Future Business Journal

RESEARCH **Open Access**

Measuring countries relative efficiencies in using development assistance: a data envelopment analysis approach

Mohamed F. Sakr[1], Kamal Samy Selim[2] and Sherin Gamaleldin Taha[3*]

Abstract

Despite the presence of a considerable corpus of literature investigating the impact of aid on nations' development, the efficiency of utilizing this finite pool of development finance remains ambiguous. The main aim of this study is to address the existing research gap by examining the efficiency of utilizing such development assistance in achieving three specific Sustainable Development Goals (SDGs) from 2002 to 2020 using a Data Envelopment Analysis (DEA) methodology. Moreover, this study examines the theoretical underpinnings that show a correlation between the impact of aid on development and the governance and political structure of countries. The findings indicate that the efficiency of development assistance often falls short of optimal, underscoring the necessity for more attention to its administration, particularly in low-income countries. The efficiency of development assistance can be significantly enhanced by organizational improvements, resulting in a significant increase beyond 80%. The confirmation of the robustness of the findings was attained by the application of the bootstrapping methodology. Hence, it is crucial to recognize that while augmenting the levels of development assistance may hold significance, it alone may not be adequate to guarantee efficient utilization in bridging the financial gap required to meet the desired objectives of the SDGs by 2030.

Keywords Foreign aid, Operations research, Sustainable development, Efficiency, Optimization techniques, International political economy, Debt management

JEL Classification F35, C44, Q01, H21, C61, F50, H63

Introduction

The efficacy of development aid in achieving development objectives remains a subject of ongoing debate, despite over five decades of scholarly research and the application of various approaches for evaluating its impact [26]. In light of the emergence of the COVID-19 pandemic and the ongoing conflict in Ukraine, there has been a heightened urgency around humanitarian and development issues, particularly in developing countries. Consequently, uprising calls to increase development finance needed to address the shortfall in funding for the SDGs [34], this in spite of not reaching a definitive resolution to the ongoing argument on the recognized impact of these inflows on the development outcomes of recipient states [33].

Official development assistance (ODA) is considered as the largest source of development aid allocated by developed states, such as the development assistance committee

*Correspondence:
Sherin Gamaleldin Taha
sherine.heikal@gmail.com; sherin_taha2016@feps.edu.eg
[1] Economics Department, Faculty of Economics and Political Science, Cairo University, Giza, Egypt
[2] Socio-Computing Department, Faculty of Economics and Political Science, Cairo University, Giza, Egypt
[3] Economics Department - Faculty of Economics and Political Science, Cairo University, Giza, Egypt

(DAC) member countries.[1] Its inflows to developing countries have been intricately linked to the political and economic frameworks of several historical periods, including the Cold War, the Post-Cold War, and Globalization Era. To improve its effectiveness on countries' development on ground, a notable advancement in the agenda for providing aid occurred in the twenty-first century, recognizing the imperative of attaining the Millennium Development Goals (MDGs) by the year 2015 [21]. The MDG framework, which encompassed nation-led initiatives and strategies aimed at poverty reduction, effective governance, and viable macroeconomic policies, emerged as the central focus of aid-driven development [26, 41]. However, upon evaluation of the progress made toward achieving the MDGs in 2015, it was seen that numerous developing countries exhibited inadequate performance due to deficient policies, institutional limitations, lack of subsequent initiatives, and various other contributing factors [31].

Later in 2015 the acceptance of the "Addis Ababa Action Agenda" subsequently positioned the 2030 Agenda for Sustainable Development and its 17 SDGs as important components within the international framework for funding development. Consequently, these goals have become pivotal objectives for the provision of development assistance [49]. Recent data from the OECD indicate that ODA has attained a cumulative sum of $211.3 billion in the year 2022 [35]. In light of the prevailing global issues, there is an escalating demand for a significant augmentation in ODA, transcending the existing provision. Whereas in contemporary discussions, there has been considerable scrutiny on the efficacy of ODA in facilitating developmental progress. According to Carbonnier's [8], ODA demonstrates inefficiency, financial mismanagement, and the perpetuation of market distortions, resulting in an augmented dependence of recipient countries on developed nations.

Considering the escalating global climatic and financial issues, development aid is becoming increasingly scarce. Therefore, it is imperative in contemporary international development cooperation to thoroughly examine how countries efficiently utilize such limited development finance resources in financing primary development outcomes. Thus, this paper contributes to this scholarly discourse by investigating the relative efficiency of recipients in using their ODA to reach main development objectives. Given that ODA has been designated to fund the SDGs since the Addis Ababa Action Agenda, the paper aims to assess the efficiency of ODA in achieving primary SDGs by deploying a DEA linear programming model.

Technical efficiency has been the primary focus of efficiency analysis using DEA models. This concept is derived directly from the Pareto Koopmans efficient frontier production function, which is a mathematical expression that determines the greatest amount of output that can be produced from a given set of inputs used by a decision maker; a firm or industry or a country. [7]. As described by Wu and others [52], DEA methodology endogenously generates a nonparametric frontier that encompasses all possible data combinations of countries, which serve as the primary decision-making units (DMUs) inside the reference set in the model. The points located on this frontier correspond to the set of efficient combinations of inputs and outputs, or in other words, the best practices. The efficiency ratings of DMUs are subsequently computed in relation to this frontier.

This study uses the DEA technique to measure the relative efficiency of recipient countries in employing their received development aid in the form of ODA as a main input to attain primary SDGs as the main outputs from 2002 to 2020. It offers a conceptual structure for evaluating the recipient countries of ODA in relation to their efficient utilization of development aid to successfully achieve significant developmental objectives. Furthermore, it identifies countries that exhibit outstanding relative performance in this domain. Within this setting, the primary objective of the study is to explicitly investigate and provide comprehensive responses to four significant research questions. To what extent have ODA inflows been efficiently utilized in the achievement of primary development objectives in recipients' countries. The second inquiry pertains to the identification of countries that exhibit better management of these resources in comparison with others, with the aim of attaining essential development objectives. This research intends to revisit the theoretical framework of foreign aid, which posits a connection between economic and institutional policies and the subsequent influence of aid on a country's economic growth [6, 29]. According to Sembene [40], there is a clear indication that higher income countries exhibit superior institutional and governance performance compared to lower-income countries. The present study examines a central hypothesis that posits a positive relationship between the level of income in a country and its ability to effectively administer development assistance. The third inquiry investigates the impact of the quantity of assistance received on a country's efficiency scores. Finally, research examines if efficiency of using ODA inflows have changed over time and identifies the underlying factors that contribute to these variations.

[1] According to the Organization for Economic Cooperation and Development (OECD), ODA is government aid designed to promote and specifically targets the economic development and welfare of developing countries, excluding any assistance for military purposes. The provision of such development assistance can occur through bilateral channels, where it is sent directly from a donor to a recipient, or through multilateral mechanisms facilitated by international organizations like the United Nations or the World Bank. ODA encompasses the provision of grants and soft or concessional loans, wherein the grant portion constitutes a minimum of 25% of the overall loan amount.

This study uses seven distinct DEA models to assess the comparative performance of 86 countries that have received ODA between the years 2002 and 2020. The analysis focuses on evaluating their respective achievements in relation to three primary SDGs that are of particular significance, which are: Goal 3, promoting good health and well-being, Goal 4, quality education, and Goal 8, decent and sustainable economic growth.

The subsequent sections of this paper are organized in the following manner. Section "Literature review" provides an overview of the existing literature. Section. "Methods" describes the DEA models that were utilized in the analysis. The process of selecting variables, providing descriptive statistics, and specifying the sources of data is presented in Sect. "Data". Section. "Results and discussion" of the document provides an in-depth analysis and interpretation of the obtained results, followed by a comprehensive discussion of their implications, in addition to addressing the topic of sensitivity analysis and statistical inferences. Moving on to Sect. "Conclusion", that includes policy implications derived from the findings of the study. Additionally, this section acknowledges the limits of the research and suggests areas for future investigation.

Literature review

The discourse surrounding aid and development has undergone continuous evolution. Two primary perspectives can be identified in examining this relationship within the ongoing literature. The first perspective focuses on assessing the effectiveness of aid on countries economic growth and development, which has resulted in the emergence of three distinct lines of evidence. Firstly, there is evidence suggesting a negative detrimental relationship between aid and the economic growth of recipient countries [25]. Secondly, there is evidence indicating a positive relation between aid and economic growth, but this relation is contingent upon specific conditions, such as the amount of aid provided and the policies implemented by the recipient countries [6, 11]. Lastly, there is evidence suggesting a positive relation between aid and economic growth, regardless of the political and institutional framework in place [2, 22, 23, 36].

The second perspective focuses on measuring the efficiency of using aid in achieving development goals. According to the OCED, efficiency—as one of the six evaluation criteria adopted by the OECD/DAC in assessing the Quality of ODA—is defined as "the conversion of inputs into outputs, outcomes and impacts, in the most cost-effective way possible, as compared to feasible alternatives in the context" ([32], p. 58). Based on this perspective, development aid efficiency is considered as a distinct input within the overall process of achieving significant developmental outcomes. Accordingly, countries as decision-maker units (DMUs) should manage their resources of aid to achieve the maximum development outcomes possible, reaching the well-known "Pareto–Koopmans" efficient status where "it is not possible to improve any input or output without worsening some other input or output." Cooper et al. ([14], p. 45).

The literature on aid efficiency from this perspective has been undertaken from several perspectives, both at the micro-level of individual projects and at the macro-level, to assess efficiency in reaching different development outcomes, but not specifically in accomplishing SDGs. The research undertaken by Martin-Perez and Martin-Cruz [28] assesses the efficacy of 48 projects that received funding from the Spanish Agency for International Development Cooperation in the countries of Morocco and Mozambique. The results of the study indicate that Morocco exhibited a greater degree of efficacy in the implementation of the International Cooperation Scheme in comparison with Mozambique.

At the macro-level, Alda and Cuesta [1] assess the efficacy of humanitarian aid in achieving its primary goal of "preserving lives and mitigating suffering." The researchers employed humanitarian aid as the independent variable, while the dependent variables consisted of the inverse of the number of refugees displaced by an emergency, the inverse of the estimated individual death count, and a collection of control variables including the Gini index, poverty levels, growth rate, world governance indicators, conflict intensity, and homicide rate. The researchers discovered that the efficacy of humanitarian assistance in mitigating the influx of migrants is comparatively limited, indicating a significant scope for enhancement in light of the existing magnitude of help provision. Hwang et al. [24] conducted a study to assess the effectiveness of the Korean ODA through the application of a DEA model. The results of their analysis indicate that Asian countries exhibit lower levels of efficiency when compared to other areas.

Methods

Two distinct approaches for assessing efficiency have been developed based on the widely recognized concept of "Pareto–Koopmans efficiency." These approaches are commonly referred to as accounting methods and frontier analysis methods, sometimes known as best-practice techniques [10]. According to Martin-Perez and Martin-Cruz [28], the accounting procedures involve straightforward calculations that determine the proportion of inputs utilized in relation to the outcomes attained. The second classification of methodologies pertains to frontier analysis, which involves comparing the ratios of actual outputs to inputs with a best-practice frontier that represents the most efficient allocation of resources. The estimation of this frontier can be conducted by the utilization of parametric econometric approaches, commonly referred to as "Stochastic Frontier Analysis" methods, or through nonparametric DEA techniques [17].

Data envelopment analysis (DEA)

In contrast to the Stochastic Frontier Analysis approaches, DEA is a linear programming model that establishes a connection between inputs and outputs without necessitating the explicit specification of the functional relationship between them [5]. The model has the ability to internally produce optimal practices or combinations, as well as identify the different weights assigned to inputs and outputs. This consideration of heterogeneity among DMUs is a key aspect of the model [52]. The usage of DEA has been employed to assess the performance of countries and regions, either through cross-sectional or time-series approaches [30]. Both radial models and non-radial slack-based DEA models are commonly employed in the assessment of cross-sectional performance DMUs. On the other hand, the evaluation of DMUs' performance over time is often accomplished through the utilization of Windows Analysis and Malmquist productivity index (MI). It is worth noting that the MI approach is more extensively adopted in practice, as highlighted by Cooper and others [14].

The radial and non-radial models

The radial CCR DEA model, established by Charnes et al. [9], is based on [20] model for assessing productive efficiency of DMUs with one input and one output. It is used to measure technical efficiency for production function technologies that exhibit constant returns to scale (CRS). The model is subsequently adapted to accommodate variable returns to scale (VRS) production function technologies by Banker et al. [3] in what is known as the BCC model. In contrast to the CCR model which assesses aggregate technical efficiency (ATE), the BCC model exclusively evaluates pure technical efficiencies (PTE). Therefore, it can be inferred that the identified inefficiencies are mostly attributed to administrative and managerial issues, rather than inadequate operating scale levels, also known as scale inefficiencies.

The efficiency score is commonly defined as the ratio of the weighted sum of outputs to the weighted sum of inputs in situations where numerous input and output factors are present (Eq. 1).

$$\mathrm{ES} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \tag{1}$$

According to the CCR model, the efficiency of a specific DMU denoted by the subscript "z" within a reference set of DMUs (j=1, 2... n) is determined by maximizing the ratio specified in Eq. (1), while ensuring that the corresponding ratios for all other DMUs in the set are less than or equal to one. This can be demonstrated based on the subsequent format:

$$\begin{aligned} &\max h_z = \left[\frac{\sum_{r=1}^{s}(u_r y_{rz})}{\sum_{i=1}^{m}(v_i x_{iz})}\right] \\ &\text{S.t } \frac{\sum_{r=1}^{s}(u_r y_{rj})}{\sum_{i=1}^{m}(v_i x_{ij})} \leq 1; j = 1,2,\ldots,n \\ &u_r, v_i \geq 0; r = 1,2,\ldots s, i = 1,2,..m \end{aligned} \tag{2}$$

where x_{ij} are inputs, y_{rj} are outputs for the jth DMU, while u_r, v_i are outputs and inputs weights that are resolved by the solution of this problem. The previous functional programing can be replaced with the following linear programing problem:

$$\begin{aligned} &F_z(x_z y_z) = \max\theta \\ &\text{S.t} \\ &\sum_{j=1}^{n}\left(\lambda_j y_{rj}\right) \geq \theta y_{rz};\ \ r = 1,..,s \\ &\sum_{j=1}^{n}\left(\lambda_j x_{ij}\right) \leq x_{iz};\ \ i = 1,..,m \\ &\lambda_j \geq 0; j = 1,\ldots,n \end{aligned} \tag{3}$$

This linear program should be solved for each DMU in the sample, where λ_j is inputs and outputs weights vector. The efficiency score, $\theta_{z'}$, quantifies the extent to which observable outputs can be proportionally increased while maintaining the same level of inputs. The production possibility set in this linear programming model is characterized by being closed, convex, and demonstrating CRS as well as strong disposability. The CCR model can be readily adapted to incorporate VRS in the BBC model by introducing a convexity constraint $\sum_{j=1}^{n}\left(\lambda_j\right) = 1$ to (3), hence forming a convex hull enveloping data points more tightly than CRS with efficiency score equal or greater than those obtained in CCR model [10]. As stated earlier, the BCC model exclusively assesses efficiency in terms of pure technical efficiency while disregarding scale efficiencies. Consequently, each DMU is solely compared to other DMUs that operate at a comparable operating scale. Therefore, the BCC model shows more efficient single DMUs in the same sample than the CCR model. Furthermore, the efficiency values obtained for each individual DMU using the BCC model surpass those estimated by the CCR model [44].

DEA models can be classified into two categories: input-oriented (IO) and output-oriented (OO). The selection of the analysis orientation is contingent upon the problem's characteristics and is associated with the decision units' capacity to regulate either input or output variables. OO models focus on maximizing the level of outputs while considering the controllable or subject variables as inputs. The objective is to optimize the outputs given the inputs. On the other hand, IO models aim to minimize the level of inputs while achieving a specific level of outputs. However, based on the duality theory of linear programming, it is evident that both models' ideal values result in identical production possibility sets [14].

The CCR and BCC models are radial models that aim to uniformly increase (decrease) all outputs (inputs) by a consistent proportion [37]. Therefore, it is conceivable for these methods to result in suboptimal efficiency due to their failure to consider the potential presence of slack inputs or outputs, together with their corresponding spots on the frontier. This implies that additional modifications can be made to either the inputs or outputs without negatively impacting other inputs or outputs, hence enhancing the efficiency of the DMUs [14]. Furthermore, the utilization of super efficiency radial models in the identification of highly efficient decision units may give rise to the issue of infeasibility, as highlighted by Ray [37].

Therefore, a more recent collection of additive non-radial models has been established [13]. Tone [46, 47] introduced a non-radial non-oriented slack-based (SBM) model and a super-SBM (SSBM) model. These models incorporate input and output slacks in the calculation of efficiency scores, ensuring that units with no input or output slacks are assigned unity efficiency measures. Additionally, the SSBM model ranks the efficient units. In the context of these models, it is important to note that only those DMUs that do not exhibit input excesses or output shortfalls, sometimes referred to as "slacks," are deemed efficient.

The formulation of SBM non-radial non-orientated additive linear program model according to [47] is as follows:

$$\begin{aligned}
&\min \delta = t - \frac{1}{m}\sum_{i=1}^{m}\left(\frac{S_i^-}{x_{iz}}\right)\\
&\text{S.t}\\
&1 = t + \frac{1}{s}\sum_{r=1}^{s}\left(\frac{S_r^+}{y_{rz}}\right)\\
&tx_{iz} = \sum_{j=1}^{n} x_{ij}\Pi_j + S_i^- \quad ,(i = 1,2,\ldots,m)\\
&ty_{rz} = \sum_{j=1}^{n} y_{rj}\Pi_j - S_r^+ \quad ,(r = 1,2,\ldots,s)\\
&\Pi_j \geq 0(\forall \boldsymbol{j}), S_i^-(\forall \boldsymbol{i}) \geq 0, S_r^+(\forall \boldsymbol{r}) \geq 0, t < 0,
\end{aligned} \tag{4}$$

where t is a positive scaler,S_i^-, S_r^+ are inputs surplus and outputs shortage, respectively, and known as "slacks." For adjusting for the VRS, the constraint $\sum_{j=1}^{n}(\lambda_j) = 1$ is imposed on λ.

The DEA model employs best-practice units as a point of reference for other group units. For each inefficient DMU, DEA finds a group of efficient units that can serve as benchmarks for improvement [10]. In the existing body of literature, both radial and non-radial DEA models have been employed for the purpose of efficiency evaluation. When determining the appropriate model to utilize, it is observed that non-radial models are recommended in cases where slacks are deemed to be a substantial contributor to inefficiency [39]. Both inputs-oriented and outputs-oriented DEA models are employed for the purpose of identifying efficient decision units. According to Cooper and others [14], the efficiency scores of input-oriented DMUs vary between 0 and 1. Efficient units consistently receive a score of 1, while inefficient units receive scores below 1. In the output-oriented models of DEA, the scores assigned to efficient units are equal to 1, whereas the scores for inefficient units are larger than 1. Both approaches provide the identification of necessary modifications needed in the inputs or outputs of the inefficient DMUs in order to enhance efficiency. Within the context of SBM additive models, the efficiency scores of DMUs span from 0 to 1. The DMUs that exhibit considerably higher efficiency are characterized by scores of 1 and no slacks. According to Tone [45], in the SSBM model, the highest performers are characterized by scores that exceed 1, with the top-ranked performance achieving the greatest score.

In order to assess the efficacy of development aid, we employed seven specific DEA models. These models were implemented using the freely available R software tool. In the DeaR package conducted by Coll-Serrano et al. [12], these modes are as follows: (1) Radial CCR input-oriented model (CCR IO), (2) Radial CCR output-oriented model (CCR OO), (3) Radial BCC input-oriented model (BCC IO), (4) Radial BCC output-oriented model (BCC OO), (5) Non-radial non-oriented SBM additive model assuming CRS (SBM CSR), (6) Non-radial non-oriented SBM additive model assuming VRS (SBM VRS), (7) Super-SBM models to the SBM efficient DMUs (SSBM).

Malmquist total factor productivity index

The Malmquist index (MI) was initially proposed by Malmquist in 1953 and subsequently expanded upon by Diewert et al. [15]. This index serves as a tool for evaluating productivity disparities between two enterprises over a given period by employing distance functions. Additionally, Fare and Grosskopf [18] extended the use of Farrell measures of technical efficiency by developing a method to assess the productivity of DMUs through the use of a DEA model. The authors split the growth of productivity into two distinct components: temporal improvements in

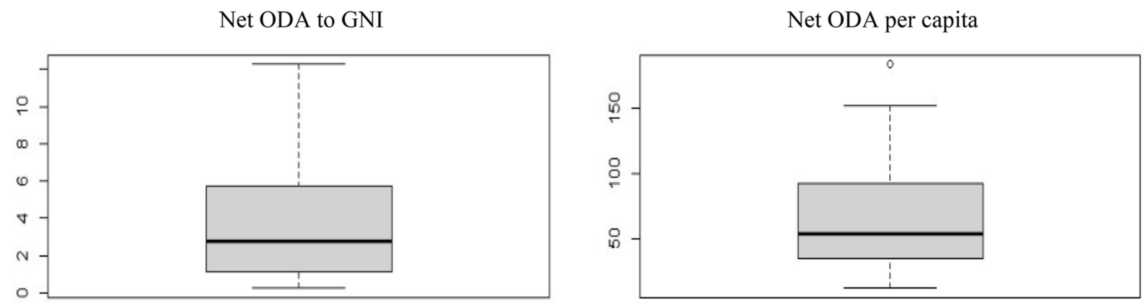


Fig. 1 Box plots for net ODA percentage to GNI and ODA per capita

technical efficiency and temporal changes in the technology employed in the manufacturing process. The measure of productivity known as the MI can be understood as the result of two distinct factors. The first factor, referred to as the "Catch-Up" or efficiency change (EFFCH), involves the movement toward or away from the efficiency frontier. The second factor, known as the "Frontier-shift" or technological change (TECHCH), represents the shift in the efficiency frontier itself between the two periods due to advancements in technology [19]. According to Coelli et al. [10], the productivity of a DMU experiences an increase from period t to $t+1$ when it is able to achieve the same outputs using fewer inputs, or when it is able to create more outputs using the same inputs.

Fare et al. [18, 19] conducted a study in which they developed four linear programming models to calculate the measure the productivity index (MI) between time periods t and $t+1$ for every DMU z, where z∈J=[1, 2,… n]. The initial two linear programming models are analogous to the CCR model in Eq. (3) to measure the efficiency of: $F_Z\left(x_z y_z\right)$, $\mathrm{F}_z^{t+1}(x_{z,}^{t+1}\mathrm{y}_z^{t+1})$ in a single period. Both models are utilized to capture the phenomenon known as the "catch up effect" or efficiency change (EFFCH), as expressed in the following formula:

$$\text{EFFCH } = F_Z\left(x_z y_z\right)/\mathrm{F}_z^{t+1}(x_{z,}^{t+1}\mathrm{y}_z^{t+1}) \tag{5}$$

The last two models are classified as mixed period measures, and are derived through the utilization of the subsequent linear programming model.

$$\begin{aligned}
&\mathrm{F}_z^t\left(x_{z,}^{t+1}\mathrm{y}_z^{t+1}\right), = max\theta \\
&\text{S.t} \\
&\sum_{j=1}^{n}\left(\lambda_j^t \mathrm{y}_{rj}^t\right) \geq \theta \mathrm{y}_{rz}^{t+1}, \quad r = 1,..,s \\
&\sum_{j=1}^{n}\left(\lambda_j^t \mathrm{x}_{ij}^t\right) \leq \mathrm{x}_{iz}^{t+1}, \quad i = 1,\ldots,m \\
&\lambda_j \geq 0, \quad j = 1,\ldots,n
\end{aligned} \tag{6}$$

In order to ascertain the factors contributing to the change in aggregate technical efficiency, namely scale efficiency change (SECH) and/or pure technical efficiency change (PTECH), the VRS model is calculated by incorporating the constraint $\sum_{j=1}^{n}\left(\lambda_j^t\right) = 1$ in Eq. (6). Subsequently, both mixed period measurements are employed in order to ascertain the technology change impact (TECHCH), as outlined by the subsequent formula:

$$\text{TECHCH } = \mathrm{F}_z^t(x_{z,}^{t+1}\mathrm{y}_z^{t+1})/\mathrm{F}_z^{t+1}(x_{z,}^t\mathrm{y}_z^t), \tag{7}$$

The calculation of the MI for DMU z involves the multiplication of both changes TECHCH and EFFCH. If the value of MI and any of its components is equal to 1, it signifies that there has been no change in productivity. If the value is less than 1, it indicates a decline in productivity, but a value larger than 1 suggests an improvement in productivity from year t to year $t+1$.

Data

According to the World Bank World Development Indicators database, a total of 141 countries received ODA between 2002 and 2020, with a cumulative net ODA of approximately $89 billion. However, there is significant variation among countries in terms of their reliance on development aid. On average, some countries received net ODA that exceeded 20% of their Gross National Income (GNI) during this period. For instance, the Syrian Republic received net ODA equivalent to more than 27% of its GNI, while Tuvalu and Serbia received 47% and 37% of their GNI as net ODA, respectively. In contrast, certain countries received a negligible proportion of their GNI as net ODA. Examples include China (0.01% of GNI), Argentina (0.02%), Brazil (0.03%), and Algeria (0.1%), among others. It is important to note that DEA models are unable to account for unsystematic distortions in the datasets. Consequently, in order to identify a group of countries that consistently receive similar levels of ODA, outliers were identified using boxplots based on

Table 1 Variables used in the DEA model

	Definition	Type	Source
ODA	Net official development assistance consists of disbursements of loans made on concessional terms (net of repayments of principal) with a grant element of at least 25%	Input	https://databank.worldbank.org/source/world-development-indicators
HPC	Current health expenditure per capita, PPP (current international $) (HPC PPP)	Output	https://databank.worldbank.org/source/sustainable-development-goals-(sdgs)
PRG	Pregnant women receiving prenatal care (% of total)	Output	https://databank.worldbank.org/source/sustainable-development-goals-(sdgs)
SCH	School enrollment, primary and secondary (% of girls to boys enrolled), gender parity index	Output	https://databank.worldbank.org/source/sustainable-development-goals-(sdgs)
GDP	GDP per capita, PPP (current international $)		https://databank.worldbank.org/source/world-development-indicators

Table 2 Descriptive statistics of inputs and output variables considered in the DEA analysis. Source: Computed by the Authors

	ODA (million$)	HPC (million$)	PRG (%)	GDP (million$)	SCH (%)
Mean	64.07	396.25	86.58	7138.69	0.95
SD	41.27	351.7	13.4	5382.62	0.1
Median	52.3	296.8	91.67	5974.53	0.99
Max	183.96	1515.57	100	24,529.26	1.13
Min	11.43	28.25	42.8	744.44	0.54
Range	172.53	1487.32	57.2	23,784.82	0.59
Skewness	0.9	1.27	− 1.58	1.05	− 1.46
Kurtosis	3.02	4.05	4.92	3.88	5.23
Jarque–Bera	11.686	26.88	49.26	18.27	48.27
Critical value	0.003	0.000	0.000	0.000	0.000

two criteria: net ODA per capita and the percentage of net ODA to GNI (refer to Fig. 1).

After removing the outliers, the final list of DMUs comprises 86 countries which represents 62% of all countries receiving ODA during the period of study.

Selection of inputs and outputs

The main objective of the paper is to measure the relative efficiency of countries receiving ODA in utilizing this finance in their development pursuits. As suggested by Dyson and others (2001) to uphold the discriminatory power of the DEA model, three primary criteria have been addressed in this paper. Firstly, the identification of appropriate variables for measuring development aid (inputs). Secondly, the identification of significant indicators of development that exhibit a positive correlation with development aid (outputs). Furthermore, adhering to the rule of thumb that the number of DMUs should be at least twice the sum of the inputs and outputs variables, the inputs should be minimized while the outputs should be maximized, and to have a large sample size. ODA per capita is accordingly selected to be the DEA model main input since as indicated by the UNDP, it is a measure of recipient country's dependency on development aid [48].

As previously stated, the primary aim of ODA flows has been to foster development. Mainly, facilitating countries in attaining their MDGs and subsequently the SDGs. In order to identify appropriate outputs, a collection of variables has been gathered from the World Bank SDGs database. The selection was based on the availability and completeness of the time-series data during the specific research period. The inclusion of output variables in DEA models is contingent upon the presence of a positive relationship between the input and output variables. Consequently, the final selection of output variables is limited to those that exhibit a significant positive correlation with ODA per capita.

Table 1 presents a comprehensive compilation of the selected variables, including their respective definitions and sources of data. On the other hand, Table 2 offers a summary of the descriptive statistics.

The Jarque–Bera test results reveal that the data do not follow a normal distribution, as evidenced by the p values ($p < 0.05$) for all variables, leading us to reject the

Table 3 Efficiency scores for the relatively more efficient countries and for income groups using radial and non-radial DEA models. Source: Computed by the Authors

DMUs	BCC OO	BCC IO	CCR OO	CCR IO	SBM VRS	SBM CRS	SE*	Rank
Fiji	1.00	1.00	6.31	0.16	1.00	0.13	0.13	–
Pakistan	1.00	1.00	1.02	0.98	1.00	0.68	0.68	–
Barbados	1.00	1.00	1.94	0.51	1.00	0.44	0.44	–
Colombia	1.00	1.00	1.13	0.88	1.00	0.84	0.84	8
Croatia	1.00	1.00	1.19	0.84	1.00	0.62	0.62	–
Libya	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1
Montenegro	1.00	1.00	4.77	0.21	1.00	0.14	0.14	–
Serbia	1.00	1.00	5.53	0.18	1.00	0.14	0.14	–
South Africa	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2
St. Lucia	1.00	1.00	5.91	0.17	1.00	0.14	0.14	–
Suriname	1.00	1.00	4.48	0.22	1.00	0.20	0.20	–
Ukraine	1.00	1.00	1.30	0.77	1.00	0.72	0.72	10
Dominican Republic	1.00	1.00	1.00	1.00	1.00	1.00	1.00	5
Ecuador	1.00	1.00	1.00	1.00	1.00	1.00	1.00	4
Maldives	1.00	1.00	5.61	0.18	1.00	0.14	0.14	–
Mongolia	1.00	1.00	7.39	0.14	1.00	0.12	0.12	–
Antigua and Barbuda	1.00	1.00	4.08	0.25	1.00	0.20	0.20	–
Uzbekistan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	3
Bangladesh	1.00	1.00	1.00	1.00	1.00	1.00	1.00	6
Paraguay	1.01	0.99	1.08	0.93	0.93	0.89	0.95	7
Egypt, Arab Rep	1.03	0.85	1.19	0.84	0.75	0.75	1.00	9
Azerbaijan	1.04	0.83	1.21	0.83	0.72	0.71	1.00	–
Angola	1.17	0.92	1.20	0.83	0.71	0.61	0.86	–
Honduras	1.00	0.99	4.20	0.24	0.57	0.16	0.28	–
All countries	1.08	0.48	4.15	0.37	0.38	0.27	0.71	–

**SE* Scale efficiency = SBM CRS/ SBM VRS

BCC OO Radial BCC output-oriented model, *BCC IO* Radial BCC input-oriented model, *CCR IO* Radial CCR input-oriented model, *CCR OO* Radial CCR output-oriented model, *SBM VRS* Non-radial non-oriented SBM additive model assuming VRS, *SBM CSR* Non-radial non-oriented SBM additive model assuming CRS

Efficiency scores for all countries are in Appendix

null hypothesis. Normality testing is a crucial component of statistical analysis for making inferences about the data, notwithstanding its importance. Fortunately, this is not the case for DEA models. The virtue of these models lies in their axiomatic, nonparametric treatment of the frontier. In contrast with stochastic analysis, these models attribute all deviation from the frontier solely to inefficiencies, without considering any stochastic noise [27]. As mentioned in Ray ([38], p. 8), DEA models main assumptions are: (I) All observed input–output bundles are feasible, (II) the production possibility set is convex, and (III) inputs and outputs are freely disposable.

Results and discussion

Countries development aid relatives efficiencies

This section presents the analysis of the efficiency scores derived from DEA models, namely the radial input-orientated and output-oriented CCR, BCC, non-radial non-oriented SBM, and SSBM models. Table 3 presents the technical efficiency scores for countries that demonstrated relatively efficient utilization of their ODA in achieving SDGs between 2002 and 2020. The findings suggest that, on average, the overall efficiency of aid in promoting countries' GDP per capita, health care, and education is relatively low. Hence, there is potential for improvement considering the current level of development aid provided. These results align with the findings by Alda and Cuesta [1], as well as that by Hwang et al. [24].

Based on the CCR IO model results as shown in Table 3, the overall estimated ATE score is 0.37, which indicates that same development outcomes could have been achieved with only 37% of the ODA received. Otherwise, countries should have increased their outputs by more than 400% given the existing level of ODA received as evident by the CCR OO model results. Further we investigate, the efficiency of the management process of ODA using the BCC models. As previously noted in case of BCC models, usually there are more efficient countries compared to that

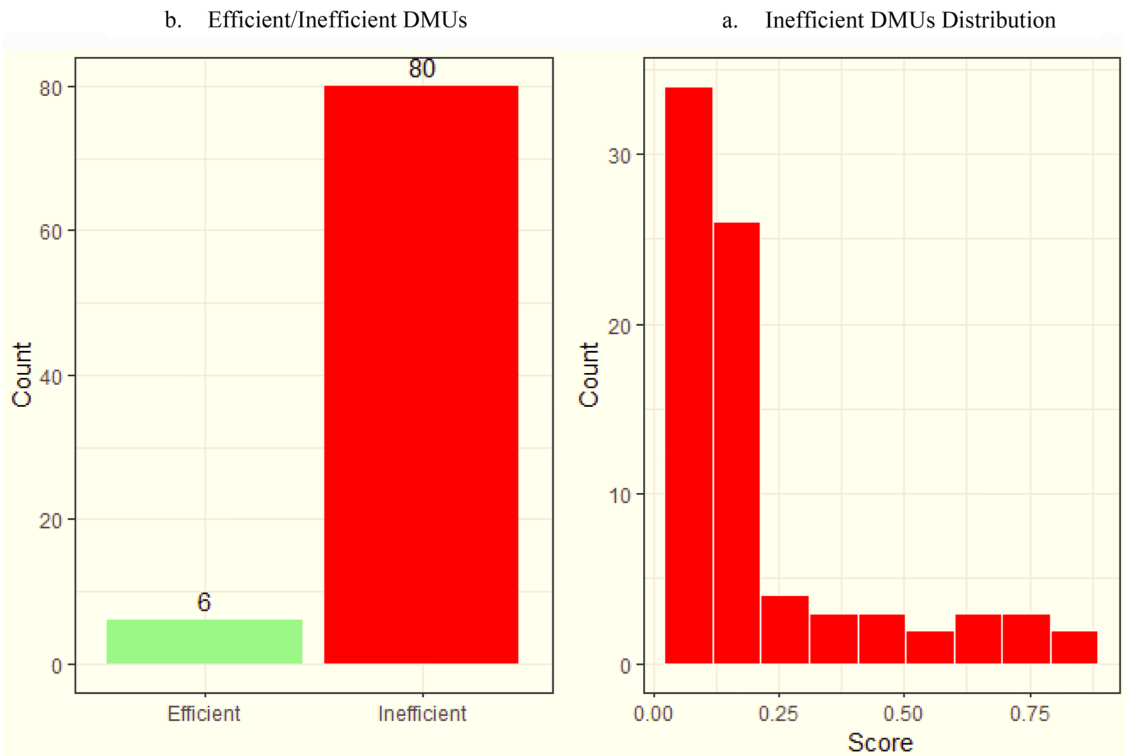


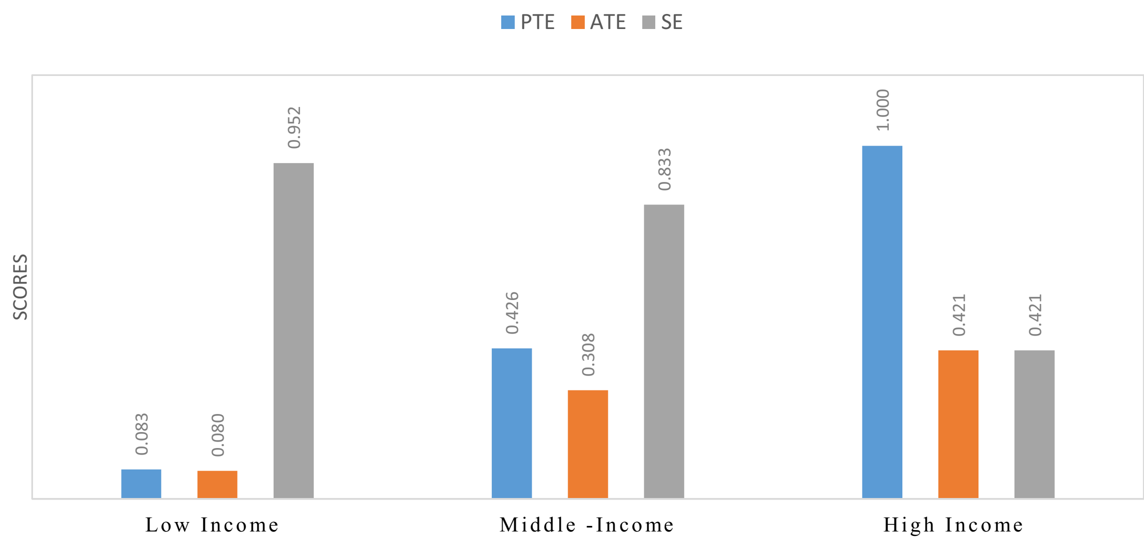
Fig. 2 Efficient and inefficient DMUs distribution according to SBM CCR model. This figure shows on the left the distribution of inefficient countries, showing the majority of inefficient unit with scores < 0.25, where on the right, it shows a display of the numbers of efficient and inefficient units

in the CCR model. The ratio of efficient countries between the two models is 20 to 6. The BBC model results show that same outcomes could have been achieved with 48% of ODA received, or else the outcomes could have been more than doubled if ODA had been efficiently managed. Accordingly, around 83% of aggregate inefficiencies in using ODA is attributed to PTE or to administration and management factors, whereas only 35% is due to scale inefficiencies.

Moreover, the findings underscored the presence of slacks. According to the findings of the SBM CRS and SBM VRS models, the average effectiveness of aid is 0.27 and 0.38, respectively, which is lower than that observed in the CCR model. This suggests that the greater efficiency scores observed in certain countries can be attributed to the presence of surplus outputs and/or inputs, resulting in an overestimation of efficiency scores in radial models. Hence, it can be argued that SBM models offer more precise efficiency ratings. Nevertheless, it is important to acknowledge that similar to the radial model, the main causes of inefficiencies in this case are primarily linked to mismanagement rather than operating scale, accounting for 85% and 38%, respectively.

The distribution of countries' efficiency scores is depicted in the left graph of Fig. 2, as per the results of the SBM CCR model. The right graph of the same figure displays the count of efficient and inefficient countries. There are a total of 86 countries under consideration, classified into two categories based on their efficiency levels. Among these, six countries are categorized as efficient, while the remaining 80 countries are classified as relatively inefficient. Notably, the majority of inefficient countries, specifically 58 countries, have attained efficiency scores below 0.25, indicating a significantly low level of efficiency. Low-income countries are typically classified as relatively inefficient, while a significant number of middle-income countries have been seen to exhibit substantially higher levels of efficiency.

Furthermore, it was shown that certain middle-income countries had greater ATE scores in comparison with high-income countries, contrary to initial expectations. They even represent the top six highly ranked countries as shown in Table 3. The BCC SBM model results provide a more comprehensive understanding when examining the disaggregation of ATE into its primary constituents, PTE and SE, specifically for income countries groups. Figure 3 illustrates the variations between the efficiencies average scores based on income category of countries. In high-income countries, it is seen that the PTE scores are consistently at unity, indicating optimal management of the development aid they get. Furthermore, it is noteworthy



Note: PTE: Pure technical efficiency, ATE: Aggregate Technical efficiency, SE: Scale efficiency

Fig. 3 Technical and scale efficiency according to income countries group (2002–2020). This figure shows the average efficiencies of countries according to their income group using only the results of the SBM CCR models to ensure the inexistence of any input or outputs slacks in the final display of the findings

Table 4 Efficiency scores for income countries groups using radial and non-radial DEA models. Source: Computed by the Authors

DMUs	BCC OO	BCC IO	CCR OO	CCR IO	SBM VRS	SBM CRS	SE*
Low income	1.18	0.26	4.60	0.25	0.08	0.08	0.95
Middle income	1.06	0.51	4.12	0.39	0.43	0.31	0.83
High income	1.00	1.00	2.40	0.53	1.00	0.42	0.42

*SE = SBM CRS/ SBM VRS

BCC OO Radial BCC output-oriented model, *BCC IO* Radial BCC input-oriented model, *CCR IO* Radial CCR input-oriented model, *CCR OO* Radial CCR output-oriented model, *SBM VRS* Non-radial non-oriented SBM additive model assuming VRS, *SBM CSR* Non-radial non-oriented SBM additive model assuming CRS

that all inefficiencies in these countries are solely attributed to scale-related factors. This elucidates the comparatively lower ATE of the aforementioned countries in relation to the middle-income countries that are listed at the top. The countries that have demonstrated a combination of pure technical and aggregate efficiency, along with optimal scale efficiency in utilizing their ODA resources, are Libya, South Africa, Uzbekistan, Ecuador, Dominican Republic, and Bangladesh. This conclusion is drawn from the outcomes of both the radial and non-radial models. According to the findings derived from the non-radial SBM CRS model only, the countries that follow in showcasing the greatest ATE are Paraguay, Colombia, Egypt, and Ukraine.

In low-income countries, Table 4 shows that the mismanagement of development aid accounts for over 99% of their ATE, with SE scores nearing unity. The average PTE scores and ATE scores are 0.083 and 0.080, respectively. On average, middle-income countries exhibit a relatively low PTE score of 0.43. However, their inefficiencies primarily stem from management issues (82%) rather than scale-related challenges (24%). Yet, they demonstrate greater efficiency in utilizing their resources compared to low-income countries. The findings presented in this study align with the findings reported by Alda and Cuesta [1] who observed that the efficiency of humanitarian aid is higher in middle-income countries compared to lower-income countries. Moreover, it provides empirical support for the theoretical framework of foreign aid, which postulates a correlation between aid's impact on a nation's economic development and institutional and economic policies. As duly acknowledged by the World Bank [51], that good management has been a decisive component in the allocation of aid to middle-income countries, particularly from multilateral organizations, in contrast to that allocated to low-income countries.

Table 5 Efficiency scores for the least efficient countries using radial and non-radial DEA models. *Source*: Computed by the Authors

DMUs	BCC OO	BCC IO	CCR OO	CCR IO	SBM VRS	SBM CRS	SE*
South Sudan	1.12	0.09	11.01	0.09	0.03	0.02	0.86
Congo, Dem. Rep	1.13	0.32	3.12	0.32	0.04	0.04	0.91
Niger	1.42	0.26	4.40	0.23	0.05	0.05	0.98
Guinea-Bissau	1.05	0.21	5.21	0.19	0.05	0.05	1.00
Mali	1.38	0.17	6.20	0.16	0.06	0.05	0.95
Haiti	1.08	0.15	6.83	0.15	0.06	0.06	0.93
Burkina Faso	1.14	0.22	4.74	0.21	0.06	0.06	0.96
Eritrea	1.20	0.23	4.38	0.23	0.07	0.06	0.96
Comoros	1.08	0.17	6.24	0.16	0.06	0.06	0.97
Papua New Guinea	1.22	0.20	5.23	0.19	0.07	0.06	0.91
Average	1.18	0.20	5.74	0.19	0.05	0.05	0.94

*SE = SBM CRS/ SBM VRS

BCC OO Radial BCC output-oriented model, *BCC IO* Radial BCC input-oriented model, *CCR IO* Radial CCR input-oriented model, *CCR OO* Radial CCR output-oriented model, *SBM VRS* Non-radial non-oriented SBM additive model assuming VRS, *SBM CSR* Non-radial non-oriented SBM additive model assuming CRS

Table 4 displays the ten countries with the lowest efficiency scores as determined by the SBM CCR model. Among these countries, eight were classified as low income, while the remaining two fell into the lower middle-income category, specifically Comoros and Haiti. As indicated in the results, these countries have to lower, in average terms, 94.6% of the net ODA they use in order to attain the same outcomes if they assign the presently allocated resources in the best feasible way. The average PTE of these countries stands at 5%. Therefore, the inefficiencies observed can be mostly attributable to the mismanagement of the money received in the form of ODA (Table 5).

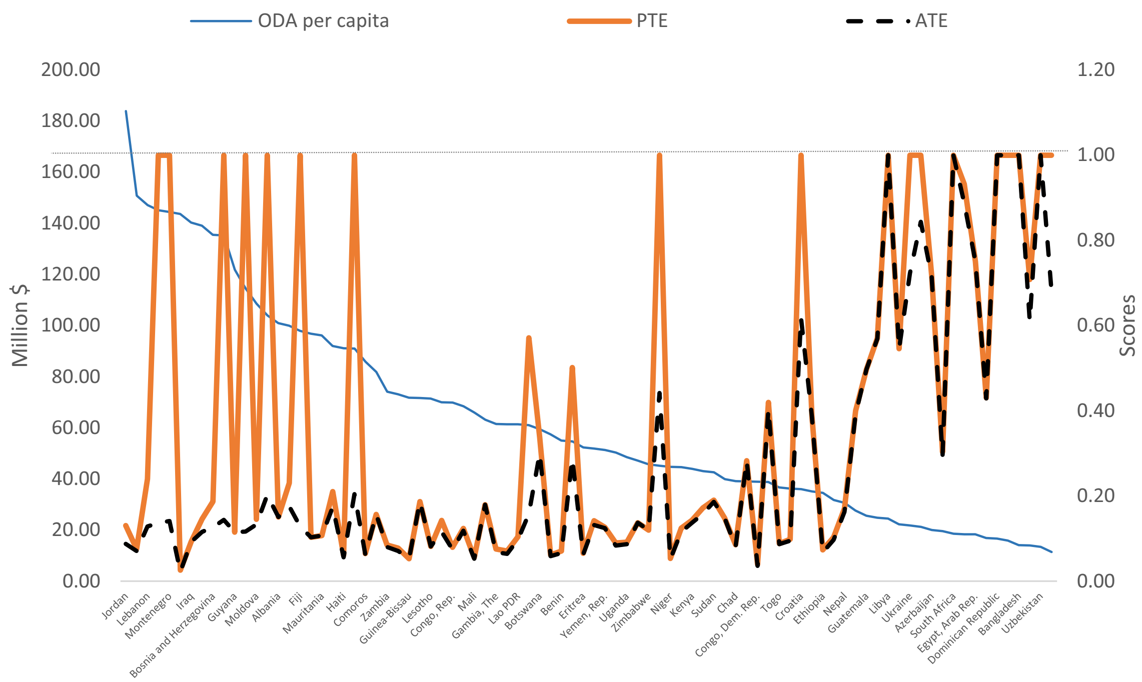
To explore the relation between a country's efficiency scores and the level of ODA received. Figure 4 illustrates a negative correlation between the magnitude of ODA and the scores of both ATE and PTE. The presence of this negative relation has also been demonstrated by the utilization of a Pearson correlation test (refer to Table 6). According to the findings, the negative correlation that was observed between ODA and PTE is weaker. As depicted in Fig. 4, only seven countries were able to attain optimal PTE scores. These countries that fall under the high-income and upper medium-income categories include the Maldives, Montenegro, Serbia, Mongolia, Antigua & Barbuda, Fiji, and Suriname. This suggests that these countries demonstrate a comparatively higher level of efficiency in managing elevated levels of ODA in comparison with other nations. Moreover, this observation provides a rationale for the somewhat larger inefficiencies in the magnitude of these countries when compared to the best-performing countries, which were managing a considerably smaller amount of ODA.

As previously mentioned, DEA models provide for each inefficient DMU a reference set from the efficient DMUs set used as benchmark for these inefficient DMUs. According to this reference set, the inefficient DMU can adjust its inputs or outputs to reach the efficient frontier for achieving optimal results with regard to GDP per capita, education, and health. Figure 5 shows the countries that appear most as benchmarks for inefficient DMUs. South Africa came as reference for 39 countries, Dominican Republic for 31 inefficient countries, Ecuador for 12, Libya for 8, and Uzbekistan for 2 relatively inefficient countries.

Measuring productivity change of using development aid over time

The MI was calculated to measure the temporal change in productivity of using ODA between 2002 and 2020. As previously stated, when the MI index or any of its components have a value below 1, it signifies a decrease in the productivity of the DMU throughout the specified period. Conversely, values exceeding 1 show an enhancement in productivity, while a value of 1 signifies a state of stagnation. The MI for the 86 countries was calculated applying the subsequent linear programming model in Eqs. (6) and (7) using the deaR software package developed by Coll-Serrano et al. [12].

The findings indicate that the average total factor productivity, as influenced by ODA, has exhibited limited fluctuations across all countries from 2002 to 2020. The metric consistently hovers around the level of unity, with its nadir observed in the year 2020, where it attains a score of 0.91. The decrease in production can be primarily attributed to a decrease in technical efficiency (EFFCH) rather than a decrease in technological change



Note: PTE: Pure technical efficiency, ATE: Aggregate Technical efficiency

Fig. 4 Countries ODA per capita and efficiency scores on average (2002–2020). This figure shows the relation between the average level of ODA per capita for each country and their scores of efficiency in utilizing this level of aid as reflected by the aggregate technical efficiency scores (ATE), and their efficiency scores in managing this level of aid as reflected by their pure technical efficiencies (PTE) scores

Table 6 Correlation between ODA and efficiency scores using person test

	ODA	PTE	ATE
ODA	1.00		
PTE	−0.21(0.04) **	1:00	
ATE	−0.57(0.00) *	0.75(0.00) *	1:00

**$p < 0.05$

*$p < 0.01$

(TECHCH), as depicted in Fig. 6. The primary cause of regression in EFFCH can be attributed to variations in scale rather than management. This is evident from the data shown in Table 7, where the PTECH scores remain constant throughout the whole study period.

In high-income countries, the rise in productivity is influenced by both technological change (TECHCH) and efficiency change (EFFCH), as depicted in Fig. 7. In middle-income countries and low-income countries, shifts in productivity are mostly influenced by EFFCH, specifically through alterations in scale rather than management. While there is no universally acknowledged trend in the productivity of development aid from 2002 to 2020, some countries, such as Croatia (1.04), Serbia (1.04), and Eritrea (1.02), had little progress. In contrast, it is noteworthy that 23 countries have successfully sustained their aid use productivity over this timeframe, whereas a majority of 53 out of the total 94 countries experienced a decline in this regard. The countries exhibiting the lowest MI scores were Fiji (0.96), Lebanon (0.96), South Sudan (0.95), Mauritius (0.95), Maldives (0.94), and Montenegro (0.94).

Sensitivity analysis and robustness of the results

For statistical inference, a bootstrap–DEA model is calculated using the deaR package that uses the algorithm proposed by [42] who have first introduced the approach. The primary purpose of bootstrapping is to obtain estimated efficiency scores by performing multiple iterations of sampling, in order to obtain bias-corrected efficiency scores within confidence intervals. The bias-corrected efficiency scores are generated using a specified number of iterations, with B = 2000 representing the maximum number of bootstrap iterations.

According to Song et al. [43], increasing the number of iterations leads to improved accuracy of the results.

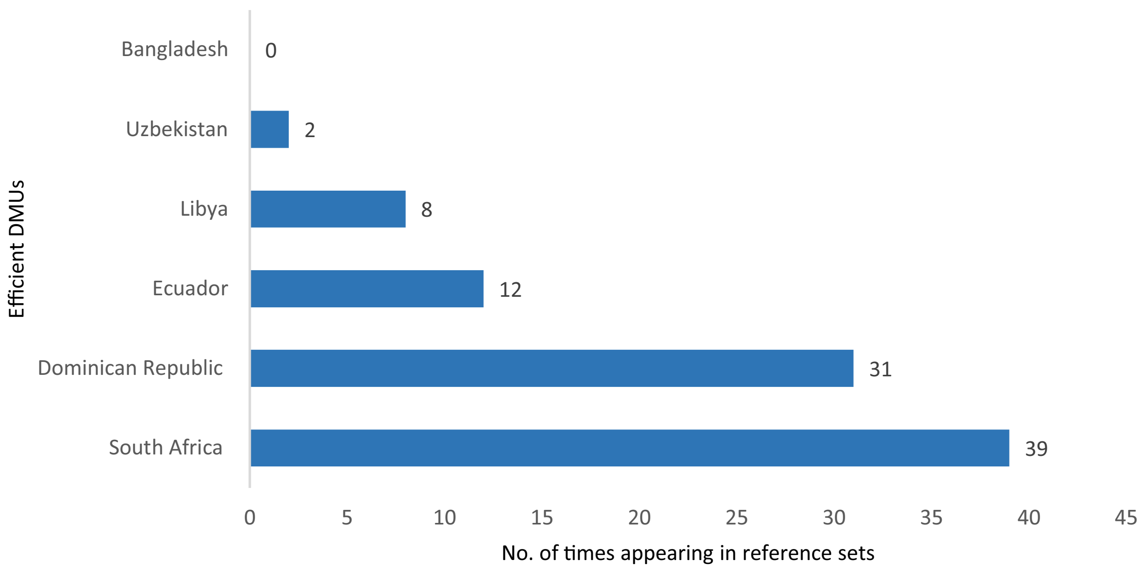


Fig. 5 Inefficient DMUs reference set according to SBM CCR model. This figure shows the set of efficient countries that can be used as reference for the relatively inefficient ones to adjust their inputs and outputs levels to reach efficiency based on the DEA model results

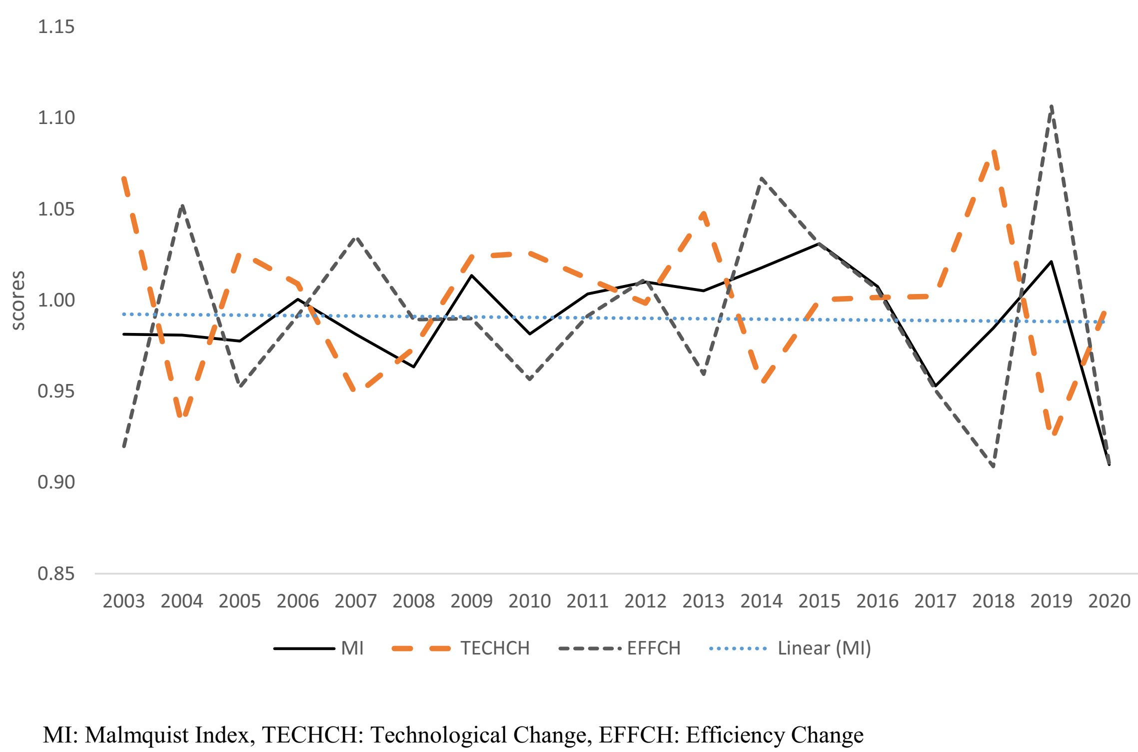


Fig. 6 Malmquist index summary of annual means for all countries (2002–2020). This figure shows the development in the productivity of ODA for all countries combined over the period under study in reaching the main SDG goals. Distinguishing between the development in productivity that is attributed to changes in technology (TECHCH) and that due to changes in efficiency levels (EFFCH)

Additionally, wider confidence intervals are associated with higher levels of confidence. The bootstrap model employed in this study utilizes the maximum number of iterations, while maintaining a confidence level of $\alpha=0.05$, which is identified ahead in the commands of the deaR model. The data depicted in Fig. 8 illustrate that there is a minimal

Table 7 Malmquist index summary of annual means for all countries 2002–2020. Source: Computed by the Authors

Period	MI	TECHCH	EFFCH	PTECH	SECH
2003	0.98	1.07	1.05	1.00	0.92
2004	0.98	0.93	0.91	1.00	1.05
2005	0.98	1.03	1.00	1.00	0.95
2006	1.00	1.01	1.01	1.00	0.99
2007	0.98	0.95	0.93	1.00	1.03
2008	0.96	0.97	0.94	1.00	0.99
2009	1.01	1.02	1.04	1.00	0.99
2010	0.98	1.03	1.01	1.00	0.96
2011	1.00	1.01	1.02	1.00	0.99
2012	1.01	1.00	1.01	1.00	1.01
2013	1.01	1.05	1.05	1.00	0.96
2014	1.02	0.95	0.97	1.00	1.07
2015	1.03	1.00	1.03	1.00	1.03
2016	1.01	1.00	1.01	1.00	1.01
2017	0.95	1.00	0.96	1.00	0.95
2018	0.98	1.08	1.07	1.00	0.91
2019	1.02	0.92	0.94	1.00	1.11
2020	0.91	1.00	0.91	1.00	0.91

MITECHCH Technological Chang, *EFFCH* Efficiency change, *PTECH* Pure technical efficiency change, *SECH* Scale efficiency change

discrepancy between the corrected efficiency values and the DEA efficiency values. The maximum departure observed is 0.07, while the minimum deviation is 0.01.

In addition, tendencies are similar with deviation, where higher deviation corresponds with wider gap between the bootstrap and DEA efficiency estimates. Further low level of deviation ensures the consistency of the DEA efficiency model estimates, as the greater the deviation, the worse is the accuracy of the estimates. Figure 9 illustrates that the efficiency estimates obtained by DEA analysis fall within the confidence intervals, with a proximity to the lower bound. This observation suggests that the efficiency estimates are both consistent and unbiased.

Conclusion

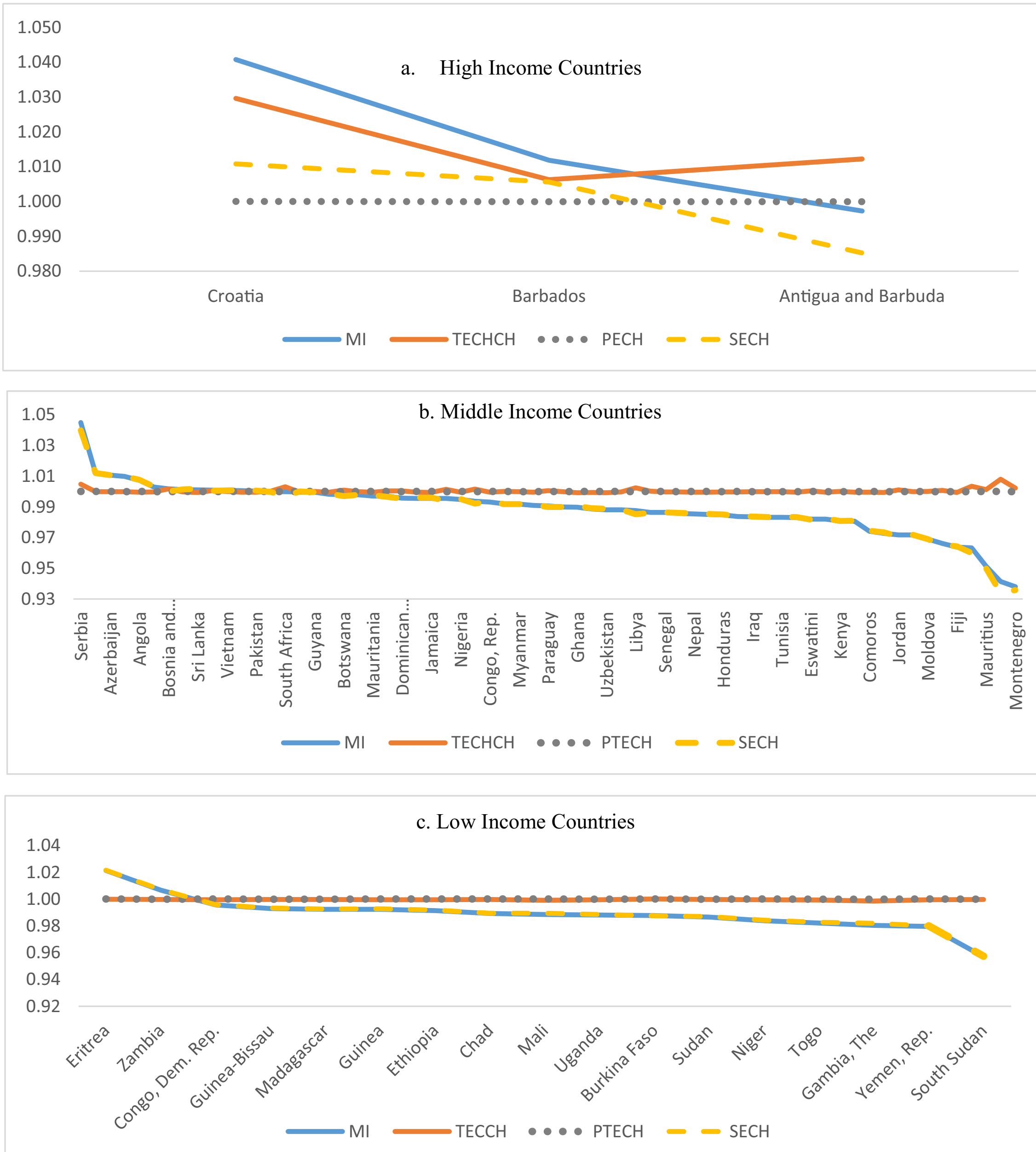
The current body of scholarship on development aid has not yet arrived at a definitive consensus regarding its impact on on-the-ground development. This study utilized a DEA methodology to assess the efficiency of using development aid allocation in relation to three primary SDGs: good health and well-being, quality education, and decent and economic growth. During the period from 2002 to 2020, both radial and non-radial DEA models have been utilized to assess the relative efficiencies of 86 countries that received net ODA. These models were employed to identify the top performers among these countries and to measure the changes in relative productivity resulting from the utilization of aid over the course of the study period.

The findings indicate that there exists a remarkable potential for enhancing developmental outcomes, considering the existing level of ODA received by recipient countries. This can be accomplished by making adjustments to the administrative procedures governing these inflows. The primary factor contributing to the subpar performance and inefficiency of ODA in relation to the three specified SDGs was identified as inadequate management practices. The middle-income countries group had superior performance in utilizing their development aid, exhibiting both pure technical efficiency and scale efficiency, hence achieving Pareto efficiency in development aid utilization. In general, it was seen that middle-income countries showed a higher level of efficiency in the management of their ODA in comparison with low-income countries. Additionally, middle-income countries exhibited greater scale efficiency when compared to high-income countries; however, they manage smaller amounts of ODA per capita. The preceding findings validate the central premise of the study, which posits that countries with higher income demonstrate relatively greater efficiency in the management of their ODA in comparison with those with lesser income. However, the attainment of Pareto efficiency in aid utilization is limited to only six middle-income countries, which are considered the top performers.

The productivity of development aid appeared to exhibit a consistent level of stability over the course of time. However, minor alterations have been seen. The changes observed in high-income countries are commonly attributed to advancements in technology and improvements in scale efficiency. In contrast, variances in middle- and low-income countries are primarily attributed to differences in scale efficiency alone. There is no observed correlation between improvements in aid management and changes in productivity.

While the findings suggest that the management of development aid is suboptimal, particularly in low-income countries, it is important to note that this does not imply a reduction in the allocation of ODA to these nations, given their heightened vulnerability. Contrarily, these findings underscore the significance of enhancing the management framework of development aid, in conjunction with endeavors to generate additional financial resources to fulfill the SDGs by 2030. There is a need to thoroughly reconsider the entirety of the aid system to enhance its accountability and effectively demonstrate that the allocated resources are being efficiently utilized to enhance the quality of life for individuals in developing nations.

This objective can be accomplished by: (1) Allocating development aid at first to enhance the governance



MI: Malmquist Index, TECHCH: Technological Change, EFFCH: Efficiency Change, PTECH: Pure Technical Efficiency Change, SECH: Scale Efficiency Change

Fig. 7 Malmquist index summary of annual means for countries income groups (2002–2020). This figure shows the development in the productivity of ODA for according to countries income groups over the period under study in reaching the main SDG goals. Distinguishing between the development in productivity that is attributed to changes in technology (TECHCH) and that due to changes in efficiency; in management (PTECH) and/or in scale efficiency (SECH)

structure in the recipient countries, a comprehensive analysis of aid governance structure inside the more efficient performers can help in this regard, (2) the implementation of results-based management schemes to facilitate organizational modifications, and (3) the establishment of a unified data platform for tracking aid usage in investments toward achieving SDGs across all countries' reporting systems.

Like any other methodology, DEA also has its own limitations. The method employed is considered relative, so it may not yield sufficient data to determine whether the model's identification of the most efficient DMU is valid in absolute

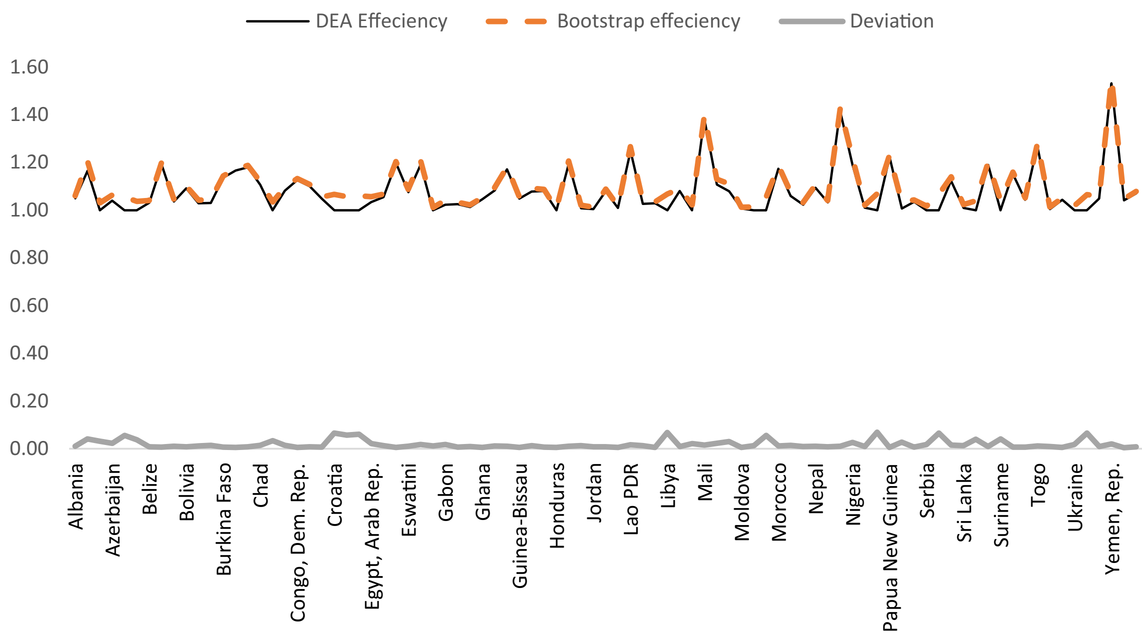


Fig. 8 Countries ODA efficiency scores and estimation bias. This figure shows a minimal gap between the efficiency scores estimated by the DEA model and that estimated by the bootstrap model corrected efficiency values at confidence level of $\alpha = 0.05$

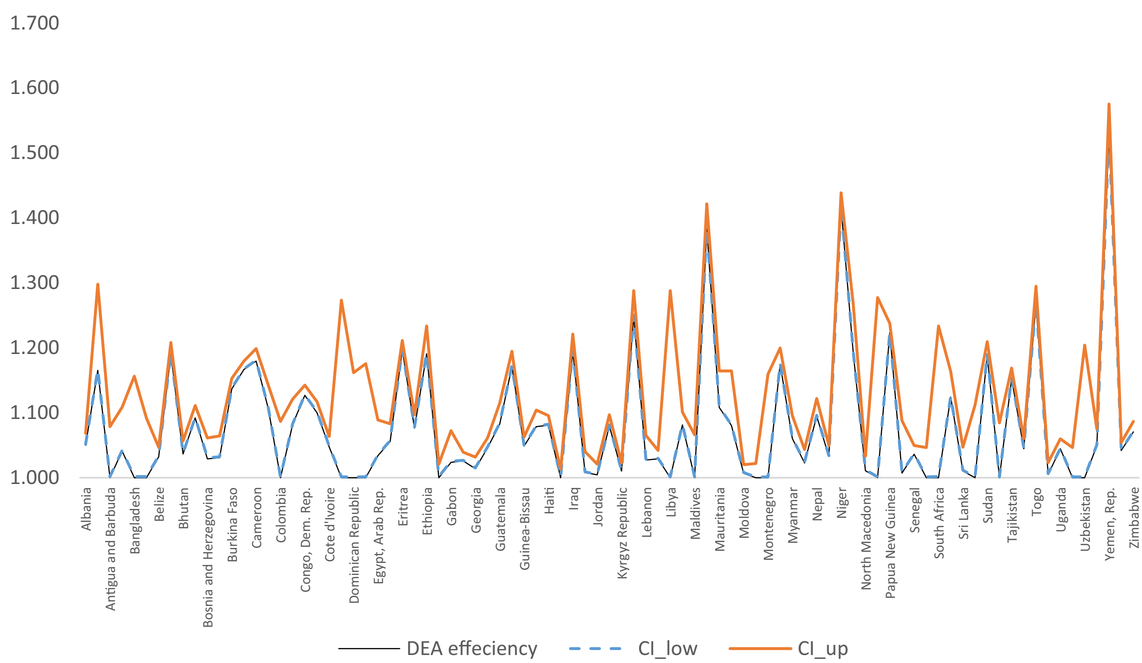


Fig. 9 Countries DEA efficiency scores and bootstrap confidence intervals. This figure shows the efficiency scores estimated by the DEA model that falls in between the upper and lower confidence bounds ensuring DEA model estimates consistency and unbiasedness

terms [44]. The methodology is a comparative approach that is specifically utilized for assessing the efficiency of a certain group of countries. Hence, any modifications made to the countries or variables involved would yield diverse results. The application of this approach exhibits substantial promise in evaluating the efficiency of resources, namely in the assessment of the efficacy of development aid at both the micro project and sectoral scales. This area of investigation presents an intriguing avenue for further research.

Appendix

See Table 8.

Table 8 The list of all countries and their efficiency scores source: Computed by the Authors

Country name	PTE	ATE	SE
Albania	0.15	0.15	1.00
Angola	0.71	0.61	0.86
Antigua and Barbuda	1.00	0.20	0.20
Azerbaijan	0.72	0.72	1.00
Bangladesh	1.00	1.00	1.00
Barbados	1.00	0.44	0.44
Belize	0.16	0.16	1.00
Benin	0.07	0.07	0.93
Bhutan	0.08	0.07	0.94
Bolivia	0.18	0.18	1.00
Bosnia and Herzegovina	0.19	0.13	0.68
Botswana	0.34	0.30	0.89
Burkina Faso	0.06	0.06	0.96
Cambodia	0.14	0.14	1.00
Cameroon	0.12	0.12	0.93
Chad	0.09	0.08	0.94
Colombia	1.00	0.84	0.84
Comoros	0.06	0.06	0.97
Congo, Dem. Rep	0.04	0.04	0.91
Congo, Rep	0.08	0.07	0.93
Cote d'Ivoire	0.17	0.16	0.92
Croatia	1.00	0.62	0.62
Dominican Republic	1.00	1.00	1.00
Ecuador	1.00	1.00	1.00
Egypt, Arab Rep	0.75	0.75	1.00
El Salvador	0.39	0.39	1.00
Eritrea	0.07	0.06	0.96
Eswatini	0.19	0.19	1.00
Ethiopia	0.07	0.07	0.92
Fiji	1.00	0.13	0.13
Gabon	0.42	0.40	0.96
Gambia, The	0.08	0.07	0.90
Georgia	0.15	0.12	0.79
Ghana	0.14	0.13	0.93
Guatemala	0.50	0.50	1.00
Guinea	0.10	0.10	0.96
Guinea-Bissau	0.05	0.05	1.00
Guyana	0.12	0.12	1.00
Haiti	0.06	0.06	0.93
Honduras	0.57	0.16	0.28
Iraq	0.09	0.09	1.00
Jamaica	0.57	0.57	1.00
Jordan	0.13	0.09	0.67
Kenya	0.14	0.14	0.96
Kyrgyz Republic	0.12	0.12	0.96
Lao PDR	0.10	0.10	0.93
Lebanon	0.24	0.13	0.54
Lesotho	0.08	0.08	1.00
Libya	1.00	1.00	1.00
Madagascar	0.10	0.10	0.94
Maldives	1.00	0.14	0.14
Mali	0.06	0.05	0.95
Mauritania	0.11	0.11	1.00
Mauritius	0.14	0.12	0.81
Moldova	0.15	0.13	0.92
Mongolia	1.00	0.12	0.12
Montenegro	1.00	0.14	0.14
Morocco	0.28	0.28	1.00
Myanmar	0.30	0.29	0.97
Namibia	0.21	0.17	0.83
Nepal	0.17	0.16	0.95
Nicaragua	0.10	0.10	1.00
Niger	0.05	0.05	0.98
Nigeria	0.43	0.43	1.00
North Macedonia	0.23	0.18	0.76
Pakistan	1.00	0.68	0.68
Papua New Guinea	0.07	0.06	0.91
Paraguay	0.93	0.89	0.95
Senegal	0.08	0.07	0.92
Serbia	1.00	0.14	0.14
South Africa	1.00	1.00	1.00
South Sudan	0.03	0.02	0.86
Sri Lanka	0.55	0.54	1.00
Sudan	0.19	0.19	0.98
Suriname	1.00	0.20	0.20
Tajikistan	0.15	0.15	1.00
Tanzania	0.09	0.08	0.93
Togo	0.09	0.09	0.99
Tunisia	0.50	0.29	0.57
Uganda	0.09	0.09	0.95
Ukraine	1.00	0.72	0.72
Uzbekistan	1.00	1.00	1.00
Vietnam	0.40	0.39	0.98
Yemen, Rep	0.13	0.12	0.99
Zambia	0.08	0.08	0.95
Zimbabwe	0.12	0.12	1.00

Abbreviations

ATE	Aggregate technical efficiency
CRS	Constant returns to scale
DAC	Development assistance committee
DEA	Data envelopment analysis
DMU	Decision-making unit
EFFCH	Efficiency change
IO	Input-oriented
MDGs	Millennium development goals
MI	Malmquist productivity index
OECD	Organization for Economic Cooperation and Development
ODA	Official development assistance
OO	Output-oriented

PTE Pure technical efficiency
PTECH Pure technical efficiency change
SBM Slack-based model
SBBM Super slack-based model
SE Scale efficiency
SECH Scale efficiency change
TECHCH Technological change
VRS Variable returns to scale

Acknowledgements
We thank the anonymous reviewers for their valuable comments and suggestions, which helped improve the quality of this work.

Author contributions
Authors confirm contributions to the paper as follows: Both first and third authors contributed together in the study's conceptualization, design, and methodological framework, while implementation and computations are conducted by the third author under the guidance and supervision of the second author. The paper has been reviewed and accepted by all authors.

Funding
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This article does not contain any studies with human participants performed by any of the authors.

Informed consent
This article does not contain any studies with human participants performed by any authors.

Consent for publication
This article does not contain any individual person's data in any form.

Competing interests
The authors declare that they have no competing interests.

Received: 23 December 2023 Accepted: 21 March 2024
Published online: 12 April 2024

References

1. Alda E, Cuesta J (2019) Measuring the efficiency of humanitarian aid. Econ Lett 183:108618. https://doi.org/10.1016/j.econlet.2019.108618
2. Arndt C, Jones S, Tarp F (2015) Assessing foreign aid's long-run contribution to growth and development. World Dev Aid Polic Macroecon Manag Aid 69:6–18. https://doi.org/10.1016/j.worlddev.2013.12.016
3. Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci 30:1078–1092
4. Birdsall N, Kharas H (2014) The quality of official development assistance (QuODA) 3rd ed. https://www.cgdev.org/sites/default/files/QUODA_final_revised_september.pdf
5. Bowlin WF (1998) Measuring performance: an introduction to data envelopment analysis (DEA). J Cost Anal 15:3–27. https://doi.org/10.1080/08823871.1998.10462318
6. Burnside C, Dollar D (2004) Aid, policies, and growth: reply. Am Econ Rev 94(3):781–784. https://doi.org/10.1257/0002828041464524
7. Camanho AS, Silva MC, Piran FS, Lacerda DP (2023) A literature review of economic efficiency assessments using data envelopment analysis. Eur J Oper Res. https://doi.org/10.1016/j.ejor.2023.07.027
8. Carbonnier G (2010) Official development assistance once more under fire from critics. International Development Policy | Revue internationale de politique de développement 137–142. https://doi.org/10.4000/poldev.141
9. Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444. https://doi.org/10.1016/0377-2217(78)90138-8
10. Coelli T, Prasada Rao DS, O'Donnell CJ, Battese GE (2005) An Introduction to Efficiency and Productivity Analysis 2 Springer New York city. https://doi.org/10.1007/b136381
11. Paul C, Dollar D (2002) Aid allocation and poverty reduction. Eur Econ Rev 46(8):1475–1500. https://doi.org/10.1016/S0014-2921(01)00187-8
12. Coll-Serrano V, Rafael Benítez, Vicente J Bolós (2018) DeaR. Available at: https://www.uv.es/dearshiny/Tutoriales_deaR/Tutorial_deaR_english.pdf
13. Cooper W, Park KS, Pastor JT (1999) RAM: a range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. J Prod Anal 11:5–42. https://doi.org/10.1023/A:1007701304281
14. William C, Seiford LM, Tone K (2007) Data envelopment analysis: a comprehensive text with models, applications, references and DEA-Solver software. Springer New York, NY. https://doi.org/10.1007/978-0-387-45283-8
15. Diewert W, Caves D, Christensen L (1982) The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica 50(6):1393–1414. https://doi.org/10.2307/1913388
16. Dyson RG, Allen R, Camanho AS, Podinovski VV, Sarrico CS, Shale EA (2001) Pitfalls and protocols in DEA. Eur J Oper Ris, Elsev 1322:245–259. https://doi.org/10.1016/S0377-2217(00)00149-1
17. Farantos GI (2015) The data envelopment analysis method and the influence of a phenomenon in organizational efficiency: a literature review and the data envelopment contrast analysis new application. J Data Envel Anal Decision Sci 15(2):101:117
18. Fare R, Grosskopf S (1992) Malmquist productivity indexes and fisher ideal indexes. Econ J 102(410)158–160. https://doi.org/10.2307/2234861
19. Fare R, Grosskopf S, Norris M, Zhang Z (1994) Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 84(1)66:83
20. Farrell MJ (1957) The Measurement of Productive Efficiency. J Royal Stat Soci: Series A (General):120(3):253–281. https://doi.org/10.2307/2343100
21. Mavrotas G (2009) Introduction: development aid—theory, policies, and performance. Rev Dev Econ 13(3):373–381. https://doi.org/10.1111/j.1467-9361.2009.00495.x
22. Guillaumont P, Wagner L (2014) Aid effectiveness for poverty reduction: lessons from cross-country analyses, with a special focus on vulnerable countries. Revue d'economie du developpement 22:217–261
23. Hansen H, Tarp F (2001) Aid and growth regressions. J Dev Econ 64(2):547–570. https://doi.org/10.1016/S0304-3878(00)00150-4
24. Hwang YG, Park S, Kim D (2018) Efficiency analysis of official development assistance provided by Korea. Sustainability 10(8):2697. https://doi.org/10.3390/su10082697
25. Ishnazarov D, Cevik N (2017) Aid effectiveness in OIC member countries: beyond economics indicators. IJEMA 25(2):315–336
26. Jakupec V, Kelly M (2016) Official development assistance and impact assessment – theoretical and practical frameworks. in: Assessing the Impact of Foreign Aid. Elsevier, pp: 1–16. https://doi.org/10.1016/B978-0-12-803660-0.00001-5
27. Kuosmanen T, Kortelainen M (2012) Stochastic non-smooth envelopment of data: semi-parametric frontier estimation subject to shape constraints. J Prod Anal 38:11–28. https://doi.org/10.1007/s11123-010-0201-3
28. Martin-Perez V, Martin-Cruz N (2017) Efficiency of international cooperation schemata in African countries: a comparative analysis using a data envelopment analysis approach. South Afr J Econ Manag Sci 20(1):1–13. https://doi.org/10.4102/sajems.v20i1.1401
29. Menard A, Weill L (2014) Is Aid efficient? Revue d'economie politique 124:613–624
30. Mohammadi A, Ranaei H (2011) The application of DEA based Malmquist productivity index in organizational performance analysis. Int Res J Financ Econ 62(6)68–76

31. Mohieldin M, Hamzah D (2022) Islamic finance in OIC countries and sustainability. TDM 19
32. OECD (2021) Applying evaluation criteria thoughtfully. OECD Publishing, Paris. https://doi.org/10.1787/543e84ed-en
33. OECD (2023) Development co-operation report 2023: Debating the Aid System. OECD, Development Co-operation Report. https://doi.org/10.1787/f6edc3c2-en
34. OECD (2022) Global outlook on financing for sustainable development 2023: No Sustainability
35. Prydz Espen (2023) Development assistance as a catalyst for progress. In: Pirlea AF, Serajuddin U, Thudt A, Wadhwa D, Welch M (eds) Atlas of Sustainable Development Goals 2023. World Bank, Washington, DC. License: Creative Commons Attribution CC BY 3.0 IGO. https://doi.org/10.60616/jngp-ay55
36. Ram R (2003) Roles of bilateral and multilateral aid in economic growth of developing countries. Kyklos 56(1):95–110. https://doi.org/10.1111/1467-6435.00211
37. Ray SC (2004) Data envelopment analysis: theory and techniques for economics and operations research. Cambridge University Press, Cambridge
38. Ray SC (2020) Data envelopment analysis: a nonparametric method of production analysis. In: Ray SC, R Chambers R, S Kumbhakar S (eds) Handbook of production economics. Springer Singapore, pp 1–62. https://doi.org/10.1007/978-981-10-3450-3_24-1
39. Sahoo BK, Acharya D (2012) Constructing macroeconomic performance index of Indian states using DEA. J Econ Stud 39(1):63–83. https://doi.org/10.1108/01443581211192116
40. Sembene D (2018) Chapter 14. Governance, institutions, and emergence. In: Race to the Next Income Frontier. International Monetary Fund
41. Shleifer A (2009) The age of milton friedman. J Econ Literat 47(1):123–135. https://doi.org/10.1257/jel.47.1.123
42. Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manage Sci 44(1):12–30. https://doi.org/10.1287/mnsc.44.1.49
43. Song ML, Zhang LL, Liu W, Fisher R (2013) Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data. Appl Energy 112:1049–1055. https://doi.org/10.1016/j.apenergy.2013.02.064
44. Sotiroski K, Kovacs P, Aleksandra M, Sedlak O, Lakić V, Radovanov B (2023) Assessing sustainable economic development efficiency: a DEA approach. Strat Manag - Int J Strat Manag Decision Support Syst Strat Manag. https://doi.org/10.5937/StraMan2300039S
45. Tone K (2011) Slacks-based measure of efficiency. In: Cooper WW, Seiford LM, Zhu J (eds) Handbook on data envelopment analysis. International series in operations research and management science Springer Boston, MA, p 195–209. https://doi.org/10.1007/978-1-4419-6151-8_8
46. Tone K (2002) A slacks-based measure of super-efficiency in data envelopment analysis. Eur J Oper Res 143(1):32–41. https://doi.org/10.1016/S0377-2217(01)00324-1
47. Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. Eur J Oper Res 130(3):498–509. https://doi.org/10.1016/S0377-2217(99)00407-5
48. UNDP (2011) Official development assistance. In: Towards human resilience: sustaining MDG progress in an age of economic uncertainty. United Nations Development Programme, New York, USA, p 144–183
49. UN (2015) Addis Ababa Action Agenda, In: The final text of the outcome document Adopted at the Third International conference on financing for development. Presented at the Third International Conference on Financing for Development, United Nations, Addis Ababa, Ethiopia, 13–16 July
50. Veiderpass A, Andersson P (2007) Foreign Aid, Economic Growth and Efficiency Development. Swedish Agency for Development Evaluation, (SADEV) Reports 1
51. World Bank Ed. (1998) Assessing aid: what works, what doesn't, and why, A World Bank policy research report. Oxford University Press, Washington, DC
52. Wu PC, Huang TH, Pan SC (2014) Country performance evaluation: the DEA model approach. Soc Indic Res 118:835–849

Publisher's Note