent projections (2,20 vs 2,37 for NON_RENEW and 1,36 vs 3,19 for EMIS) whereas *mADD-C* ´s minimization reaches smaller sum of slacks than *mADD-V* and consequently milder benchmarks (4,72 vs 4,55 for NON_RENEW and 21,79 vs 20,95 for EMIS).

As described above, projections values can be limited by imposing bounds via $\sum_{j \in E} \lambda_j x_{ij} \leq U_i$ in (4). As an example, the EU commitments pertaining to the two used environmental indicators could be used. The EU's current 2030 target is for a 32% renewable energy share, i.e 78% of the transformed input x_1 NON_RENEW – upper bound would then be $U_1 = 9{,}42$. Similarly, x_2 EMIS could be bound by to the max 55% of the 1990 emission level by 2030, i.e. $U_2 = 24{,}7$. Upper bounds for other countries can be seen from Table A1 in Appendix. Bounds can be as well applied to adjust the best-performers´ data in the scenario analysis. Obviously, projections resulting from the model suggest the reduction that is more ambitious than the EU targets. Thus, in this particular case the constraint (4) turned out inactive.

IV. Conclusion and further research

We demonstrated how the customized closest-target model could be employed to corroborate environmental target setting by use of Slovakia´s data. Despite the lack of knowledge or estimates of (monetary) value for environmental quantities, least-distance approach generates clearly more favourable and realistic benchmarks located on different facets of the transformation set than projections from conventional DEA models. The merit of the proposed approach was illustrated through the application of diverse models that alternated in terms of their objectives and assumptions regarding returns to scale. The drawback of the adopted approach is mixed integer program formulation that does not allow for the dual shadow prices determination. On the other hand, the procedure avoids multi-stage computations. The generated benchmarks are milder in comparison with too ambitious conventional-model benchmarks and may help reduce adjustment costs. New environmental commitments could be easily adopted in the model by means of bounds imposed on generated projections. For Slovakia, the results identify Germany and Malta as best-performing peers suggesting alongside that a current level of GDP could be retained even after adopting the Climate Act environmental commitments. The EU environmental policies continue to be refined and updated to address emerging environmental challenges. The presented approach may serve as a proper tool to support this process.

Acknowledgements

The author acknowledge financial support from projects VEGA 2/0001/22 “Slovakia 2030”

References

Ali, A. I., & Seiford, L. M. (1990). Translation invariance in data envelopment analysis. *Operations Research Letters*, 9(6), 403–405.

Aparicio, J., Ruiz, J. L., & Sirvent, I. (2007). Closest targets and minimum distance to the Pareto-efficient frontier in DEA. *Journal of Productivity Analysis*, 28(3), 209–218. https://doi.org/10.1007/s11123-007-0039-5

Banker, R. D., Charnes, A., Cooper, W. W., & Affairs, P. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078–1092.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cherchye, L., & Van Puyenbroeck, T. (2001). A comment on multi-stage DEA methodology. *Operations Research Letters*, 28(2), 93–98.

Coelli, T. (1998). A multi-stage methodology for the solution of orientated DEA models. *Operations Research Letters*, 23(3–5), 143–149.

Korhonen, P. J., & Luptáčik, M. (2004). Eco-efficiency analysis of power plants: An extension of data envelopment analysis. *European Journal of Operational Research*, 154(2), 437–446.

OECD. (2008). *Handbook on constructing composite indicators: methodology and user guide*. OECD Publishing.

Portela, M. C. A. S., Borges, P. C., & Thanassoulis, E. (2003). Finding closest targets in non-oriented DEA models: the case of convex and non-convex technologies. *Journal of Productivity Analysis*, 19, 251–269.

Annex

Table A1: Data and variables (2021)

	Data						Variables				
	Renewables [share]	EMIS [t p.c.]	GDP [mil €]	Population	Final Energy Consumption [mil t oil eq.]	Emissions [share of 1990]	NON_RENEW	EMIS	GDP	U1	U2
Belgium	13,0	9,9	502 521,1	11 617 623	35,9	78,9	31,23	115,01	502,52	28,00	80,2
Bulgaria	17,0	6,6	71 077,0	6 838 937	10,3	54,4	8,55	45,14	71,08	8,03	33,1
Czechia	17,7	12,2	238 249,5	10 516 707	26,2	66,3	21,57	128,30	238,25	20,44	94,1
Denmark	34,7	8,1	342 961,7	5 873 420	13,8	59,3	9,01	47,57	342,96	10,76	34,9
Germany	19,2	9,4	3 601 750,0	83 237 124	209,7	60,2	169,50	782,43	3601,75	163,57	573,8
Estonia	38,0	11,7	31 444,9	1 331 796	2,8	42,6	1,74	15,58	31,44	2,18	11,4
Ireland	12,5	14,1	434 069,7	5 060 004	11,4	112,8	9,97	71,35	434,07	8,89	34,8
Greece	21,9	7,1	181 674,6	10 459 782	15,2	71,5	11,87	74,26	181,67	11,86	54,5
Spain	20,7	5,3	1 206 842,0	47 432 893	80,3	97,7	63,65	251,39	1206,84	62,63	141,5
France	19,3	6,0	2 502 118,0	67 871 925	143,2	76,5	115,50	407,23	2502,12	111,70	292,8
Croatia	31,3	4,8	58 290,9	3 862 305	7,0	73,9	4,81	18,54	58,29	5,46	13,6
Italy	19,0	6,7	1 787 675,4	59 030 133	113,3	75,7	91,73	395,50	1787,68	88,37	287,4
Cyprus	18,4	10,1	24 019,0	904 705	1,7	145,7	1,39	9,14	24,02	1,33	3,4
Latvia	42,1	7,1	33 616,5	1 875 757	4,1	96,2	2,37	13,32	33,62	3,20	7,6
Lithuania	28,2	5,1	56 153,5	2 805 998	5,7	33,3	4,09	14,31	56,15	4,45	10,5
Hungary	14,1	5,9	154 120,1	9 689 010	19,2	62,3	16,49	57,17	154,12	14,98	41,9
Malta	12,2	4,6	15 011,5	520 971	0,6	84,6	0,53	2,40	15,01	0,47	1,6
Netherlands	13,0	10,2	870 587,0	17 590 672	46,9	76,8	40,80	179,42	870,59	36,58	128,5
Austria	36,4	7,6	406 148,7	8 978 929	27,8	100,9	17,67	68,24	406,15	21,68	37,2
Poland	15,6	10,1	576 382,6	37 654 247	75,2	85,5	63,45	380,31	576,38	58,66	244,6
Portugal	34,0	5,1	214 741,0	10 352 042	15,7	77	10,36	52,80	214,74	12,25	37,7
Romania	23,6	3,5	241 268,4	19 042 455	25,4	29	19,41	66,65	241,27	19,81	48,9
Slovenia	25,0	6,2	52 208,1	2 107 180	4,7	90,1	3,53	13,06	52,21	3,67	8,0
Slovakia	17,4	6,2	100 323,5	5 434 712	11,4	52,2	9,42	33,70	100,32	8,89	24,7
Finland	43,1	8,9	250 920,0	5 548 241	24,9	105,8	14,17	49,38	250,92	19,42	25,7
Sweden	62,6	0,7	540 734,0	10 452 326	31,7	26,8	11,86	7,32	540,73	24,73	5,4

Source: Eurostat, author´s calculation

Table A2: Detailed results from variant DEA models (DMU 24, Slovakia)

model	Nonzero λ_j			slacks		weights			LD-related decision variables							
	[6]	[17]	[26]	s1-	s2-	v1	v2	u	d1	d2	d3	d4	b1	b2	b3	b4
BCC-I		0,838	0,162													
ADD-I-C			0,186	7,2	32,3											
ADD-I-V		0,838	0,162	7,0	30,5											
mADD-I-C	0,028			4,7	11,9	1	1	0,035	824,2	434,0	2,39	0	0	0	0	0
mADD-I-V	0,024	0,976		4,9	12,7	1	1	0,035	824,2	434,0	2,39	0	0	0	0	0

Note: -C refers to constant, -V to variable returns to scale. All models are input oriented.
Source: Eurostat, author´s calculation