Institutional Improvement: Benchmarks within Easy Grasp[1]

Eduard NEŽINSKÝ – Elena FIFEKOVÁ***

Abstract

The 2024 Nobel Prize in Economics has confirmed the importance of institutional quality in driving economic performance and framing ongoing trends. We demonstrate the importance of institutional quality and assess institutional quality of CEE countries with additional focus on the V4 countries via composite indicator under benefit-of-the-doubt aggregation weighting scheme. We investigate benchmarks in six dimensions of institutional quality World Governance Indicators as a result of employing two nonparametric performance-frontier estimation techniques. Without specifying preferences or adjustment costs, both the conventional approach and the "closest target" procedure offer decision makers a choice from a Pareto-efficient set of targets. In setting policy goals, major trade-offs should be considered between ambitions for accountability and regulatory quality, on one hand, and government efficiency and corruption control, on the other.

Keywords: *institutional quality, economic performance, benefit-of-the-doubt weighting, closest target*

JEL Classification: C14, C44, O43

DOI: https://doi.org/10.31577/ekoncas.2024.09-10.04

Article History: *Received*: October 2024 *Accepted*: December 2024

---

* Eduard NEŽINSKÝ, University of Economics in Bratislava, Faculty of Economics and Finance, Department of Economic Policy, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia; e- mail: eduard.nezinsky@euba.sk, ORCID: 0000-0003-2771-4276 and Center of Social and Psychological Sciences of the Slovak Academy of Science, Institute for Forecasting, Šancová 56, 811 05 Bratislava, Slovakia; e-mail: eduard.nezinsky@savba.sk

** Elena FIFEKOVÁ, Center of Social and Psychological Sciences of the Slovak Academy of Science, Institute for Forecasting, Šancová 56, 811 05 Bratislava, Slovakia; e-mail: elena.fifekova@savba.sk, ORCID: 0000-0003-3783-0414

[1] The authors acknowledge financial support from projects VEGA 2/0001/22 *Slovakia 2030* and VEGA 1/0781/21 *Industrial Policy under the Conditions of Deindustrialisation and Automation*.

Introduction

As a rich volume of research shows, the role of institutions in economic development is of utmost importance. Numerous empirical studies have provided insights into the impact of institutions on various aspects of economic growth and prosperity. The contribution of institutions in economic development is multifaceted and essential for fostering sustainable growth and prosperity. Institutions provide the necessary framework, rules, and structures that shape economic behaviour, promote stability, and facilitate efficient resource allocation.

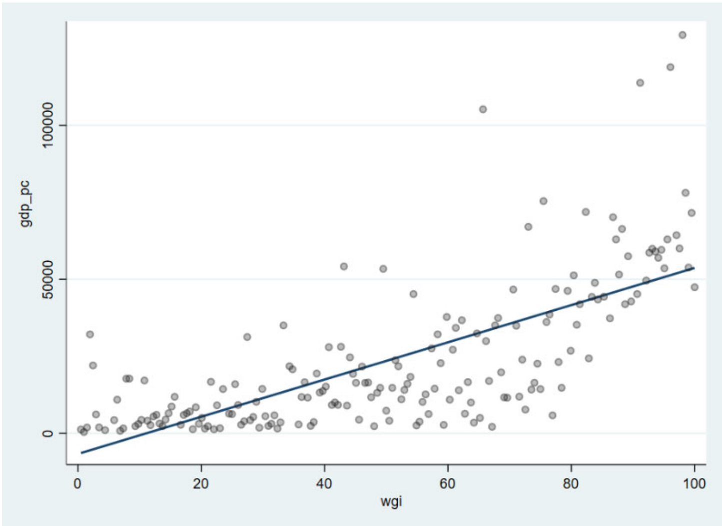
High institutional quality refers to the presence of robust legal frameworks, efficient governance structures, transparent regulations, and strong protection of property rights. These factors create an environment that is conducive to innovation, investment, and technological advancements. Institutional quality can positively impact automation and digitalization in several ways. It provides a stable and predictable business environment, encourages foreign direct investment, fosters entrepreneurship, and protects intellectual property rights. Additionally, strong institutions can facilitate the development of digital infrastructure, such as reliable and secure communication networks, which are essential for the effective implementation of automation and digital technologies. Furthermore, institutions play a crucial role in shaping policies related to automation and digitalization. They can establish regulatory frameworks, data protection laws, and cybersecurity measures that promote trust, security, and responsible use of technology. Institutions also influence the development of skills and education systems that support the workforce in adapting to technological changes. Thus, while automation and digitalization have their own dynamics and impacts, the role of institutional quality consists in creation of an enabling environment that supports and accelerates the adoption and beneficial outcomes of automation and digitalization. The unconditional correlation of institutions with economic development is depicted in Figure 1. Institutional performance is measured by aggregated dimensions of World Governance Indicators, further elaborated upon later, while the level of economic development is proxied by income (GDP) per capita.

A positive correlation is to be observed – wealthier countries tend to have more advanced or better performing institutions. Acemoglu et al. (2005) identified differences in *economic* institutions as the fundamental cause of differences in economic development while Rodrik (1999) examined the institutional impact on the sustainability of growth.

In a broader sense, "institutions are the rules of the game in a society" which "structure incentives in human exchange, whether political, social, or economic" (North, 1990). Institutional change played a crucial role in transition period for Central and East European (CEE) countries as confirmed by the empirical work.

The attractiveness of institutional quality for foreign direct investment was confirmed at the time by Brunetti et al. (1997) or Grogan and Moers (2001).

F i g u r e 1
Income per capita (PPP, Dollar) and Institutional Quality



Source: UNCTADstat, authors' elaboration.

A proper quantitative measure of institutional quality has been evolving as a particular strand of research. Assessing the quality of institutions "per se", without directly referencing economic or other performance metrics, offers several distinct merits including objective assessment, clarity of analysis or avoidance of confounding factors. As for a multi-faceted phenomenon, a number of subindicators have been developed to capture various dimensions of institutional quality assessing the effectiveness and performance of institutions. The latter may involve evaluation of factors such as governance, service delivery, financial performance, human resources, stakeholder engagement, legal and regulatory environment, and social impact. Various methods and indicators are used, including surveys, interviews, document analysis, and performance metrics. It is important to tailor the measurement approach to the specific institution and its context. Thus presently, a number of internationally comparable indicators have been developed comprising Economic Freedom of World Indicators, International Country Risk Guide (ICRG), World Bank's Doing Business, Freedom House Democratization Index, data from Global Competitiveness Report (WEF) or Worldwide Governance Indicators.

Aggregation of partial subindicators typically involves either Principal Component Analysis (Knack and Keefer, 1995) or building composite indicators with fixed weights. Non-parametric multicriteria decision methods such as DEA (data envelopment analysis) provide flexible weighting schemes. We take a closer look at the latter in the first section, proposing to apply least-distance procedure in the institutional quality analysis domain. In the second section, the paper proceeds to the empirical investigation of institutional quality as economic performance determinant worldwide followed by a two-staged DEA analysis of the institutional quality itself. We demonstrate the distinction between the conventional radial DEA and the least-distance variation. The final section concludes.

1. Methodology and Data

Regression Analysis

Regression analysis will be used to demonstrate the importance of institutional quality within the economic development framework. A simplistic version empirically links the level of economic development with a number of key determinants as adopted from the growth literature via a linear regression model. To account for nonlinearities, a transformation of the variables entering the model may be conducted. Since we use the regression for mere qualitative statement not aiming at the precise value of estimated coefficients, we resort to using a cross-sectional model.

Assuming that the relationship between variables operates with an unspecified time lag and aiming to minimize potential simultaneity we consider linear relationship in the form of

$$y_{+T} = \beta_0 + \sum\nolimits_j \beta_j x_j + \varepsilon \qquad \text{(OLS)}$$

where x_j stand for determinants of the forwarded value of dependent variable T periods ahead while ε is contemporaneous error term. Models with lagged dependent variable in which one could possibly control for time invariant unobservables would require use of panel data and advanced estimation techniques such as GMM. The latter approach is beyond the scope of this study.

Benefit-of-the-Doubt Weighting Scheme

Quantitative assessment of multidimensional realities involves compilation of observed facts from.

Pursuing the standard procedure, multiple domains reflected in subindicators are aggregated into composite indicator computed as the weighted sum $\sum\nolimits_{r=1}^{s} w_r y_r$. In the expression, multiple outputs y_r (r running from 1 to s) present the data to be evaluated whereas w_r stand for the respective aggregating weights.

The latter are determined *ex ante* features particular drawbacks and may be subject to a critique. In alternative schemes weights are determined endogenously given the data. In macroeconomics as well as the broader socio-economic analyses, the *benefit of the doubt* (BoD) approach introduced by Melyn and Moesen (1991) and later developed by in Cherchye (2001) and Cherchye et al. (2004) has been widely adopted. Under BoD, entity under evaluation faces index-maximizing problem

$$\max \quad I^{BoD} = \sum\nolimits_{r=1}^{s} w_r y_{r0} \qquad (r = 1, 2, ..., s) \tag{1}$$

$$\text{s.t.} \quad \sum\nolimits_{r=1}^{s} w_r y_{rj} \le 1 \qquad (j = 1, 2, ..., n) \tag{2}$$

$$w_r \ge 0 \tag{3}$$

DMU_0 (decision making unit labelled "0") with performance indicators y_{r0} determines the most favourable aggregating coefficients w_r. For the ease of interpretation and to avoid unboundedness, the magnitude of the performance score is constrained by one. All the other competing DMUs are bound to meet this constraint evaluating their own set of outputs by the weights w_r proposed by DMU_0. Best performers attain the highest possible score of 1 (100%) from the optimization while poor performers are forced to choose weights yielding lower values of the total indicator.

Computationally, the pure output setting of equations (1) – (3) is equivalent to the reduced form of the basic radial input-oriented Data Envelopment Analysis (DEA) model introduced by Charnes, Cooper and Rhodes (CCR, 1978). This equivalence is established by incorporating a single "dummy input" with a constant value of 1 for each Decision-Making Unit (DMU). In the DEA framework, the dual representation of the problem can be visualized as the "performance possibility frontier" (PPF), which serves as the benchmark set for underperforming DMUs and embodies "envelopment of the data". By keeping unit input value fixed, the optimal mix of performance indicators (benchmarks) is determined through the projection of DMU data onto this frontier.

For the sake of computational efficiency, it is possible to alter the model's orientation from an input-oriented radial approach to an output-oriented one. This flexibility is facilitated by the close correspondence between the input-oriented CCR model (CCR-I) and the output-oriented CCR model (CCR-O). Specifically, the optimal objective value obtained from the input-oriented model is the reciprocal of that from the output-oriented model, resulting in an identical performance score ranging from 0 to 1 (see Cooper et al., 2007, p. 58). Consequently, switching the orientation preserves the original index-maximizing objective, maintains the ranking of DMUs, and does not alter the set of best-performing units identified by the model. Reduced output oriented radial model in its *envelope* form is stated as follows:

$$\max \quad \varphi \tag{4}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} y_{rj}\lambda_j \geq \varphi y_{r0} \qquad (r = 1, 2, ..., s) \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j \leq 1 \qquad (j = 1, 2, ..., n) \tag{6}$$

$$\lambda_j \geq 0 \tag{7}$$

where λ_j stand for intensity variables according to which a DMU_j contributes to generation of the PPF, a boundary of the multioutput possibility set. Since only best performers can effectively contribute to the frontier generation, nonzero λ_j indicate *best practice* performers – relevant *peers* for DMU under consideration.

Projections and Closest Target Approach

Objective value φ captures indirect measure of the distance between the datapoint DMU_0 and the PPF frontier constructed by (5) – (7). In basic CCR model the *radial* measure φ not only determines ranking but acts as a factor of performance adjustment for inefficient DMUs. Inactivity of constraints (5) allow for *slacks* in respective dimensions that represent the potential sources for improvement not accounted for in φ. In alternative DEA models, no specific focus is placed on either inputs or outputs. Slacks can be directly managed as deviations from the optimal mix of performance subindicators, and models can be given an optional orientation by omitting the slacks from the objective function.

From a managerial perspective, the main interest of an underperforming entity should consist in setting benchmarks to guide performance improvement. DEA models simultaneously provide measure of performance reflected in objective function along with the identifiers of relevant peers (nonzero λ_j). The latter demonstrate a degree of resemblance in the mix of subindicators with the evaluated DMU. The target mix of benchmarks is obtained as a projection of DMU under assessment is onto the PPF and presents an artificial datapoint (DMU) that is combined from existing best-performers. In conventional DEA models the projection is yielded via maximization of the distance from the boundary which helps finding the "extreme" best-performers' datapoints but fails in offering the least-demanding adjustment scheme. Since the PPF frontier is the collection of Pareto-efficient potential benchmarks, one can use "least distance" as the criterion in the second stage of the procedure to pick their "closest-target" benchmark from it. There is a volume of research both attempting to engineer procedures to determine the "closest target" and applying the LD in empirical investigation in a variety of areas (Gonzalez and Alvarez, 2001; Cherchye and van Puyenbroeck, 2001; Portela et al., 2003; Aparicio et al., 2007; Aparicio et al., 2014; Ruiz et al., 2015; Rodríguez-Vallejo et al., 2019; Ehrenstein, 2020; Kao, 2022).

For the sake of intended use, we customize Aparicio et al. (2007) *mADD* approach. The latter resorts to a simpler version of unweighted additive model that will directly deal with the commensurable raw performance indicators. We use the LD model with „dummy" input vector of ones for each DMU and output orientation (*mADD-O*):

$$\min \quad \sum_{r=1}^{s} s_{r0}^{+} \qquad (r = 1, 2, ..., s) \tag{8}$$

$$\text{s.t.} \quad \sum_{j\in E} \lambda_j x_{ij} = x_{i0} \qquad (i = 1, 2, ..., m) \tag{9}$$

$$\sum_{j\in E} \lambda_j y_{rj} = y_{r0} + s_{r0}^{+} \qquad (r = 1, 2, ..., s) \tag{10}$$

$$\sum_{j\in E} \lambda_j y_{rj} \leq U \tag{11}$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \qquad j \in \mathrm{E} \tag{12}$$

$$v_i \geq 1 \qquad (i = 1, 2, ..., m) \tag{13}$$

$$\mu_r \geq 1 \qquad (r = 1, 2, ..., s) \tag{14}$$

$$d_j \leq \mathrm{M} b_j \qquad j \in \mathrm{E} \tag{15}$$

$$\lambda_j \leq \mathrm{M}(1 - b_j) \qquad j \in \mathrm{E} \tag{16}$$

$$b_j \in \{0,1\} \qquad j \in \mathrm{E} \tag{17}$$

$$d_j \geq 0 \qquad j \in \mathrm{E} \tag{18}$$

$$\lambda_j \geq 0 \qquad j \in \mathrm{E} \tag{19}$$

$$s_{r0}^{+} \geq 0 \qquad (r = 1, 2, ..., s) \tag{20}$$

In general version of *mADD-O*, the original *mADD* model of Aparicio et al. (2007) is modified in several ways. Program (8) – (20) utilizes the set *E* of best-performing peers that needs to be determined beforehand. For this purpose one may use any of conventional DEA models. The original *mADD* seeks to minimize the L1-norm distance from the DMU_0 to the frontier, expressed via sum of slack variables. This retains the linearity of the problem as compared to Euclidean L2 norm. In output-oriented version we force each projected input to remain unchanged (9) which implies zero input slacks. Excluding the latter from the problem reduces the objective to mere minimizing the sum of output slacks in (1). Output slacks capture the deviation of the actual performance y_{r0} in r^{th} dimension from the desired benchmark (projection) generated by relevant peers indicated by means of nonzero λ_j in the left-hand side of (10). Slack and intensity variables s_{r0}^{+} and λ_j are bound to be non-negative by (20) and (19) in a usual way. The magnitude of projection can be bounded from above according to the nature of the data (11). In constraint (12) dual variables are used in the spirit of Aparicio et al. (2007), bounded by (13) – (14) as in conventional additive models. Conditions (12), (17) and (18) constitute the core contribution of the least-distance extension to standard additive DEA models. Due to binary variable (17) the problem becomes computationally more challenging mixed integer linear programming (MILP).

Data

In Section I, a variety of institutional quality indicators were mentioned. For international comparison in this study, we utilize World Governance Indicators (WGI), a comprehensive and widely used resource for measuring governance quality globally (Kaufman et al., 2009). The WGI dataset consists of six composite indicators that capture different dimensions of governance:

VACC – Voice and Accountability
PSTAB – Political Stability and Absence of Violence/Terrorism
GEFF – Government Effectiveness
REGQ – Regulatory Quality
RLAW – Rule of Law
CCOR – Control of Corruption

The indicators are derived from various data sources, including surveys, expert assessments, and other governance-related datasets. The data is aggregated, standardized, and transformed into scores that range from approximately –2.5 to +2.5, with higher scores indicating better governance performance. For the use in models as DEA that require nonnegative quantities, the scores are linearly rescaled into percentages from ordered dataset. For regression analysis, the variables are sourced from UNCTAD and the World Bank. Apart from GDP p.c., data on human capital index (HCI) and technology index were collected. In the former, the World Bank's Human Capital Project (HCP) based on evidence from rigorous microeconometric empirical studies outcome, health and education components are combined in a way that reflects their contribution to worker productivity. The latter, Frontier Technology

Readiness Index from UNCTAD, covers national capacities to use, adopt and adapt technologies. After dropping observation with missing data, the final dataset counts 132 countries.

2. Results and Discussion

In the first step we document importance of institutional quality within the framework of economic level determinants. Three regressions models (I) – (III) were run with altering lead value of $T \in \{2, 3, 4\}$ indicated in (OLS) equation. Thus GDP p.c. from years 2020, 2021 and 2022 were regressed on three factors evaluated at 2009. The variable *institutions* refers to the total aggregated value of WGI for 2019. The other factors comprise *human capital* and *technology* described in the section above.

T a b l e 1

Determinants of Income per capita

	(I)	(II)	(III)
Const	✔	✔	✔
Institutions	0.0076 *** (0.0027)	0.0083 *** (0.0028)	0.0084 *** (0.0028)
Human capital	2.9488 *** (0.6828)	2.9972 *** (0.6767)	2.9544 *** (0.6689)
Technology	1.6130 *** (0.4043)	1.5801 *** (0.4060)	1.5535 *** (0.4055)
N	132	132	132
R^2	0.83	0.82	0.82

Notes: log of *GDPp.c.* as dependent variable, robust standard errors in parentheses.
Source: UNCTAD, World Bank, authors' calculation.

As can be seen from Table 1, all three factors contribute significantly to the attained level of economic development. For illustration sake, we consider the simple specification sufficient and the lack of a number of conceivable controls non-essential.

Proceeding to the analysis of institutions quality itself, we define a "technology" as the set of all attainable combinations of outputs (performance values) and consider its boundary a PPF. The latter acts as a reference for performance assessment. To determine a broader set of potential benchmark-generating entities, we run an ordinary DEA model. For computational ease we employ the radial variation (1) – (3) since the convex technology in all models, regardless of the orientation of the objective, is constructed in the same way. Thus, we identified nine countries that are located on the PPF – New Zealand, and Singapore, Andorra, Switzerland, Denmark, Finland, Iceland, Luxembourg, Norway. From the latter, Iceland is the only best-performer against which no underperforming European country is benchmarked and we exclude it therefore from the set of peers for having a too specific mix of performance values.

Having identified the set of peers, i.e. the set *E*, we run the proposed *mADD-O* model (8) – (20) concentrating on eleven CEE countries. Fixed input quantities x_{ij} in (9) are set to unit value. In order to ensure realistic values for the projections, the upper bound *U* is set to 100 in (11). For the sake of comparison, ranking generated by the two assessment methods is displayed in Table 2 where scores for CCR come directly from the solution of the model while *mADD-O* scores are calculated by means of linear rescaling of the sum of slacks from the objective function (8), higher value corresponding to the lower sum of slacks, i.e. to closer location to the boundary and therefore the better relative performance. For both models correspondings ranks *r_CCR* and *r_mADD-O* are also displayed.

T a b l e 2

Difference in Scores and Ranking for CEE Countries

	mADD-O	***r_mADD-O***	***CCR***	***r_CCR***
Bulgaria	0.000	11	0.680	10
Croatia	0.276	9	0.879	2
Czechia	0.718	2	0.932	1
Estonia	0.804	1	0.723	9
Hungary	0.326	7	0.771	7
Latvia	0.614	5	0.869	3
Lithuania	0.703	3	0.859	4
Poland	0.313	8	0.762	8
Romania	0.093	10	0.655	11
Slovakia	0.406	6	0.784	6
Slovenia	0.615	4	0.850	5

Source: UNCTAD, authors' calculation.

From Table 2, the most dramatic change of assessment can be seen for Croatia and Estonia whose rankings have been nearly swapped while the other countries' rankings only saw minor changes. These results demonstrate that least-distance projection may significantly deviate from the radial one. The detailed solutions for *mADD-O* are to be seen in Appendix Table B. In the following step we use solutions from the models to determine and compare benchmarks for the six dimensions of institutional quality. For any DMU_0, the latter can be computed from constraint (3) either using the left-hand side and solutions for λ_j or from the right-hand side adding actual performance in particular indicator y_{r0} and the respective identified slack s_{r0}^{+}.

For the sake of clarity and space-saving, the correspondences are exhibited in Table 3, focusing on a restricted set of V4 countries only. In the bottom part, performance indicators for Andorra and Singapore are shown. The two DMUs act as peers for all V4 countries as could be seen from nonzero identifiers in Appendix Table A.

Table 3
Slacks and Generation of Projections for V4 Countries

		VACC	PSTAB	GEFF	REGQ	RLAW	CCOR	SUM
Czechia	data slack proj.	81.2 0.0 81.2	83.0 15.5 98.6	82.2 15.5 97.7	87.5 1.8 89.3	84.1 9.3 93.5	72.6 16.7 89.3	58.8
Hungary	data slack proj.	58.9 0.0 58.9	75.9 22.1 98.1	71.6 27.3 99.0	68.8 26.4 95.2	69.7 26.5 96.2	56.3 38.1 94.4	140.5
Poland	data slack proj.	63.8 0.0 63.8	61.3 36.8 98.2	63.5 35.2 98.7	76.0 17.9 93.9	65.4 30.3 95.6	70.2 23.1 93.3	143.3
Slovakia	data slack proj.	76.8 0.0 76.8	63.7 34.8 98.5	69.2 28.7 97.9	77.9 12.6 90.5	74.5 19.5 94.0	62.0 28.2 90.3	123.8
Andorra Singapore	data	82.6 40.6	98.6 97.6	97.6 100.0	88.9 100.0	93.3 98.6	88.9 98.6	

Source: UNCTAD, authors' calculation.

Particularly low performance of Singapore in Voice and Accountability (VACC) is under the BoD weighting scheme offset by Government efficiency and Rule of law. This results in low benchmark levels for underperforming countries resulting in zero slack S1+. In general, low performance in particular dimensions may be problematic if such a country aspires to be constituting benchmark for an under-performer. Thus, low Singapore's VACC may contribute to unacceptably low targets for European countries with higher levels of accountability. Alongside, from the eleven CEE countries, Estonia stands out in terms of identified peers – in its projections Luxembourg and New Zealand are involved (see Appendix Table B). The evaluator can reflect their preferences as to desired lower bound of the performance in particular domains by restricting the relevant variable in the model or exclude a well-performing country that does not meet predefined criteria from the set of potential peers. The performance of Baltic countries is generally relatively good in Regulation quality which is evidenced by low values of the respective slack S4+. On the other hand, the most deficient domains is Corruption in Bulgaria, Romania and Hungary (S6+). Czechia dominates V4 outperforming the other members in all domains.

In Table 4 the comparison of the radial and least-distance targets for CEE countries is provided. Projections for the radial CCR-O are computed as outputs scaled by the factor determined by the score value adjusted further by a slack in the respective dimension. Projections for least-distance *mADD-O* model are determined via (10). In both models the same performance possibility set is utilized. Therefore, any projection onto the frontier is Pareto-efficient and as such, cannot fully dominate another set of suggested benchmarks. Zooming in on V4 countries in Table 4, one can observe a common pattern of trade-offs.

T a b l e 4

Projections from Radial and Least-Distance Models

	Model	VACC	PSTAB	GEFF	REGQ	RLAW	CCOR
Bulgaria	CCR-O mADD-O	83.1 56.5	86.7 98.0	69.3 99.1	99.6 95.8	78.4 96.6	71.4 94.9
Croatia	CCR-O mADD-O	89.6 64.7	96.0 98.2	97.2 98.6	95.8 93.6	83.2 95.5	81.8 93.0
Czechia	CCR-O mADD-O	92.3 81.2	94.5 98.6	93.5 97.7	99.6 89.3	95.7 93.5	82.6 89.3
Estonia	CCR-O mADD-O	95.8 89.4	75.4 97.5	95.9 94.8	99.5 92.8	96.4 95.1	96.4 92.9
Hungary	CCR-O mADD-O	76.5 58.9	98.6 98.1	93.0 99.0	89.2 95.2	90.5 96.2	73.0 94.4
Latvia	CCR-O mADD-O	87.7 75.4	80.2 98.4	90.1 98.0	99.6 90.8	96.2 94.2	89.5 90.6
Lithuania	CCR-O mADD-O	94.5 82.1	84.6 98.6	94.0 97.6	99.5 89.1	96.2 93.3	92.4 89.1
Poland	CCR-O mADD-O	83.6 63.8	80.4 98.2	83.2 98.7	99.6 93.9	85.8 95.6	92.1 93.3
Romania	CCR-O mADD-O	98.2 64.3	95.1 98.2	72.7 98.6	96.2 93.8	98.4 95.6	80.8 93.1
Slovakia	CCR-O mADD-O	98.0 76.8	81.3 98.5	88.4 97.9	99.4 90.5	95.1 94.0	79.2 90.3
Slovenia	CCR-O mADD-O	90.9 77.3	83.8 98.5	99.5 97.9	88.8 90.3	97.8 93.9	89.4 90.2

Source: Authors' calculation.

Voice and accountability dimension is identified as strongly deficient by CCR-O, offering, compared to *mADD-O,* considerable adjustment. For Czechia, the VACC target value is 92.3 contrasting with the least-distance benchmark of 81.2. For Hungary, Poland and Slovakia, CRR-O vs least-distance benchmarks are 76.5 *vs* 58.9, 83.6 *vs* 63.8 and 98.0 *vs* 76.8 respectively. On the other hand, CCR-O is less demanding in Government efficiency or Control of corruption domains. In GEFF the largest difference is for Poland (83.2 vs 98.7) and Slovakia (88.4 vs 97.9) while in CCOR the largest spread shows for Hungary (73.0 vs 94.4) and mere a slight difference for Poland (92.1 vs 93.3). The common pattern is that in VACC and REGQ (except for Hungary) are traded off for less ambitions in GEFF and CCOR. Unless more information is provided, the target sets resting on a boundary (PPF) are indistinguishable. However, decision makers' preferences can be easily incorporated in the models. Specifically, the sum of slacks in (4) that is used to determine closest-distance, could be altered to a weighted sum. In case adjustment costs, economic or social, are estimated for individual domains, one could alter the model to an allocation (cost) efficiency version.

It is possible as well to avoid multiple peers and ensure a single one country's performance data to act as benchmarks. For this purpose, constraint (19) shall be altered to a binary choice $\lambda_j \in \{0,1\}$ coupled with the condition $\sum_{j \in E} \lambda_j = 1$. This would result in nonconvex boundary provide by free disposal hull (FDH) model that allows a policy maker to focus on a single best-performer to follow.

Conclusion and Further Research

Institutional quality proved to be robustly associated with the level of economic development worldwide. The subsequent analysis was conducted utilizing six dimensions of institutional quality captured by World Governance Indicators in the non-parametric frontier framework. From the perspective of an underperforming subject, the "least-distance" approach may sound to suggest a more easily attainable and cost-saving mix of targets than projections offered by conventional models. Since benchmarks represented by Pareto-efficient points on performance possibility frontier are not discernible from the perspective of performance evaluation, without additional criteria, such as costs or marginal rate of substitution between the goals achievement, competing models only offer alternative mix of benchmarks for a decision maker to choose from.

Employing benefit-of-the-doubt weighting scheme for aggregation via conventional radial DEA model along with customized version of least-distance additive DEA model, benchmarks for eleven CEE countries were generated by two dominant best-performers – Andorra and Singapore. Policy makers may prefer to either impose additional restrictions as to the choice of potential peer countries that may not be considered to be compatible with the institutional setting of the assessed country or even force the model to indicate a single top-performer a benchmark. Evaluator may also wish to specify desired bounds for variables in the model requesting minimal standards to be met. The latter may reflect specific political goals or commitments in individual domains. Although at the V4 tier Czechia appears to be a regional leader, it is lagging behind the global best-performers. The presented approach does not provide structural model of the interplay between the underlying factors and the outcomes in multidimensional institutional environment. Rather, as a multicriteria decision making tool, it offers an indication of potential relative underperformance by means of ranking and tangible targets for performance improvement. The analysis of institutions and economic performance may be further extended within the fully-fledged input-output DEA framework involving various socio-economic outcomes. Potentially, the nonparametric approach of this kind may be insightful in intertemporal analysis revealing contribution of institutions to the level of economic development etc. and as such, be fruitful to corroborate data-based goal setting in policy-making aimed at improving institutions.

References

ACEMOGLU, D. – JOHNSON, S. – ROBINSON, J. A. (2005): Institutions as a Fundamental Cause of Long-Run Growth. Handbook of Economic Growth, *1*, pp. 385 – 472.

APARICIO, J. – BORRAS, F. – ORTIZ, L. – PASTOR, J. T. (2014): Benchmarking in Healthcare: An Approach Based on Closest Targets. Managing Service Productivity: Using Frontier Efficiency Methodologies and Multicriteria Decision Making for Improving Service Performance, pp. 67 – 91.

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*, No. 3, pp. 209 – 218. Available at: <https://doi.org/10.1007/s11123-007-0039-5>.

BRUNETTI, A. – KISUNKO, G. – WEDER, B. (1997): Institutions in Transition: Reliability of Rules and Economic Performance in Former Socialist Countries. Vol. 9708. World Bank Publications.

CHARNES, A. – COOPER, W. W. – RHODES, E. (1978): Measuring the Efficiency of Decision-Making Units. European Journal of Operational Research, *2*, No. 6, pp. 429 – 444. Available at: <https://doi.org/10.1016/0377-2217(78)90138-8>.

CHERCHYE, L. (2001): Using data Envelopment Analysis to Assess Macroeconomic Policy Performance. Applied Economics, *33*, No. 3, pp. 407 – 416.

CHERCHYE, L. – MOESEN, W. – VAN PUYENBROECK, T. (2004): Legitimately Diverse, Yet Comparable: On Synthesizing Social Inclusion Performance in the EU. JCMS: Journal of Common Market Studies, *42*, No. 5, pp. 919 – 955.

CHERCHYE, L. – VAN PUYENBROECK, T. (2001): A Comment on Multi-Stage DEA Methodology. Operations Research Letters, *28*, No. 2, pp. 93 – 98.

COOPER, W. W. – SEIFORD, L. M. – TONE, K. (2007): Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition. In Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition. Springer. Available at: <https://doi.org/10.1007/978-0-387-45283-8>.

EHRENSTEIN, M. – CALVO-SERRANO, R. – GALÁN-MARTÍN, Á. – POZO, C. – ZURANO-CERVELLÓ, P. – GUILLÉN-GOSÁLBEZ, G. (2020): Operating within Planetary Boundaries without Compromising Well-Being? A Data Envelopment Analysis Approach. Journal of Cleaner Production, *270*. Available at: <https://doi.org/10.1016/j.jclepro.2020.121833>.

GONZALEZ, E. – ALVAREZ, A. (2001): From Efficiency Measurement to Efficiency Improvement: The Choice of a Relevant Benchmark. European Journal of Operational Research, *133*, pp. 512 – 520.

GROGAN, L. – MOERS, L. (2001): Growth Empirics with Institutional Measures for Transition Countries. Economic Systems, *25*, No. 4, pp. 323 – 344.

KAO, C. (2022): Closest Targets in the Slacks-Based Measure of Efficiency for Production Units with Multi-Period Data. European Journal of Operational Research, *297*, No. 3, pp. 1042 – 1054.

KAUFMANN, D. – KRAAY, A. – MASTRUZZI, M. (2009): Governance Matters VIII: Aggregate and Individual Governance Indicators, 1996 – 2008. [World Bank Policy Research Working Paper, 4978.]

KNACK, S. – KEEFER, P. (1995): Institutions and Economic Performance: Cross-Country Tests Using Alternative Institutional Measures. Economics and Politics, *7*, No. 3, pp. 207 – 227.

MELYN, W. – MOESEN, W. (1991): Towards a Synthetic Indicator of Macroeconomic Performance: Unequal Weighting When Limited Information Is Available. Public Economics Research Papers, pp. 1 – 24.

NORTH, D. C. (ed.) (1990): Institutions, Institutional Change and Economic Performance. In Institutions, Institutional Change and Economic Performance. Cambridge University Press, pp. 141 – 146. Available at: <https://doi.org/DOI: 10.1017/CBO9780511808678.017>.

OECD, JOINT RESEARCH CENTRE (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*, pp. 251 – 269.

RODRÍGUEZ-VALLEJO, D. F. – GALÁN-MARTÍN, Á. – GUILLÉN-GOSÁLBEZ, G. – CHACHUAT, B. (2019): Data Envelopment Analysis Approach to Targeting in Sustainable Chemical Process Design: Application to Liquid Fuels. AIChE Journal, *65*, No. 7, pp. e16480.

RODRIK, D. (1999): Where Did All the Growth Go? External Shocks, Social Conflict, and Growth Collapses. Journal of Economic Growth, *4*, pp. 385 – 412.

RUIZ, J. L. – SEGURA, J. V. – SIRVENT, I. (2015): Benchmarking and Target Setting with Expert Preferences: An Application to the Evaluation of Educational Performance of Spanish Universities. European Journal of Operational Research, *242*, No. 2, pp. 594 – 605.

UNCTAD (2023): UNCTADstat. Retrieved June 29, 2023. Available at: <https://unctadstat.unctad.org/wds/ReportFolders/reportFolders.aspx>.

Appendix

Table A

Data for CEE and Institutionally Best-Performing Countries

	VACC	PSTAB	GEFF	REGQ	RLAW	CCOR
Andorra	82.6	98.6	97.6	88.9	93.3	88.9
Denmark	98.6	80.7	99.0	98.1	99.0	100.0
Finland	99.5	85.4	98.6	99.0	100.0	99.5
Iceland	93.7	95.8	95.7	91.8	96.2	95.2
Luxembourg	97.6	94.3	96.6	99.5	96.6	96.2
New Zealand	99.0	96.7	88.9	97.6	98.1	99.0
Norway	100.0	90.1	98.1	95.2	99.5	98.1
Singapore	40.6	97.6	100.0	100.0	98.6	98.6
Switzerland	98.1	92.5	99.5	95.7	97.6	96.6
Bulgaria	56.5	59.0	47.1	67.8	53.4	48.6
Croatia	64.7	69.3	70.2	69.2	60.1	59.1
Czech Republic	81.2	83.0	82.2	87.5	84.1	72.6
Estonia	89.4	70.3	89.4	92.8	89.9	89.9
Hungary	58.9	75.9	71.6	68.8	69.7	56.3
Lithuania	82.1	73.6	81.7	86.5	83.7	80.3
Latvia	75.4	68.9	77.4	85.6	82.7	76.9
Poland	63.8	61.3	63.5	76.0	65.4	70.2
Romania	64.3	62.3	47.6	63.0	64.4	52.9
Slovakia	76.8	63.7	69.2	77.9	74.5	62.0
Slovenia	77.3	71.2	84.6	75.5	83.2	76.0

Source: UNCTAD, authors’ calculation.

T a b l e B

Complete Solutions of the mADD-O Model for CEE Countries

	L1	L2	L3	L4	L5	L6	L7	L8	S1+	S2+	S3+	S4+	S5+	S6+	v	u1	u2	u3	u4	u5	u6
Bulgaria	0.379	0	0	0	0	0	0.621	0	0	39.0	52.0	28.0	43.2	46.4	7549.9	1.6	63.4	1.0	10.0	1	1
Croatia	0.575	0	0	0	0	0	0.425	0	0	28.8	28.4	24.4	35.4	33.9	7092.2	1.0	61.5	1.0	7.5	1	1
Czechia	0.966	0	0	0	0	0	0.034	0	0	15.5	15.5	1.8	9.3	16.7	7092.2	1.0	61.5	1.0	7.5	1	1
Estonia	0.579	0	0	0.105	0.316	0	0.000	0	0	27.3	5.3	0.0	5.2	3.0	5231.1	2.6	23.4	10.8	1.0	15.87	1
Hungary	0.437	0	0	0	0	0	0.563	0	0	22.1	27.3	26.4	26.5	38.1	7549.9	1.6	63.4	1.0	10.0	1	1
Latvia	0.828	0	0	0	0	0	0.172	0	0	29.6	20.6	5.3	11.5	13.7	7092.2	1.0	61.5	1.0	7.5	1	1
Lithuania	0.989	0	0	0	0	0	0.011	0	0	25.0	15.9	2.5	9.7	8.8	7092.2	1.0	61.5	1.0	7.5	1	1
Poland	0.552	0	0	0	0	0	0.448	0	0	36.8	35.2	17.9	30.3	23.1	7092.2	1.0	61.5	1.0	7.5	1	1
Romania	0.563	0	0	0	0	0	0.437	0	0	35.9	51.0	30.8	31.2	40.3	7092.2	1.0	61.5	1.0	7.5	1	1
Slovakia	0.862	0	0	0	0	0	0.138	0	0	34.8	28.7	12.6	19.5	28.2	7092.2	1.0	61.5	1.0	7.5	1	1
Slovenia	0.874	0	0	0	0	0	0.126	0	0	27.2	13.3	14.9	10.8	14.2	7092.2	1.0	61.5	1.0	7.5	1	1

	d1	d2	d3	d4	d5	d6	d7	d8	b1	b2	b3	b4	b5	b6	b7	b8
Bulgaria	0	1000.0	690.0	129.2	0.0	431.3	0	282.1	0	1	1	1	0	1	0	1
Croatia	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Czechia	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Estonia	0	251.5	128.0	0.0	0.0	34.3	0	0.0	0	1	1	0	0	1	0	0
Hungary	0	1000.0	690.0	129.2	0.0	431.3	0	282.1	0	1	1	1	0	1	0	1
Latvia	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Lithuania	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Poland	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Romania	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Slovakia	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1
Slovenia	0	1000.0	701.7	157.4	28.6	442.2	0	297.4	0	1	1	1	1	1	0	1

Source: UNCTAD, authors' calculation.